Uncovering and Addressing Blink-Related Challenges in Using Eye Tracking for Interactive Systems

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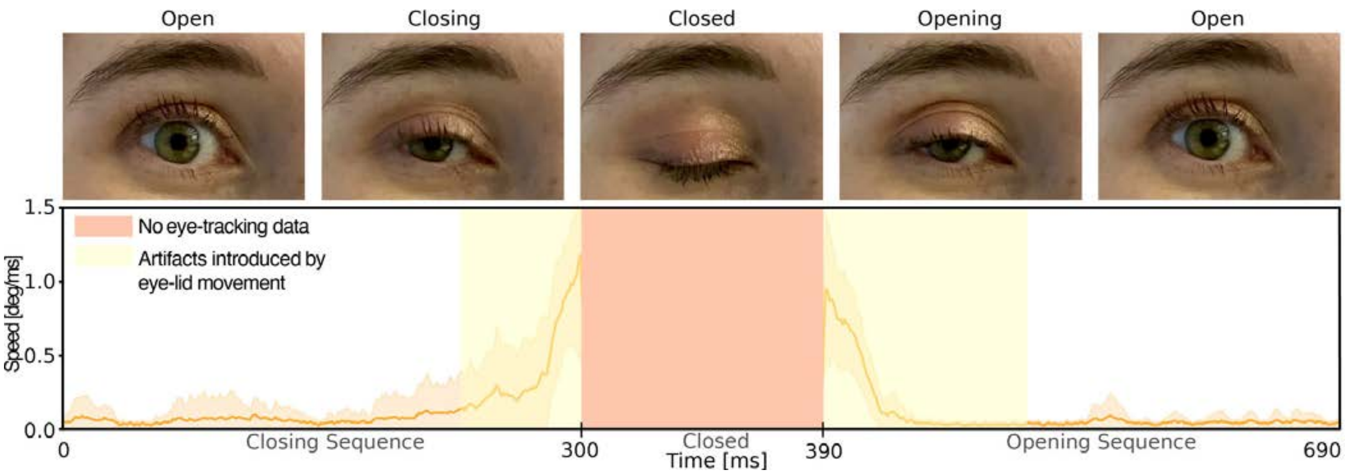

Figure 1: Raw eye movement speed before and after a blink with a gap of 90 ms where the eye tracker cannot obtain data. Highlighted in yellow are the areas before and after a blink that contain artifacts introduced by eyelid movements.

ABSTRACT

Currently, interactive systems use physiological sensing to enable advanced functionalities. While eye tracking is a promising means to understand the user, eye tracking data inherently suffers from missing data due to blinks, which may result in reduced system performance. We conducted a literature review to understand how researchers deal with this issue. We uncovered that researchers often implemented their use-case-specific pipeline to overcome the issue, ranging from ignoring missing data to artificial interpolation. With these first insights, we run a large-scale analysis on 11 publicly available datasets to understand the impact of the various approaches on data quality and accuracy. By this, we highlight the pitfalls in data processing and which methods work best. Based on our results, we provide guidelines for handling eye tracking data for interactive systems. Further, we propose a standard data processing pipeline that allows researchers and practitioners to pre-process and standardize their data efficiently.

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CCS CONCEPTS

• **Human-centered computing** → *Human computer interaction (HCI).*

KEYWORDS

human computer interaction, eye tracking, blinks, interactive systems

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1 INTRODUCTION

Nowadays, eye tracking is a major additional input channel for multi-model interactions [54, 121, 197]. On the other hand, optical and infrared eye tracking data suffer from data loss. This data loss happens when the eye tracker cannot estimate the pupil direction from the image of the eye, as occurs at a high frequency due to human blinks, see Figure 1. However, both traditional methods of understanding user behaviors and prediction models (e.g., intent prediction) struggle with missing data and require additional pre-processing steps to handle this. Subsequently, we see diverse blink detection methods and how to account for the gaps in the input data stream. Grootjen et al. [68] recently demonstrated a lack of standardized processes to overcome the challenges raised by eye blinks. The lack of standardized approaches for data processing presents a significant challenge to the reproducibility and comparability of results across different studies. Ignoring input affected by missing data in interactive systems is one approach commonly used. However, this introduces an input lag and unexpected jumps and jitters in the input stream, reducing the usability of systems drastically [124, 126]. Moreover, processing and predicting interactions using machine learning (e.g., using RNN and LSTM) is becoming more common; however, they typically require a consistent data input stream without gaps in the data. Therefore, we currently have no understanding of how removing or infilling data might impact real-world applicability and, thus, usability.

Various interactive systems make use of eye tracking for system enhancement, e.g., direct manipulation [121, 157], action prediction [214], and gestures [48, 216]. Lately, such systems used neural networks to improve on traditional feature extraction approaches, e.g., [4, 214]. However, neural networks cannot easily handle missing information as it occurs during a blink. Therefore, the most prominent way of dealing with missing data from the eye tracker is to remove the data containing blinks, e.g., [52, 69, 204]. Other studies have attempted to fill in the missing information, e.g., Stein et al. [184]. These systems employed use-case-specific and device-specific approaches. However, reproducibility and generalizability were not a concern; thus, they did not evaluate the impact of fine-tuning, e.g., the impact of the specific parameters for the infilling method. Additionally, blinks introduce artifacts into the remaining eye tracking data [2, 39, 53], see Figure 1. However, it is uncommon for current systems to address these artifacts; thus, systems generally ignore the input. It is therefore crucial to establish a comprehensive and consistent approach to pre-processing eye tracking data to ensure the reliability and validity of interactive systems using eye tracking.

Evaluating these different infilling methods on a large-scale dataset will bring an understanding of potential generalization issues and allow us to formalize recommendations to overcome them. Therefore, future researchers will know how to apply these methods to enable online processing and prediction in interactive systems effectively. Thus, we reviewed all scientific publications of eye tracking studies until the end of 2022 and how they deal with missing data from the ACM digital library and IEEE, inspired by the PRISMA method [145]. Here, we contribute an overview of common approaches to identifying blinks and processes to deal with the missing data. Based on these insights, we perform experiments to understand how today's approaches affect data quality. We used 11 open-source eye tracking datasets for our experiments in order to foster high rigor and external validity. First, we analyze the eye tracking datasets concerning potential data loss that occurs through blinks. Second, we analyze artifacts before and after gaps in the input stream as part of the blink sequence and use this to motivate additional data to be cut off. With these findings, we introduce artificial blinks into the datasets by varying the amount of missing data and window sizes for the different eye tracker frequencies. This allowed us to compare different infilling methods against each other.

In our literature survey ($N = 140$), we found that 42.9% had shortcomings in the reporting, e.g., missed reporting about data handling, lacked important reporting, or acknowledged the presence of missing data but did not include any further details or removed blinks, and 11.4% simply removed the samples affect by gaps. Finally, 45.7% of the literature surveyed explained ways to deal with the missing data, including interpolation and imputation methods. This highlights the need for standardization in processing eye tracking data for interactive systems. We show that there is a big spread in blink frequency from different datasets, which is in line with existing literature. When not processing samples containing missing data, we show that the combination of blink frequency and window size heavily influences the amount of usable data. We highlight the presence of artifacts introduced by eyelid movements surrounding missing data, which are not addressed in the majority of the reviewed literature. We show that these artifacts from eyelid movements can influence 70 ms of data proceeding and 118 ms following a "closed eye" and that these should be removed. Based on existing literature and our findings, we explore different infilling methods and propose a pipeline that standardizes pre-processing eye tracking data to deal with blinks and allows the resulting data to be used in interactive systems.

2 RELATED WORK

First, we provide a short overview of the reasons for blinks and how blinks are used in interactive systems for human-computer interaction (HCI). Next, we provide insight into different ways of blink detection. For the final part of our related work, we provide more use-cases for eye tracking in interactive systems.

2.1 Reasons for Blinks

A blink is defined as "a temporary closure of both eyes, involving movements of the upper and lower eyelids" [26]. One blink lasts roughly one-third of a second and human adults blink approximately 12 times per minute [56]. This natural eye motion is responsible for regularly replenishing the precorneal tear-film and protecting the eye from drying out. However, there is a variety of factors impacting the frequency of blinks outside of this responsibility, including but not limited to the presence of air pollutants [185], contact lenses [40], monitors [151], time of day [185], mental workload [31, 196, 198, 208], age [185], psychoticism [41], and individual differences [47].

While eyelid movements introduce a profound and transient modification in the position of the eyes, various human-computer interaction (HCI) studies use blink data in interactive systems such as driver fatigue detection [22, 73], lie detection [114, 128], detection of mild cognitive impairment [110], anti-face spoofing [63, 72, 148], and human-computer interfaces [3] among many others. However, the frequency of blinks is influenced by many factors, which can heavily impact the accuracy of these interactive systems.

2.2 Blink Detector

Many different methods have been developed for detecting blinks. Although the output is binary, i.e., either eye open or eye closed, we can divide the blink detection methods into a series of categories according to requirements. These methods can be intrusive, e.g., EOG [146], Doppler sensor [189], or glasses with special close-up cameras observing the eye [58]. However, many modern systems rely on non-intrusive methods that use a camera with or without illuminators. In the following, we highlight two blink detection approaches that can be used in interactive systems.

2.2.1 Built-In Blink Detector. The EyeLink 1000 parser[1] (SR Research Ltd., Ottawa, ON, Canada) includes a blink detection mechanism. Here, a blink is defined as part of the eye position data, where the pupil size is very small or the pupil in the camera image is missing or severely distorted by eyelid occlusion. The EyeLink 1000 parser senses the partial occlusion of the pupil preceding and following a blink, marking these as a saccade. In their manual, the manufacturer recommends discarding fixations shorter than 100 ms proceeding and following a blink in order to eliminate most artifacts from the blink process.

The BeGaze parser[2] (SensoMotoric Instruments GmbH., Toltow, Germany) includes a built-in detector for blinks. Here, a blink is defined as a special case of a fixation, where eye data is not present, i.e., the pupil diameter is either zero or outside a dynamically computed valid pupil range. If either of these conditions is met, then a blink event is created where the event is expanded to include the transition period between valid gaze data and the blink. This transition period is set to look at pupil diameter changes; if these exceed an internal threshold value, then it is assumed to be a part of the blink. If the blink is shorter than 70 ms, then it is discarded.

Both of these built-in parsers have one limitation: they cannot differentiate between a true blink and a period where eye tracking was simply lost for other reasons. For both parsers, blinks do not have a maximum duration.

2.2.2 Custom Blink Detector. On the other end of the spectrum, building a custom blink detector is also an option. Over the last couple of years, there has been a plethora of publications that feature custom blink detection models (e.g., Al-Hindawi et al. [7], Appel et al. [11], Królak and Strumiłło [109]). Al-Gawwam and Benaissa [6] proposed a blink detection method using facial features from a video sequence instead of looking specifically at the eyes, which proves to be robust against various illumination and facial expressions. Another example of a custom blink detector comes from Hu et al. [80], where they showed a fast and accurate blink detection model based on AdaBoost and ANN that uses pictures of eyes to classify for a blink or not. While these approaches introduce interesting new blink detection methods, they are all camera-based and cannot be applied to data already gathered with existing eye trackers.

2.3 Eye Tracking in Interactive Systems

Eye tracking is used in interactive systems in various ways and has been used as, for example, as a tool for target selection, as input via gaze gestures, and as a measurement tool. The eye is sufficiently capable to allow interactions between humans and computers by using gaze gestures as input via an eye tracker [49]. Another study by Traoré and Hurter [195] showed that intentional blinks could be used as a technique to navigate through a menu and interact with the environment. More specifically, they showed that it is feasible to use this technique also in an air traffic control system, which is a high-risk scenario.

Dwell time is another input parameter for gaze in interactive systems and has been the object of study on several occasions [9, 51, 99]. Using dwell time as an input, users can select an item or navigate a menu in an interactive system by placing their gaze at the target for a certain length of time. Vertegaal [200] evaluated several eye tracking and manual input devices in the selection of visual targets, and demonstrated that the performance of eye tracking in combination with dwell time outperforms traditional input using a mouse.

Gaze predictions can allow for the evaluation of interactive systems without needing a user. Predicting gaze, e.g., through the use of saliency maps or task-specific models, such as EZ Reader for reading, can allow for the evaluation of what will be looked at. Examples of this are [61, 129], where they used gaze prediction in short videos, which can then be used in interactive media applications such as customized advertisements in videos through identified regions of interest. Another application of gaze prediction in interactive systems is pre-rendering scenes in VR [209].

One use-case of blinks for interactive systems uses eye tracking as an input method. The work of Krapic et al. [105] used blinks as the input modality to click. Other eye tracking studies using eye movements for interactive systems include Palacios-Ibáñez et al. [147]. Here, the authors reported nothing about the missing data. However, because they used the Tobii software, an assumption can be made they used a Tobii eye tracker, which in turn logs values that are missing as (0, 0) instead of NANs. The work of Bremer et al. [30] used linear extrapolation based on the previous three frames to infill missing values for their prediction of locomotion intent from gaze data, which is the same as the work of Bremer et al. [29], Stein et al. [184]. Asish et al. [16] reported that about 10% of their data was missing per participant and infilled these missing values with the average of each participant.

3 LITERATURE REVIEW ON CURRENT APPROACHES TO ADDRESS BLINKS

We conducted a structured literature review to identify the wide range of approaches used in dealing with eye tracking data in interactive systems. In detail, we aim to review the blink detection methods and algorithms used. For this, we follow the four-phase procedure of the PRISMA [145] guidelines on reporting systematic reviews. Figure 2 visualizes the PRISMA flowchart.

3.1 Method

We follow the PRISMA guidelines to review prior work, which is in line with other papers [17, 23, 75] in the HCI domain. The review focuses on three key aspects: the *Method* used for handling blinks, the use of blink *Detectors*, and the *Task* that users carry out.

3.1.1 Identification. We defined the eligibility criteria, namely, exclusion criteria as shown in Figure 2. We defined the inclusion criteria as papers involving eye tracking data and their handling of missing data. From the databases, we selected the ACM digital library and IEEE as they are representative of high-quality and mature research published in the field of interactive systems and eye tracking. At the same time, we acknowledge that this excludes other

[1] https://www.sr-research.com/eyelink-1000-plus/, accessed 2024–02–27
[2] https://www.dpg.unipd.it/sites/dpg.unipd.it/files/BeGaze2.pdf, accessed 2024–02–27

venues interested in eye tracking data (e.g., ARVO, Journal of Vision and Thieme Medical Publishers, and Journal of Academic Ophthalmology). However, the ACM Digital Library and IEEE Xplore are major libraries for interactive systems and, thus, best fit the aim of this review. We conducted our search given our inclusion criteria, selecting papers with terms relevant to eye tracking and terms that indicate the presence of missing data. Specifically, we used the following search string:

```
("eye tracking" OR "gaze tracking" OR "eye
     movements" OR "gaze movements")
AND ("missing data" OR "missing value" OR
                "data gaps")
AND E-Publication Date: (* TO 12/31/2022)
```

We manually saved all resulting records in a CSV file for screening.

3.1.2 Screening. We excluded all tables of content and posters, papers that do not include a study, and papers that do a study with non-human subjects as shown in Figure 2. For this, the first author then screened each paper while not using automated tools. The goal of the initial screening is to keep all papers that could help us understand how current papers deal with missing data. Thus, we excluded papers based on the exclusion criteria in Figure 2. We excluded 1) *table of contents* ($n = 61$); 2) *posters* ($n = 1$); 3) papers with *non-human subjects* ($n = 1$) as they do not add to our investigation; 4) *not original work* as they only review or comment on others' work but do not process eye tracking data ($n = 21$); 5) even though eye tracking was in the keywords, we had to exclude works, which is *not eye tracking* ($n = 95$); and 6) we excluded results that do not entail a *user study* as no validation was done ($n = 37$). In this step, we reduced the number of included papers from 402 to 186.

For the second step, the first two authors then read the remaining 186 papers after the initial screening. Here, we excluded papers based on two criteria: *not relevant* ($n = 31$) to the inclusion criteria and *not an empirical study* ($n = 15$), see Figure 2. The two people who screened the papers again did this independently to minimize potential bias. The inter-rater reliability was 97% on the exclusion criteria and discrepancies were resolved through discussions.

3.1.3 Included Papers. We included the remaining 140 publications in the review[3]. The first two authors independently coded each of these papers without the use of automated tools.

Without specifying a codebook beforehand, the two authors each coded the *Method* used for handling blinks, the possible use of blink *Detectors*, and the *Task* the users carried out. As we did not establish a codebook beforehand, we did not expect high inter-rater reliability on the open-ended text. Despite this, we had an inter-rater reliability of 79.5% for coding the *Detectors*, 53.4% for the *Method*, and 13.7% for the *Task*. As before, we resolved all discrepancies in discussions, resulting in the final codes reported in Table 1 and Appendix A.

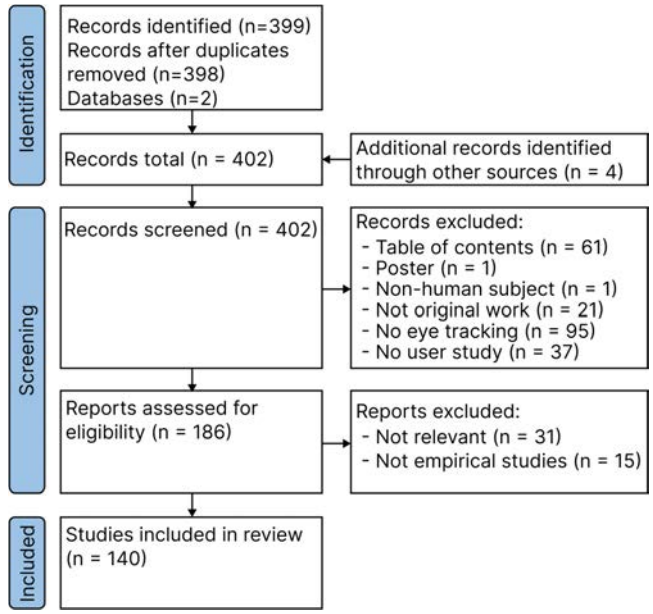


Figure 2: Literature search and inclusion phases and rates using the PRISMA flowchart.

Table 1: Different methods for handling missing data

Method	Count	Publications
Insufficient Information		
Nothing reported	44	[8, 15, 24, 33–36, 44, 60, 66, 77, 89, 90, 100, 101, 108, 112, 123, 125, 135, 139, 142, 149, 152–155, 158, 160, 164, 172, 173, 176, 180, 188, 190, 193, 194, 202, 203, 206, 207, 210, 224]
No handling of missing data	15	[43, 50, 52, 57, 71, 83, 87, 111, 113, 122, 150, 170, 177, 215, 217]
Removing blinks, not defining them	1	[102]
Included in Detailed Review		
Removed missing data	16	[1, 13, 14, 21, 28, 32, 46, 69, 91, 96, 106, 137, 144, 167, 201, 222]
Interpolation – linear	19	[4, 5, 18–20, 28, 81, 85, 88, 97, 103, 104, 140, 141, 167, 169, 186, 199, 219]
Interpolation – polynomial	2	[95, 191]
Interpolation – bilinear	1	[118]
Interpolation – spline	3	[28, 204, 221]
Interpolation – cubic spline	4	[74, 136, 163, 179]
Interpolation – Other	14	[13, 45, 64, 67, 76, 119, 127, 162, 178, 192, 211, 218, 220, 223]
Imputation	7	[38, 117, 132–134, 187, 212]
WEKA	2	[82, 165]
Aggregating	4	[86, 120, 138, 166]
Winsoring	1	[25]
Reconstructing	1	[143]
Averaging	2	[70, 92]
Extrapolate	2	[27, 184]
Other	6	[42, 55, 159, 181, 205, 213]

3.2 Selected Papers

Table 1 gives an overview of how the 140 papers dealt with missing data. The earliest paper in our selected papers is from 1993. We note that 60 papers reported insufficient information on how they handled missing data, see Table 1; thus, we cannot include them in further analyses. However, they provide evidence for the need for better reporting guidelines. We showcase a subset of 81 papers in Appendix A to highlight the work that deals with missing data.

[3]These 140 papers are marked with a • in the references of this paper.

Papers with Insufficient Information. An overwhelming majority of the papers (44/140) did not report how they dealt with missing data from their experiments or they acknowledged the existence of missing data but did not elaborate on how they handled the missing data, see Table 1. Some of these papers mention the removal of participants who are missing over a certain amount of data (e.g., [60, 111, 125, 142]) or trials where missing data reached a threshold (e.g., [46, 102]). However, they did not elaborate on what they did with trials and participants who had missing data but were not excluded in the analysis, i.e., how they dealt with remaining missing data was not described. Moreover, we identified 15 papers that did not handle missing data while acknowledging the issue around missing data. Finally, one paper did remove blinks but gave no information on the criteria for removal or how they were removed.

Papers with Helpful Information. Sixty papers had insufficient information to be fully included in this review. In the following, we will categorize the remaining 81 papers on how they dealt with missing data.

Although all reviewed work comes from either the ACM digital library or IEEE Xplore, the work reviewed was published in several venues. From the work reported in Appendix A and reports on dealing with blinks, the most predominant venue was the ACM Symposium on Eye Tracking Research and Applications (ETRA), with 12 papers. Beyond that there were venues like ICMI (6), IEEE EMBC (4), CHI (3), IEEE Access (3), and several others. Regarding eye tracking systems, the most popular brand is the Tobii brand, where 36 papers in the reviewed work used one of the Tobii eye trackers for their research; out of these, the Tobii 1750 (4) is the most popular. After Tobii, the SMI brand is also well-represented with 15 papers. Here the SMI RED250 is the most common (4). Studies that have used a mobile eye tracker also seem to favor the EyeTribe (6) and the Tobii Pro Glasses 2 (5).

The tasks we identified in the reviewed work are even more diverse than the selection of eye trackers. The most common task is visual search (15) and driving simulators (15), closely followed by free viewing (14), video watching (9), reading (8), and input method (4). Here, using eye tracking as an input method is interesting as it is the only task (n > 1) where all reviewed work used an interpolation method to deal with the missing data from the eye tracker.

3.3 Findings on Detecting Blinks

Most (73/81) of the reviewed literature reports that they classified missing data as a blink. For the Tobii eye trackers without a blink detector, authors often classified blinks as points where the pupil size is outside a pre-determined range or when the tracker loses the pupil temporarily, e.g., [52, 69, 204]. Other papers (3/81) mention excluding data before and after the missing data. For example, Bafna et al. [19] specifies blinks as missing data 75-500 ms long and, additionally, they remove a further 200 ms before and after the missing data to combat the artifacts before and after the blink. Appel et al. [13] removed data up to 100 ms before and after a blink to counter artifacts, and Appel et al. [12] removed parts from the pupil signal that "had an unreasonably large slope right before and after a sequence of missing data" [12].

EyeLink provides users with a built-in parser[1] and SMI provides the BeGaze parser[2]. Thus, both have their own integrated parsers for blinks; however, not all studies we found during our literature review using those eye trackers report on using the respective parser. More specifically, out of the surveyed papers, over half of the work using an EyeLink (e.g., [117, 153]) and using an SMI (e.g., [12, 13, 24, 34, 95, 104, 133]) did not report on using the built-in parsers or any other parser. However, they report the missing data, which they handled with use-case specificity. As such, we identified that *the methods used for blink detection are inconsistent in the current literature and improving this has a potential positive impact on research replicability and quality.*

3.4 Findings on Dealing With Blinks

As discussed in Section 3.3, there are integrated solutions for detecting blinks (e.g., EyeLink parser[1] and BeGaze parser[2]). However, there are no out-of-the-box solutions integrated into the current eye trackers that handle blinks once they are identified. Traditionally, researchers dealing with missing data have so far proposed a set of methods, such as replacing by mean/median [168] and last observed carried forward [175]. However, this does not work for time-series data due to the underlying speed and possible acceleration of the eye movement. As such, the most common method identified in our literature review applies linear interpolation (19/81) closely followed by removing the data containing missing data (16/81), see Appendix A. However, our review revealed numerous use-case-specific methods for handling missing data. Here, the most common method was interpolation (43) of various forms and imputation (7), followed by a wide range of adapted approaches. While these methods are less prevalent and more widespread in the reviewed literature, they have the advantage of retaining the data to be used in interactive systems.

Interpolation. Interpolation is the most popular option in our review as 43/81 papers employed a form of interpolation to replace the gaps in the data. In the reviewed work, we identified different kinds of interpolation, including linear (19), polynomial (2), bilinear (1), spline (3), cubic spline (4), and others (14). For example, Kinnunen et al. [97] assumed the continuity of the data and, thus, applied linear 1-D interpolation independently for both axes. In Wang et al. [204], the authors removed data when the pupil size was outside a pre-defined range, after which they applied spline interpolation to infill the missing values. As there is no consensus on how to interpolate eye tracking data, the effects of such methods also need to be more adequately understood. *This can lead to inaccurate or even wrong interactions in interactive systems with low reproducibility chances.*

Remove Blinks. Removing the data that contain blinks is the second most popular among the reviewed work (16/81). However, some papers reported elaborate criteria to be met to retain parts or all of the data affected by a blink. For example, Ishii et al. [86] and Nakano and Ishii [138] did not analyze samples with blinks longer than 200 ms; however, if the blink was shorter, then they cut out the missing values. Others allowed for 20% missing data during a trial [25, 164] or they retained trials where the missing data was less than 1 s [70]. *While it is clear that removing all missing data helps the overall performance, this approach is not useful for interactive systems.*

Uncommon Methods. Lastly, we identified a series of other methods using a variety of tools and methods, e.g., imputation (7), WEKA (2), aggregating (4), and winsoring (1). To impute missing values, Li et al. [117] used an unsupervised Expectation-Maximization algorithm on their data, and Cole et al. [38] used the observed session transition probabilities to fill in the missing data. We could not identify which specific method is most suitable for dealing with blinks based on the reviewed literature. A large portion of the reviewed work (16) removes missing data where this exists, additionally to the work the removes whole participants or trials. *This results in significant data loss; therefore, other ways of dealing with the missing data could be more appropriate.*

4 EVALUATING THE FITNESS OF APPROACHES

Although our literature review uncovered trends that researchers use more often, there is no overall consensus for the "best" approach. Additionally, we did not find any evaluations comparing the many approaches to establish guidelines for future interactive systems. Thus, in the following, we compare the different identified approaches. First, we collect a wide range of open-source eye tracking datasets, see Table 2. Second, we showcase the implications of the most common approaches to detecting and dealing with blinks. After that we use the acquired data to run the previously identified infilling methods (see Table 1) and evaluate against each other.

4.1 Datasets

To motivate the importance of our work and evaluate our identified infilling methods, we acquired 11 different open-source eye tracking datasets. All datasets retrieved are part of published and peer-reviewed work from various venues. An overview of the acquired datasets is provided in Table 2. We acquired all 11 datasets independently of the literature review. They are all available online via https://osf.io/ and https://github.com/. For direct links, see Section 9 where we provide links to the datasets on our Eye Tracking Guidelines page, allowing us to extend the list with future published datasets.

4.2 Pre-Processing

We first processed the datasets so that they all had the same format, which enabled us to work with the data more easily. If needed, we used the parsers for the EyeLink[1] and SMI[2] data to create the initial tabular files. To format all data equally, we turned all x and y screen gaze coordinates into degrees of visual angle, allowing us to compare them independently from the specific apparatus used (e.g., distance to the screen and screen size). We included only data from the left eye whenever binocular eye tracking data was available. We sampled all time in milliseconds (ms); if there were gaps in timestamps that were bigger than one second (e.g., those created through pausing an experiment), then we split the data into different parts to ensure we do not associate pre- and post-gap data. Where there was missing data (i.e., zero or *Not a Number*), we consider the data as part of a blink. However, we did not consider the missing data of only one sample (e.g., 1 ms for 1000 Hz and 33.3 ms for 30 Hz) as part of a blink as prior work reported blinks to last about one-third of a second [56]. Thus, we did not analyze such short occurrences[4]. With our pre-processing, we aim to reduce external factors not caused by a human eye blink (e.g., breaks in the experiment, looking away from the tracker). Hence, we argue that blinks primarily cause the remaining gaps.

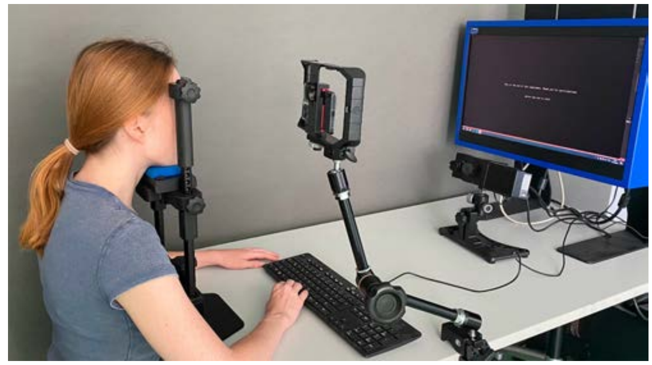


Figure 3: Experimental setup used for the verification of data gaps.

4.3 Blink Verification

By comparing a high-speed RGB video stream of the eye to recorded eye tracking data, we can ensure that blinks indeed cause the gaps. To maintain high ecological validity, we first searched for publicly available datasets of paired data containing blinks. However, none of the datasets of eyes contain blinks. Thus, the data required for such a comparison are not publicly available. Thus, we decided to conduct an experiment to capture the real eye movement and the eye tracker data simultaneously.

In this experiment, we used an EyeLink 1000 plus from SR Research to capture the eye tracking data at 1000 Hz and a Motorola 30 Ultra to capture the RGB video stream from the blinks at 240 fps as shown in Figure 3. After a nine-point calibration and validation, we presented a dot on the center of a ViewPixx (22.5 inch, 1920×1200, 120 Hz) monitor and asked the participant to blink one time once this dot turned green. We had one participant perform 10 trials. The data from this experiment was used to verify that the missing data and the preceding and following artifacts follow a similar trajectory as real blinks[5].

5 RESULTS

In this section, we first report on the statistics from the surveyed datasets, see Table 2. Namely, we investigate the blink frequency, duration of missing data, and inter-blink interval[6]. Second, we report on the effective data loss that occurs through the common rolling window approach and the fact that windows containing missing data cannot be processed (i.e., zero or *Not a Number*). Third, we investigate the behavior before and after a gap to understand the impact of the eye closing and opening. Finally, we investigate

[4]We acknowledge that this could include data missing for other reasons; however, due to the vast amount of data considered in the analysis this would only amplify our findings.

[5]We acknowledge that these are all voluntary blinks and that there are differences between voluntary and involuntary blinks, e.g., duration [79].

[6]In the following, we will assume all gaps in the data, i.e., missing data, as to be part of a blink.

Table 2: Overview of the used datasets, listed from the oldest to the newest (and alphabetically for authors from the same year)

				Eye Tracker			Screen		
	Author(s)	Year	Venue	Company	Device	Freq. [Hz]	Inch	Aspect Ratio	Distance [cm]
S01	Foster et al. [62]	2017	Psychol Sci.	EyeLink	1000 Plus	1000	17	16:9	100
S02	Marzecová et al. [131]	2017	Biolo. Psychol	EyeLink	1000	500	19	4:3	57
S03	Krstić et al. [107]	2018	EJPE	SMI	RED-m	60	15.6	16:9	60
S04	Marzecová et al. [130]	2018	Scientific Rep.	EyeLink	1000	500	19	4:3	57
S05	Schuetz et al. [174]	2019	ACM CHI	EyeLink	1000 Plus	1000	113	8:5	180
S06	Annerer-Walcher et al. [10]	2021	Cogn. Sci.	SMI	RED250	250	24	16:9	70
S07	Felßberg and Dombrowe [59]	2022	Vision Res.	EyeLink	1000 Plus	1000	27	16:9	85
S08	Hollenstein et al. [78]	2022	LREC	EyeLink	1000 Plus	1000	27	16:9	85
VR01	Stein et al. [184]	2022	IEEE VR	Tobii	Pro	90	3.5	9:10	–
VR02	Steil et al. [182]	2019	ACM ETRA	Pupil Labs	Add-on	30	5.7	8:9	–
M01	Steil et al. [183]	2018	ACM ETRA	Pupil Labs	Pro	30	–	-	–

the impact of the five most common infilling methods found in the literature review, see Table 1.

5.1 Analysis

In this work, we adopt a Bayesian approach for data analysis, specifically employing Bayesian linear mixed models (BLMM). This approach has gained recent prominence [93, 115, 171] and offers several advantages over classical statistics. One of the advantages, as discussed by Kay et al. [94], is the incorporation of prior knowledge from eye tracking data. Additionally, Bayesian statistics facilitate effect estimation in small sample sizes and allow readers to evaluate effect sizes, including those close to zero, rather than solely determining the presence or absence of effects. Consequently, we utilize Bayesian parameter estimation to estimate effect sizes and quantify uncertainty surrounding these estimates by leveraging the information in our data and the applied priors. For all our models, we use the package *brms* to compute 10 Hamilton-Monte-Carlo chains with 20,000 iterations each and 10% warm-up samples. All Rubin-Gelman [65] statistics were well below 1.1 for effective sample size.

We explored the effect of different weakly informative priors on the data. None affected statistical inference. As a result, priors were chosen to resemble only weakly informative priors when standardizing with a prior on the Gamma distribution of the data of ($\alpha = 5, \beta = 3$) without allowing negative numbers ($\gamma > 0$). Additionally, we accounted for potential variability across datasets by incorporating a random factor on the shape parameter. This approach acknowledges that different datasets may exhibit varying characteristics and allows for more nuanced modeling. By explicitly modeling the dataset-specific effects, we capture the heterogeneity and better account for the underlying structure of the data.

Effects were considered meaningful when there was a particularly low probability ($p_b <= 2.5\%$) of the effect being zero or the opposite. We calculated p_b through the relative proportion of posterior samples being zero or opposite to the median. This metric has similar properties to the classical p-value and is an accepted substitution cf. [98, 116, 171]. Still, it quantifies the proportion of probability that the effect is zero or the opposite, given the data observed. Note that this is the reverse of the classical approach to inferential statistics, where one measures data probability given the test statistic's null hypothesis. In addition to the median of the parameter, we calculated the High-Density Interval (HDI) at 95% of the posterior distribution for all parameters, which indicates the possible range of effects given the data alongside the median of the respective parameter. Simple mean comparisons were made on standardized outcome variables. Therefore, all $\tilde{b}$ represent an effect size in standard deviations from the mean (corresponding to Cohen's d for simple effects of categorical predictors with two levels).

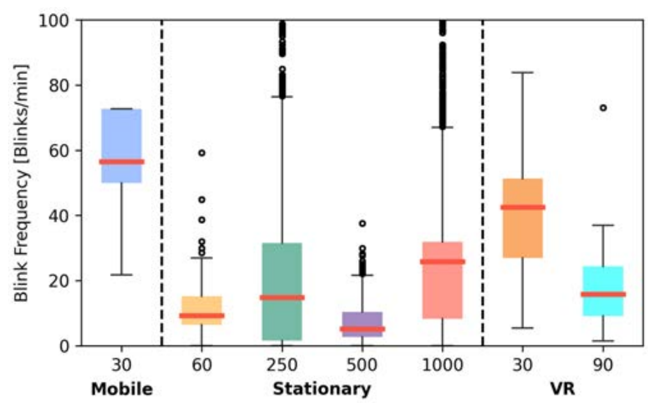


Figure 4: We visualized the blink frequencies for the different types of eye trackers gathered in the dataset, i.e., mobile, VR, and stationary, and their respective frequencies. In the datasets we analyzed, we see that participants from the 30 Hz mobile dataset have a high blink frequency and participants from the 500 Hz stationary datasets have the lowest blink frequency.

Table 3: Bayesian statistics results of the priors for blink frequency, inter-blink interval, and closed-eye time (all results are contrasted against the whole dataset)

Type	Freq.	Blink Frequency p_b	*Med.*	$HDI_{95\%}$	Inter-Blink Interval p_b	*Med.*	$HDI_{95\%}$	Closed-Eye Time p_b	*Med.*	$HDI_{95\%}$
Mobile	30	<.001	1.549	[0.457, 2.980]	<.001	1.476	[0.341, 2.843]	<.001	1.388	[0.390, 2.785]
Statio.	60	<.001	1.334	[0.356, 2.689]	<.001	2.046	[0.569, 4.015]	<.001	1.714	[0.503, 3.029]
	250	<.001	1.282	[0.354, 2.521]	<.001	2.816	[0.830, 4.821]	<.001	3.693	[1.873, 5.323]
	500	<.001	1.139	[0.294, 2.342]	<.001	1.392	[0.316, 2.803]	<.001	1.433	[0.408, 3.032]
	1000	<.001	2.509	[1.491, 3.344]	<.001	3.597	[1.078, 5.658]	.018	1.734	[0.164, 3.216]
VR	30	<.001	1.472	[0.427, 2.848]	<.001	1.385	[0.402, 2.828]	<.001	1.397	[0.373, 2.730]
	90	<.001	1.358	[0.354, 2.726]	<.001	1.497	[0.469, 2.973]	<.001	1.520	[0.442, 2.822]

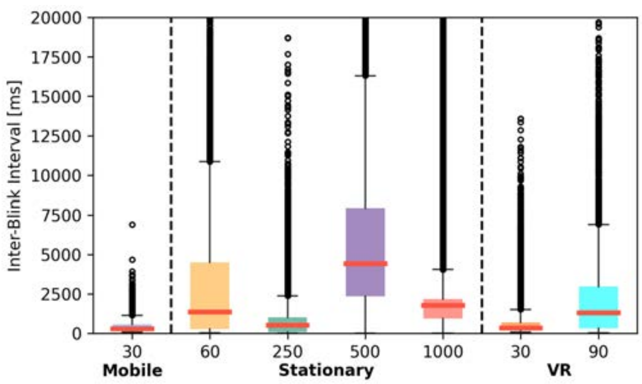


Figure 5: We visualized the inter-blink interval for the different types of eye trackers gathered in the dataset, i.e., mobile, VR, and stationary, and their respective frequencies. In the datasets we analyzed, we see that participants have no inter-blink interval while participants from the 30 Hz mobile datasets have the inter-blink interval. Error bars indicate standard errors.

5.2 Blink Frequency & Inter-Blink Interval

In Figure 4, we present the results of the blink frequency in blinks per minute across the different eye tracker frequencies and eye tracking modalities, i.e., stationary, mobile, or VR. Eye trackers with a low frequency had a generally higher blink frequency; here, the 30 Hz eye tracker had a mean of 49.3 blinks per minute ($SD = 30.5$) while the mean of the others is 25.9 blinks per minute ($SD = 37.8$). These results verify the findings that a lot of factors influence blink frequency, as is well established in the literature cf. Section 2.1. We visualize the *inter-blink interval* in milliseconds for the different frequencies and types of eye trackers in Figure 5. Next, we investigate how the different types and frequency as fixed effect affects blink frequency in a mixed effects model with the previously described intercepts and priors in Section 5.1. We found that all combinations of eye tracker Type and eye tracker Frequency had a distinguishable effect on the *blink frequency*, see Table 3.

5.3 Impact of Eyelid on Eye Tracking Quality

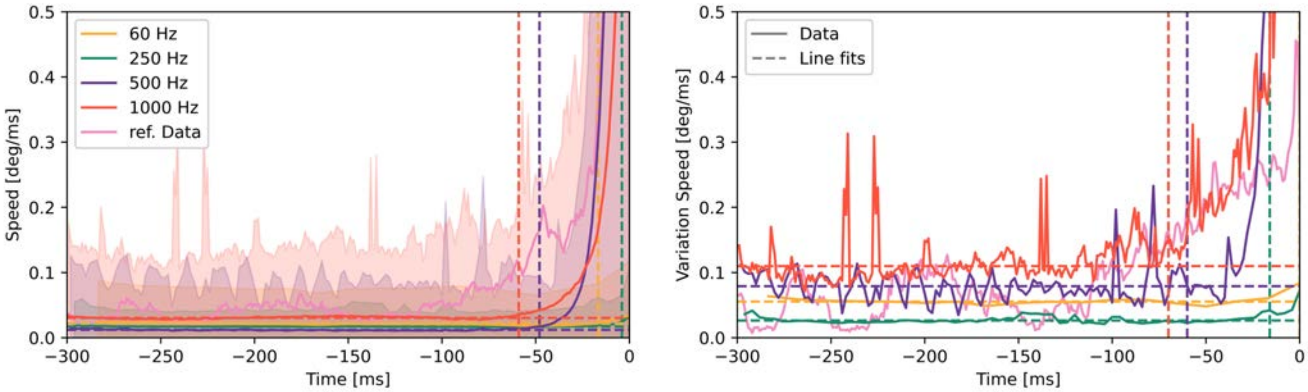
As illustrated in Figure 1, the eyelid's movement can influence the eye tracking quality even before the tracker reaches the state that the eye tracker cannot recognize the pupil anymore. In this process, the eyelid might cover the pupil partly, but the eye tracker still assumes a circular pupil shape in its tracking algorithm. Thus, we investigate the potential impacts of the eyelid before and after a blink on the tracking quality. Uncovering such an influence will allow us to derive cut-off timings before and after the blink to facilitate better overall tracking accuracy.

For this, we investigate the eye movement speed and the speed variation before and after a blink, see Figure 6, 7, and 8. First, we looked at the change in speed before and after, see Figure 6a and 7a. We found that the speed increases surrounding the blink, which diverges from the time before and after. To study the behavior, we fitted horizontal lines to the speed trajectory (visualized as dashed lines) to the data -300 to -150 ms before and 150 to 300 ms after the blink. This illustrates the difference between with and without blinks. Next, we determined the points of divergence and visualized them as vertical dashed lines. Thus, when the average speed exceeds the fitted average linked plus epsilon for the first time, we determine this to be the cut-off, where the eyelid impacts the tracking resulting in inaccurate tracking, see Table 4.

As the variation, expressed by the standard deviation in Figure 6a and 7a, shows a similar trend, we next analyze the speed variation using the same methods. First, we fitted a horizontal line and then a vertical line to determine the point of divergence. The results show that the variation of the eye movement speed following a blink is high directly after a blink and decreases over time until it stabilizes

Table 4: Identified time [ms] where data preceding and following a blink diverges from normal movement

Freq. [Hz]	Closing Sequence Speed	Closing Sequence Var. Speed	Opening Sequence Speed	Opening Sequence Var. Speed
60	−16.6	−0.0	66.6	50.0
250	−4.0	−16.0	60.0	36.0
500	−48.0	−44.0	74.0	74.0
1000	−59.0	−70.0	59.0	118.0



(a) Eye Movement Speed

(b) Eye Movement Speed Variation

Figure 6: Illustration showing variation of the recorded eye tracking data 300 ms before a blink over all different stationary frequencies. a) Mean of the eye movement speed preceding a blink for the different frequencies of the stationary eye trackers in the data, including our reference data. b) Variation of the eye movement speed preceding a blink in for the different frequencies of the stationary eye tracking in the data, including our reference data. The vertical dashed lines represent the point the points identified as the first time the line crossed the fitted function plus epsilon. In both (a) and (b), we observe a steep increase in speed and variation of speed before missing data appears. These deviations from normal seem to happen around -60 ms and -70 ms for speed and variation in speed, respectively.

around 0.1. This point depends on the frequency and eye tracker and, thus, must be individually determined.

5.4 Closed-Eye Time & Length of Missing Data

Figure 9a presents the results of the blink length across the different eye tracker frequencies and eye tracking modalities. Our results show that between frequencies and modalities, the lengths are distinguishable. In Figure 9b, we show the normalized length distribution for the stationary eye tracker frequencies. We use a Generalized Inverse Gaussian distribution [156] to model the distributions of the lengths, see Figure 9b. Our regression models yielded an R^2 value of 0.93 for 1000 Hz, 0.98 for 500 Hz, 0.99 for 250 Hz, and 0.67 for 60 Hz.

We investigated how the different types and frequencies as fixed effects affect blink frequency in a mixed effects model with the previously described intercepts and priors in Section 5. We found that all combinations of frequency and eye tracker type (stationary, mobile, and VR) had a distinguishable effect on the blink frequency. Our findings are reported in Table 3.

5.5 Baseline Analysis of Removing Sample with Missing Data

In Figure 10a, we show the relation between the usable data (i.e., data without gaps) and window length. We show that as the window length increases the chance that a window contains one or more gaps increases. We note that the most predominant method for dealing with missing data in a window is to ignore it. We show that applying this method results in a decrease in usable data for further analysis. From an interactive systems point of view, this would hinder user interaction. The data from the different stationary frequencies follow a similar trajectory of a decrease in usable data as the window size increases. We also evaluate the impact of different step sizes[7] on the usable data. These follow all the same trajectory, which suggests that there is no impact of step size on the usable data[8].

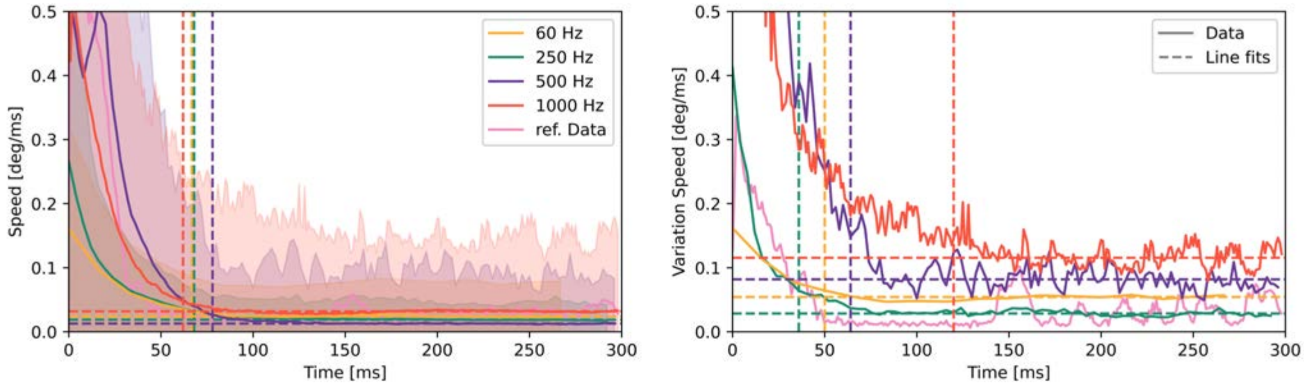
5.6 Evaluating Infilling Methods

To evaluate the different infilling methods, we used the previously generated distributions from Figure 9 to create artificial blinks in our dataset where there were no natural blinks present. We used the most extreme value as an additional cut-off from Table 4 to simulate the additional data we should remove when dealing with blinks as this data would be data that contain artifacts from the blink. We applied this to our data from the stationary eye trackers and for each frequency individually to generate roughly 40.000 blinks evenly distributed throughout the data where there are no blinks naturally present, i.e., 750 ms before or after the artificial blink. The generated blinks are about half the actual blinks in the dataset.

We calculated the error as the mean distance between the points generated by the interpolation methods and the actual data in degrees (ground truth). Following this, we applied linear, polynomial (3rd- and 4th-order), cubic spline, and spline interpolation methods over each generated blink and calculated the error. Our results show that the linear interpolation achieves the lowest mean error for 60 and 500 Hz data (0.43 and 0.09 mean degrees error, respectively) and that cubic spline interpolation achieves the lowest mean error for 250 and 1000 Hz data (0.18 and 0.54 mean degrees error, respectively). However, the results between linear and cubic spline are

[7] Evaluate the window every X samples.

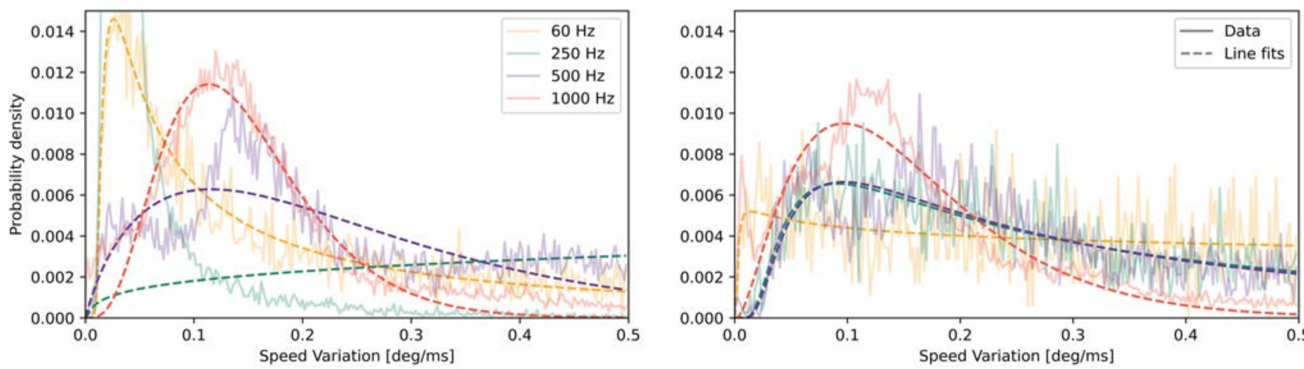
[8] We acknowledge that there are adaptive window size algorithms to deal with gaps; however, adaptive sizes are not traditionally compatible with RNN and LSTM neural network models.



(a) Eye Movement Speed

(b) Eye Movement Speed Variation

Figure 7: (a) Mean of eye movement speed following a blink for the different frequencies of the stationary eye trackers in the data, including our reference data. (b) Variation of eye movement speed following a blink for the different frequencies of the stationary eye tracking in the data, including our reference data. The vertical dashed lines represent the points identified as the first time the line crossed the fitted function plus epsilon. In both (a) and (b), we observe a steep decrease in speed and variation of speed after missing data appear. These deviations following missing data seem to normalize around 60 ms and 120 ms for speed and variation in speed, respectively.



(a) Eye Movement Speed Variation Preceding Missing Data

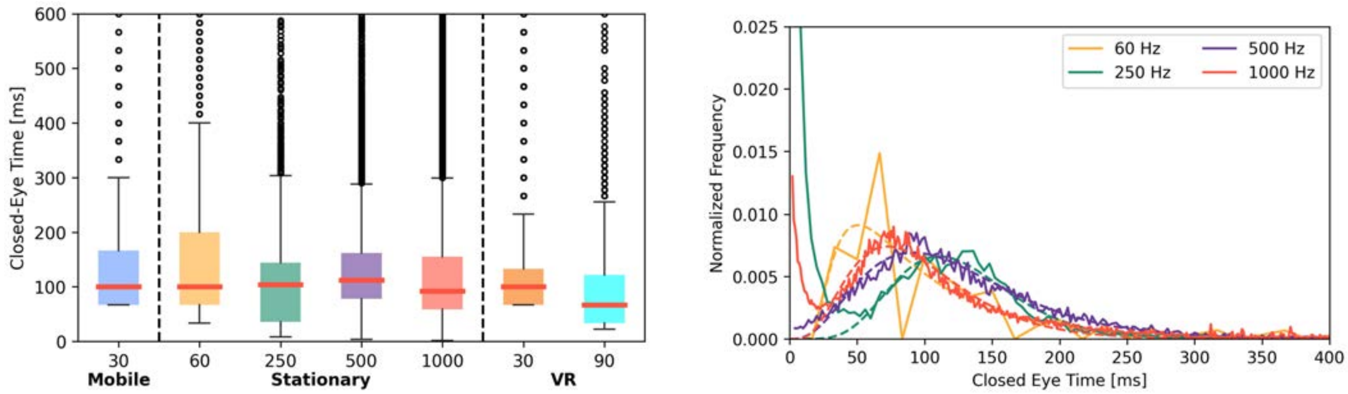
(b) Eye Movement Speed Variation Following Missing Data

Figure 8: (a) Distribution of speed [deg/ms] from 50 ms following missing data for the different frequencies of the stationary eye trackers in the data. (b) Distribution of the variation of speed [deg/ms] from 50 ms following missing data for the different frequencies of the stationary eye trackers in the data. All dashed lines represent an inverse Gaussian distribution fitted to the data with an $R^2 > 0.98$.

close. Polynomial interpolation on the 4th-order performs worst over all frequencies. We have visualized these findings in Figure 11. For more details of all the different errors, see Table 5.

6 DISCUSSION

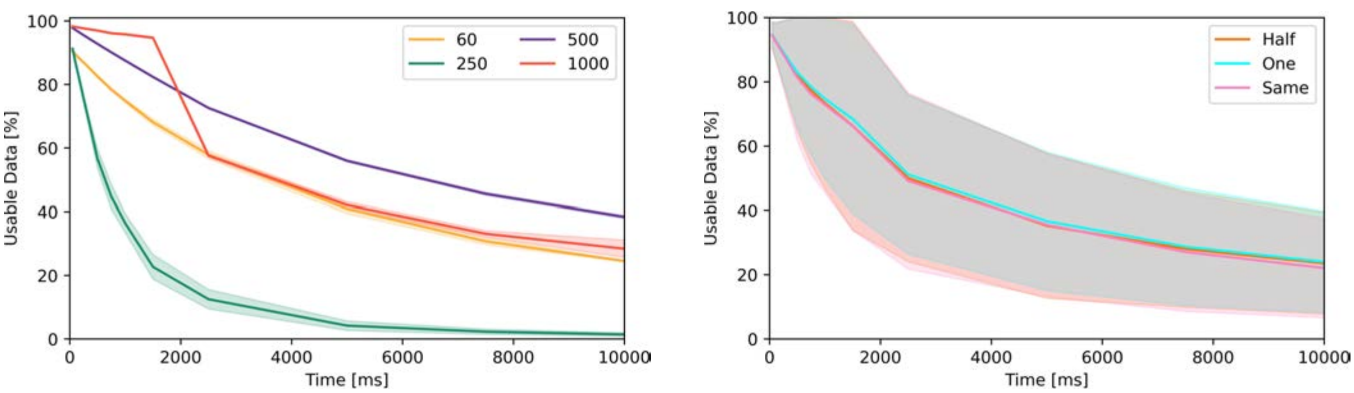
In this work, we first reviewed the literature on processing eye tracking data and then compared these methods to determine their validity. From the literature review, we found 81 papers published in the ACM digital library and IEEE Xplore until the end of 2022 regarding eye tracking and dealing with missing data. We extracted the methods used to identify blinks and algorithms used to infill the missing data. Moreover, we found that the methods are inconsistent throughout the literature. With this in mind, we performed a series of experiments to determine the impact of the different methods. For this, we used publicly available datasets recorded under various conditions, allowing us to highlight possible bias and generalizability. In the following, we discuss the most critical issues and discuss potential consequences if they are left unaddressed. These include the implications of the baseline approach on interactive systems, the effect of the eyelid on eye tracking data, the implications of infilling methods on position error, and recommendations for processing eye tracking data.



(a) Closed-Eye Time

(b) Closed-Eye Time Distribution

Figure 9: (a) We visualized the closed-eye time for the different types of eye trackers gathered in the dataset, i.e., mobile, VR, and stationary, and their respective frequencies. Error bars represent the standard error. (b) We visualized the normalized frequency of closed-eye time for the different frequencies for the stationary eye trackers. The dashed line represents an inverse Gaussian probability density function fitted to the data. In both (a) and (b), we can see that the closed-eye time is very similar independent of the frequency or type of eye tracker used, which suggests it is independent of task.



(a) Usable Data vs. Window Size

(b) Usable Data vs. Step Size

Figure 10: (a) We visualize the usable data for the different frequencies available in the stationary eye trackers. (b) We visualize the usable data for different step sizes, where half represents half the size of the window, the same represents the same step size as the window size, and one represents one step. The filled area represents the standard deviation. We observe a steep decrease in usable windows, where in a more than half of the data becomes not usable when creating windows of 10 seconds independent of frequency. In (b), we observe that step size all has a similar result in how much data is available.

Table 5: Mean error in degrees for the different infilling methods over the different frequencies of the stationary eye trackers, where M stands for Mean, SD stands for Standard Deviation, LL stands for Lower Limit, and UP stands for Upper Limit for a 95% confidence interval

	Linear				Poly 3				Poly 4				Cubic Spline				Spline			
Freq [Hz]	M	SD	LL	UP	M	SD	LL	UP	M	SD	LL	UP	M	SD	LL	UP	M	SD	LL	UP
60	0.43	0.79	0.41	0.45	0.48	1.02	0.46	0.51	1.68	15.83	1.31	2.04	0.49	0.86	0.47	0.51	0.61	1.24	0.58	0.64
250	0.19	0.21	0.19	0.2	0.3	0.3	0.29	0.3	0.31	0.74	0.29	0.33	0.18	0.18	0.17	0.18	0.25	0.27	0.25	0.26
500	0.09	0.08	0.09	0.09	0.11	0.1	0.11	0.11	0.11	0.21	0.11	0.12	0.09	0.09	0.09	0.09	0.11	0.12	0.11	0.12
1000	0.56	1.17	0.53	0.58	0.6	1.34	0.58	0.63	1.2	6.74	1.06	1.33	0.54	0.93	0.52	0.56	0.73	1.08	0.7	0.75
Avg.	0.32	0.56	0.3	0.33	0.37	0.69	0.36	0.39	0.82	5.88	0.69	0.96	0.33	0.52	0.32	0.34	0.42	0.68	0.41	0.44

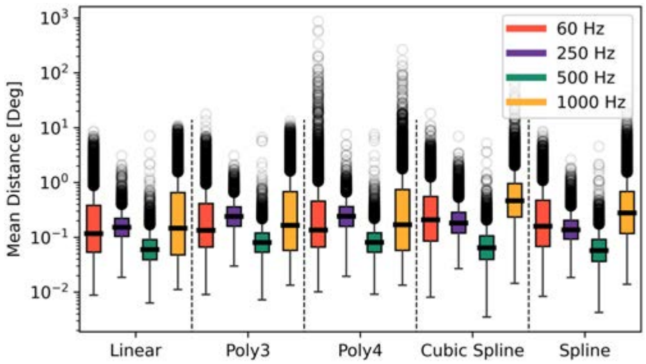


Figure 11: Error in mean distance from the ground truth in artificially introduced blinks into the data over different in-fill methods and frequencies for all stationary eye trackers. We see that the infilling using linear or cubic spline interpolation overall results in the least amount of mean distance; additionally, 4th-order polynomial infilling results in the worse.

6.1 Validity

Compromising the internal validity of eye tracking studies is a critical concern as this issue may confound any conclusions drawn from such studies. Threats to the external validity of eye tracking research pertain to specific conditions within the study rather than the broader nature of the study itself. Our literature review revealed instances where the preservation of internal validity was not consistently evident due to limited descriptions of procedures even when we only consider the data processing. For instance, we excluded 36 studies that did not report on missing data in their work, an additional 15 studies in our literature review as they did not describe how missing data is processed, and one study that reported on removing blinks but never defined blinks or reported on how they were detected. For those that removed missing data, it was only clear in a few cases if data were removed within a certain time span, trial, or participant.

For the identified papers that did report on the method of not processing eye tracking samples containing missing data, we only encountered three papers where they account for artifacts introduced around missing data, e.g., because of the movement of the eyelid. Leaving artifacts surrounding missing data in compromises the internal validity of the data even if these artifacts are not necessarily from eyelid movements. Where parsers were used (6 papers), none of these reported the settings that were used for the parsers. As things currently stand, 60/140 papers failed to provide sufficient information in this regard. As such, this presents an implication for the internal validity of their work and the conclusions drawn from such studies as they can be confounded with this issue.

6.2 Replicability

Reflecting recent concerns regarding the lack of transparency in statistical reporting within various fields considering interactive systems [37, 84], similar issues arise when considering the replicability of studies using eye tracking data. Across various instances, we observed a scarcity of clarity and essential detail necessary for successfully replicating research involving eye tracking methodologies. Descriptions and methodologies often suffer from selectiveness, incompleteness, and a non-standardized presentation of information. A significant portion of the analyzed papers lacked essential information regarding the specifics of the eye tracking data analysis used. Furthermore, we observed missing participant characteristics and experimental protocols, and various other factors.

The utilization of non-standard terminology, self-defined terms for eye tracking parameters, and occasional confusion between distinct gaze-related attributes contributed to the challenges in comprehending papers and, in some instances, rendered them practically indecipherable to readers. The decision to diverge from established terminology not only complicates the understanding of these studies but also poses a more profound threat: it undermines the broader community's ability to retrace and replicate the findings presented. This paper aims to rectify this issue by clarifying the terminology surrounding eye tracking and delineating the necessary components for effectively planning, conducting, and reporting studies involving this methodology.

6.3 Understanding External Impacts on Eye Tracking Data

In general, there are many reasons for blinks (cf. Section 2.1), which are impacted by many external factors. Especially as the mental workload has an effect (cf. [31, 196, 198, 208]), we have to assume a task dependency. With this, we expect that the datasets, recorded under various conditions, impact the blink frequency, inter-blink interval, and closed-eye time. Our Bayesian linear mixed models showed effects that the tracker type and frequency are good indicators to show that the datasets are different with respect to the three measures (blink frequency, inter-blink interval, and closed-eye time). Thus, a one-size-fits-all approach for detecting blinks in various situations is improbable. Moreover, this showcases that detection parameters that worked for one setup do not transfer to another setup. This highlights the need for adaptive approaches when detecting blinks in different interactive systems.

6.4 Effect of Eyelid

Preceding and following a blink, the eye tracking data become highly unstable. We analyzed the variation in data over the different frequencies for the stationary eye trackers. Our findings show that assuming that the blink starts when it is detected by the default parsing software, e.g., by having missing data, and following the provided recommendations by their respective manual will leave artifacts in the data. These blink artifacts could have implications for the accuracy of interactive systems and, as such, we show that up to 70 ms before a blink and 118 ms after should be additionally excluded from the samples (see Table 4).

6.5 Implications of Baseline Approach on Interactive Systems

As the window size increases, the chance of a blink appearing in this window naturally increases. The baseline approach is to remove data that contain a blink, which is, in turn, the most common approach used in the reviewed work. Using smaller sections (e.g.,

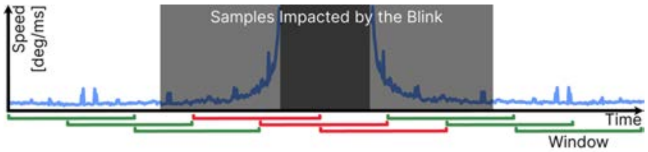


Figure 12: To showcase the implications and delay an interactive system would experience if fed eye tracking data containing missing data points, we highlight the following. The green area shows a window that is usable. Over time, this window moves toward the right where it will encounter missing data (e.g., through blinks). At this point, the interactive system can no longer use the input because LSTM / RNN models cannot handle missing data. This continues while there is at least one missing data point inside the window until it once again contains a window without missing data.

< 1 s) of eye tracking data allows for a large portion of the data to be usable. However, using larger window sizes, e.g., 10 seconds and beyond as used by Bixler and D'Mello [25] and Qvarfordt and Lee [164], results in less than half the data being usable, independent of frequency. For interactive systems, this would mean that a suspension of updates to the system will depend on the selected window size and blink length, e.g., a window size of 10 s and a blink of 100 ms will suspend the update for 20.1 seconds. Given that larger window sizes increase the accuracy of interactive systems, e.g., [161], filling in the missing data presents the opportunity to have no or fewer unusable data windows. This, in turn, will result in a smoother experience in interactive systems.

To showcase the implications of an approach that removes data containing blinks or simply ignores the presence of blinks, there will be a reduction in usable data as shown in Figure 10a. To further highlight why this introduces delays in the system, we highlight this further in Figure 12. Here, we show that all areas that are underlined with red are affected by at least one data point missing, which means that in turn, the interactive system would not be able to give a response during this time. Depending on the window size, the amount of delay would be:

$$2 \times window\ \ size\ (ms) +$$
$$missing\ \ data\ duration\ (ms) +$$
$$188\ ms\ (from\ the\ artifacts\ before\ and\ after\ the\ missing\ data) - 1\ ms$$

A window size of 1000 milliseconds and missing data of 100 milliseconds would result in a delay of 2287 milliseconds, where the interactive system would be unable to respond.

6.6 Implications of the Position Error

Given the distribution of blink length and the effect of the eyelid on variability, we created artificial blinks evenly distributed throughout the data that do not contain blinks. We then applied five interpolation methods, of which four are used in the reviewed literature. We calculated the error for each of these methods on the different frequencies of the stationary eye trackers. Our findings show that linear and spline interpolation produces the least error in mean distance to the ground truth and that a 4th-order polynomial interpolation gives the largest error.

7 RECOMMENDATIONS ON PROCESSING EYE TRACKING DATA

Given the diverse set of applications of eye tracking in the context of interactive systems, we advocate for the collaborative development of community-sourced guidelines tailored to the specific needs and practices of researchers in and around the field of interactive systems. Drawing inspiration from the approach of the Special Interest Group on Transparent Statistics from the HCI field and previous work published at CHI, we present analogous efforts in the realm of eye tracking research. Our initiative has created an initial set of guidelines, accessible at https://eyetrackingguidelines.github.io. These recommendations aim to ensure a minimum scientific quality for future eye tracking data analysis.

To allow for easy use of our recommendations, we made our code for the above-mentioned results open source, see Section 9. These include the pre-processing and formatting of the raw eye tracking data from the EyeLink and BeGaze parsers as well as the output from the Tobii and Pupil eye trackers. The evaluation of the different blink metrics, i.e., blink frequency, length, and inter-blink interval. It visualizes the data loss for several window sizes and allows for visual inspection to identify additional cut-off points preceding and following blinks. Lastly, the code allows for infilling blinks using different interpolation methods.

To use eye tracking in interactive systems to its fullest potential, we need to perform pre-processing actions beyond the abilities of the current parsers. Even when the included parsers mark blinks, certain artifacts remain in the data. Removing windows/trials/instances where blinks are present will significantly decrease available data and introduce a delay in interactive systems. As such, we recommend the following processing steps for eye tracking data.

(1) Do not remove data that contain blinks as it will cause interaction delays.
(2) Remove data with high variation preceding and following a blink based on inspection of the given dataset.
(3) Use linear or cubic spline interpolation to interpolate between blinks.

(1). We recommend against removing data that contain blinks. While this is one of the most predominant approaches in the literature reviewed, it can, depending on the window size, result in over 50% of the data becoming unusable. It can also lead to temporarily suspending updates to the interactive system, which takes more than double the time of the set window size. While we acknowledge that interactive systems in human-computer interaction rely on blinks for various interactions, the susceptibility of blinks is subject to a variety of factors, like age, air pollutants, and time of day, among others, which could impact the accuracy of interactive systems.

(2). We recommend inspecting the variation in speed [deg/ms] and variation in speed [deg/ms] preceding and following a blink. This will uncover any artifacts in the data related to blinks. The moment the eye tracker identifies a blink it can no longer track the pupil. This leaves the data from where the eyelid moves down and up dependent on the sensitivity and settings of the eye tracker, whether this is included in the blink or not. Visually inspecting the data allows for more careful interpretation. Using a linear function

on the data of 300-150 ms preceding the blink and setting an epsilon enables us to set a cut-off point between relevant data and artifacts.

(3). We recommend using either linear or cubic spline interpolation to interpolate within blinks. We identified several infilling methods during our literature review and compared the most represented ones against one another. Using linear or cubic spline interpolation results in the least amount of mean degrees of error compared to ground truth data.

8 CONCLUSION

Interactive systems that employ eye tracking use several detection methods and algorithms to deal with the missing data introduced by blinks. However, we identified that there is no consensus among the reviewed works for a general approach. For this, we reviewed all eye tracking studies until the end of 2022 that deal with blinks to identify the different blink detection methods and algorithms used to infill the missing data. In this work, we made four recommendations for interactive systems to handle missing data introduced by blinks, allowing for a smoother interaction. These include cutting off data with high variability preceding and following a blink, not removing data that contain blinks, and using linear or cubic spline interpolation to infill the missing data.

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We encourage readers to reproduce and extend our results and analysis methods. Therefore, our experimental setup, links to the collected datasets, and analysis scripts are available at https://eyetrackingguidelines.github.io.

REFERENCES

References marked with • are in the set of reviewed papers.

[1] Yasmeen Abdrabou, Yomna Abdelrahman, Mohamed Khamis, and Florian Alt. 2021. Think Harder! Investigating the Effect of Password Strength on Cognitive Load during Password Creation. In *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems (CHI EA '21)*. Association for Computing Machinery, New York, NY, USA, 1–7. https://doi.org/10.1145/3411763.3451636

[2] Larry A Abel, B Todd Troost, and Louis F Dell'Osso. 1983. The effects of age on normal saccadic characteristics and their variability. *Vision research* 23, 1 (1983), 33–37. https://doi.org/10.1016/0042-6989(83)90038-X

[3] Alejandro Acien, Aythami Morales, Ruben Vera-Rodriguez, and Julian Fierrez. 2020. Smartphone Sensors for Modeling Human-Computer Interaction: General Outlook and Research Datasets for User Authentication. In *2020 IEEE 44th Annual Computers, Software, and Applications Conference (COMPSAC)*. IEEE, Madrid, Spain, 1273–1278. https://doi.org/10.1109/COMPSAC48688.2020.00-81

[4] Abdul Rafey Aftab, Michael von der Beeck, and Michael Feld. 2020. You Have a Point There: Object Selection Inside an Automobile Using Gaze, Head Pose and Finger Pointing. In *Proceedings of the 2020 International Conference on Multimodal Interaction (ICMI '20)*. Association for Computing Machinery, New York, NY, USA, 595–603. https://doi.org/10.1145/3382507.3418836

[5] Abdul Rafey Aftab, Michael Von Der Beeck, Steven Rohrhirsch, Benoit Diotte, and Michael Feld. 2021. Multimodal Fusion Using Deep Learning Applied to Driver's Referencing of Outside-Vehicle Objects. In *2021 IEEE Intelligent Vehicles Symposium (IV)*. IEEE, New York, 1108–1115. https://doi.org/10.1109/IV48863.2021.9575815

[6] Sarmad Al-Gawwam and Mohammed Benaissa. 2017. Eye Blink Detection Using Facial Features Tracker. In *Proceedings of the International Conference on Bioinformatics Research and Applications 2017 - ICBRA 2017*. ACM Press, Barcelona, Spain, 27–30. https://doi.org/10.1145/3175587.3175588

[7] Ahmed Al-Hindawi, Marcela Vizcaychipi, and Yiannis Demiris. 2022. Faster, Better Blink Detection through Curriculum Learning by Augmentation. In *2022 Symposium on Eye Tracking Research and Applications*. ACM, Seattle WA USA, 1–7. https://doi.org/10.1145/3517031.3529617

[8] Qasim Ali, Are Dæhlen, Ilona Heldal, and Carsten Gunnar Helgesen. 2022. Development of Vision Screening Tool in Virtual Reality: A Usability Assessment Study. In *2022 E-Health and Bioengineering Conference (EHB)*. IEEE, New York, NY, USA, 1–5. https://doi.org/10.1109/EHB55594.2022.9991705

[9] Roland Alonso, Mickaël Causse, François Vachon, Robert Parise, Frédéric Dehais, and Patrice Terrier. 2013. Evaluation of head-free eye tracking as an input device for air traffic control. *Ergonomics* 56, 2 (Feb. 2013), 246–255. https://doi.org/10.1080/00140139.2012.744473

[10] Sonja Annerer-Walcher, Simon M Ceh, Felix Putze, Marvin Kampen, Christof Körner, and Mathias Benedek. 2021. How reliably do eye parameters indicate internal versus external attentional focus? *Cognitive Science* 45, 4 (2021), e12977. https://doi.org/10.1111/cogs.12977

[11] Tobias Appel, Thiago Santini, and Enkelejda Kasneci. 2016. Brightness- and motion-based blink detection for head-mounted eye trackers. In *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct*. ACM, Heidelberg Germany, 1726–1735. https://doi.org/10.1145/2968219.2968341

[12] Tobias Appel, Christian Scharinger, Peter Gerjets, and Enkelejda Kasneci. 2018. Cross-Subject Workload Classification Using Pupil-Related Measures. In *Proceedings of the 2018 ACM Symposium on Eye Tracking Research & Applications* (Warsaw, Poland) *(ETRA '18)*. Association for Computing Machinery, New York, NY, USA, Article 4, 8 pages. https://doi.org/10.1145/3204493.3204531

[13] Tobias Appel, Natalia Sevcenko, Franz Wortha, Katerina Tsarava, Korbinian Moeller, Manuel Ninaus, Enkelejda Kasneci, and Peter Gerjets. 2019. Predicting Cognitive Load in an Emergency Simulation Based on Behavioral and Physiological Measures. In *2019 International Conference on Multimodal Interaction (ICMI '19)*. Association for Computing Machinery, New York, NY, USA, 154–163. https://doi.org/10.1145/3340555.3353735

[14] Mohammed Safayet Arefin, J. Edward Swan II, Russell A. Cohen Hoffing, and Steven M. Thurman. 2022. Estimating Perceptual Depth Changes with Eye Vergence and Interpupillary Distance Using an Eye Tracker in Virtual Reality. In *2022 Symposium on Eye Tracking Research and Applications (ETRA '22)*. Association for Computing Machinery, New York, NY, USA, 1–7. https://doi.org/10.1145/3517031.3529632

[15] Majid Arianezhad, L. Jean Camp, Timothy Kelley, and Douglas Stebila. 2013. Comparative Eye Tracking of Experts and Novices in Web Single Sign-On. In *Proceedings of the Third ACM Conference on Data and Application Security and Privacy* (San Antonio, Texas, USA) *(CODASPY '13)*. Association for Computing Machinery, New York, NY, USA, 105–116. https://doi.org/10.1145/2435349.2435362

[16] Sarker Monojit Asish, Arun K. Kulshreshth, and Christoph W. Borst. 2022. User Identification Utilizing Minimal Eye-Gaze Features in Virtual Reality Applications. *Virtual Worlds* 1, 1, 42–61. https://doi.org/10.3390/virtualworlds1010004

[17] Ebrahim Babaei, Benjamin Tag, Tilman Dingler, and Eduardo Velloso. 2021. A Critique of Electrodermal Activity Practices at CHI. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (Yokohama, Japan) *(CHI '21)*. Association for Computing Machinery, New York, NY, USA, Article 177, 14 pages. https://doi.org/10.1145/3411764.3445370

[18] Areej Babiker, Ibrahima Faye, and Aamir Malik. 2013. Pupillary Behavior in Positive and Negative Emotions. In *2013 IEEE International Conference on Signal and Image Processing Applications*. IEEE, New York, NY, USA, 379–383. https://doi.org/10.1109/ICSIPA.2013.6708037

[19] Tanya Bafna, John Paulin Paulin Hansen, and Per Baekgaard. 2020. Cognitive Load during Eye-typing. In *ACM Symposium on Eye Tracking Research and Applications (ETRA '20 Full Papers)*. Association for Computing Machinery, New York, NY, USA, 1–8. https://doi.org/10.1145/3379155.3391333

[20] E. Bekele, J. Wade, D. Bian, J. Fan, Amy Swanson, Z. Warren, and N. Sarkar. 2016. Multimodal Adaptive Social Interaction in Virtual Environment (MASI-VR) for Children with Autism Spectrum Disorders (ASD). In *2016 IEEE Virtual Reality (VR)*. IEEE, New York, NY, USA, 121–130. https://doi.org/10.1109/VR.2016.7504695

[21] Esubalew Bekele, Zhi Zheng, Amy Swanson, Julie Crittendon, Zachary Warren, and Nilanjan Sarkar. 2013. Understanding How Adolescents with Autism Respond to Facial Expressions in Virtual Reality Environments. *IEEE Transactions on Visualization and Computer Graphics* 19, 4 (2013), 711–720. https://doi.org/10.1109/TVCG.2013.42

[22] Luis M. Bergasa, Jesús Nuevo, Miguel Angel Sotelo, Rafael Barea, and M. Elena Lopez. 2006. Real-Time System for Monitoring Driver Vigilance. *IEEE Transactions on Intelligent Transportation Systems* 7, 1 (March 2006), 63–77. https://doi.org/10.1109/TITS.2006.869598

[23] Joanna Bergström, Tor-Salve Dalsgaard, Jason Alexander, and Kasper Hornbæk. 2021. How to Evaluate Object Selection and Manipulation in VR? Guidelines from 20 Years of Studies. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (, Yokohama, Japan,) *(CHI '21)*. Association for Computing Machinery, New York, NY, USA, Article 533, 20 pages. https://doi.org/10.1145/3411764.3445193

[24] Nilavra Bhattacharya, Somnath Rakshit, and Jacek Gwizdka. 2020. Towards Real-Time Webpage Relevance Prediction UsingConvex Hull Based Eye-Tracking Features. In *ACM Symposium on Eye Tracking Research and Applications* (Stuttgart, Germany) *(ETRA '20 Adjunct)*. Association for Computing Machinery, New York,

NY, USA, Article 28, 10 pages. https://doi.org/10.1145/3379157.3391302

[25] Robert E. Bixler and Sidney K. D'Mello. 2021. Crossed Eyes: Domain Adaptation for Gaze-Based Mind Wandering Models. In *ACM Symposium on Eye Tracking Research and Applications (ETRA '21 Full Papers)*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3448017.3457386

[26] WP Blount. 1927. Studies of the movements of the eyelids of animals: blinking. *Quarterly Journal of Experimental Physiology: Translation and Integration* 18, 2 (1927), 111–125. https://doi.org/10.1177/001872089403600209

[27] Indu P. Bodala, Nida I. Abbasi, Yu Sun, Anastasios Bezerianos, Hasan Al-Nashash, and Nitish V. Thakor. 2017. Measuring Vigilance Decrement Using Computer Vision Assisted Eye Tracking in Dynamic Naturalistic Environments. In *2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, New York, NY, USA, 2478–2481. https://doi.org/10.1109/EMBC.2017.8037359

[28] Riccardo Brambilla, Francesco Onorati, Vincenzo Russo, Maurizio Mauri, Lorenzo Magrassi, Luca T. Mainardi, and Riccardo Barbieri. 2018. A Stimulus-Response Processing Framework for Pupil Dynamics Assessment during Iso-Luminant Stimuli. In *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, New York, NY, USA, 400–403. https://doi.org/10.1109/EMBC.2018.8512325

[29] Gianni Bremer, Niklas Stein, and Markus Lappe. 2022. Do They Look Where They Go? Gaze Classification During Walking. https://openreview.net/forum?id=XP0k6ToFK7t

[30] Gianni Bremer, Niklas Stein, and Markus Lappe. 2023. Machine Learning Prediction of Locomotion Intention from Walking and Gaze Data. *International Journal of Semantic Computing* 17, 01 (March 2023), 119–142. https://doi.org/10.1142/S1793351X22490010

[31] Jeffrey B Brookings, Glenn F Wilson, and Carolyne R Swain. 1996. Psychophysiological responses to changes in workload during simulated air traffic control. *Biological psychology* 42, 3 (1996), 361–377. https://doi.org/10.1016/0301-0511(95)05167-8

[32] Frank Broz, Hagen Lehmann, Chrystopher L. Nehaniv, and Kerstin Dautenhahn. 2012. Mutual Gaze, Personality, and Familiarity: Dual Eye-Tracking during Conversation. In *2012 IEEE RO-MAN: The 21st IEEE International Symposium on Robot and Human Interactive Communication*. IEEE, New York, NY, USA, 858–864. https://doi.org/10.1109/ROMAN.2012.6343859

[33] Tobias Bär, Jan Felix Reuter, and J. Marius Zöllner. 2012. Driver head pose and gaze estimation based on multi-template ICP 3-D point cloud alignment. In *2012 15th International IEEE Conference on Intelligent Transportation Systems*. IEEE, New York, NY, USA, 1797–1802. https://doi.org/10.1109/ITSC.2012.6338678

[34] Nora Castner, Enkelejda Kasneci, Thomas Kübler, Katharina Scheiter, Juliane Richter, Thérése Eder, Fabian Hüttig, and Constanze Keutel. 2018. Scanpath Comparison in Medical Image Reading Skills of Dental Students: Distinguishing Stages of Expertise Development. In *Proceedings of the 2018 ACM Symposium on Eye Tracking Research & Applications* (Warsaw, Poland) *(ETRA '18)*. Association for Computing Machinery, New York, NY, USA, Article 39, 9 pages. https://doi.org/10.1145/3204493.3204550

[35] Natalia Chitalkina. 2019. When You Don't See What You Expect: Incongruence in Music and Source Code Reading. In *Proceedings of the 11th ACM Symposium on Eye Tracking Research & Applications* (Denver, Colorado) *(ETRA '19)*. Association for Computing Machinery, New York, NY, USA, Article 47, 3 pages. https://doi.org/10.1145/3314111.3322866

[36] Alessandro Cierro, Thibault Philippette, Thomas Francois, Sebastien Nahon, and Patrick Watrin. 2020. Eye-Tracking for Sense of Immersion and Linguistic Complexity in the Skyrim Game: Issues and Perspectives. In *ACM Symposium on Eye Tracking Research and Applications* (Stuttgart, Germany) *(ETRA '20 Short Papers)*. Association for Computing Machinery, New York, NY, USA, Article 60, 5 pages. https://doi.org/10.1145/3379156.3391836

[37] Andy Cockburn, Carl Gutwin, and Alan Dix. 2018. HARK No More: On the Preregistration of CHI Experiments. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems* (Montreal QC, Canada) *(CHI '18)*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3173574.3173715

[38] Michael J. Cole, Chathra Hendahewa, Nicholas J. Belkin, and Chirag Shah. 2015. User Activity Patterns During Information Search. *ACM Trans. Inf. Syst.* 33, 1, Article 1 (mar 2015), 39 pages. https://doi.org/10.1145/2699656

[39] Han Collewijn, Johannes Van Der Steen, and Robert M. Steinman. 1985. Human eye movements associated with blinks and prolonged eyelid closure. *Journal of neurophysiology* 54, 1 (1985), 11–27. https://doi.org/10.1152/jn.1985.54.1.11

[40] Michael Collins, Rhonda Seeto, Louella Campbell, and Murray Ross. 1989. Blinking and corneal sensitivity. *Acta ophthalmologica* 67, 5 (1989), 525–531. https://doi.org/10.1111/j.1755-3768.1989.tb04103.x

[41] Lorenza S Colzato, Heleen A Slagter, Wery PM van den Wildenberg, and Bernhard Hommel. 2009. Closing one's eyes to reality: Evidence for a dopaminergic basis of psychoticism from spontaneous eye blink rates. *Personality and Individual Differences* 46, 3 (2009), 377–380. https://doi.org/10.1016/j.paid.2008.10.017

[42] Ricardo Couceiro, Gonçalo Duarte, João Durães, João Castelhano, Catarina Duarte, Cesar Teixeira, Miguel Castelo Branco, Paulo Carvalho, and Henrique Madeira. 2019. Pupillography as Indicator of Programmers' Mental Effort and Cognitive Overload. In *2019 49th Annual IEEE/IFIP International Conference on Dependable Systems and Networks (DSN)*. IEEE, New York, NY, USA, 638–644. https://doi.org/10.1109/DSN.2019.00069

[43] Flávio Luiz Coutinho and Carlos H. Morimoto. 2012. Augmenting the Robustness of Cross-Ratio Gaze Tracking Methods to Head Movement. In *Proceedings of the Symposium on Eye Tracking Research and Applications* (Santa Barbara, California) *(ETRA '12)*. Association for Computing Machinery, New York, NY, USA, 59–66. https://doi.org/10.1145/2168556.2168565

[44] Jonathan Currie, Raymond R. Bond, Paul McCullagh, Pauline Black, Dewar D. Finlay, and Aaron Peace. 2018. Eye Tracking the Visual Attention of Nurses Interpreting Simulated Vital Signs Scenarios: Mining Metrics to Discriminate Between Performance Level. *IEEE Transactions on Human-Machine Systems* 48, 2 (2018), 113–124. https://doi.org/10.1109/THMS.2017.2754880

[45] Emanuela L. Dan, Mihaela Dînşoreanu, and Raul C. Mureşan. 2020. Accuracy of Six Interpolation Methods Applied on Pupil Diameter Data. In *2020 IEEE International Conference on Automation, Quality and Testing, Robotics (AQTR)*. IEEE, New York, NY, USA, 1–5. https://doi.org/10.1109/AQTR49680.2020.9129915

[46] Filip Dechterenko and Jiri Lukavsky. 2014. Models of Eye Movements in Multiple Object Tracking with Many Objects. In *2014 5th European Workshop on Visual Information Processing (EUVIP)*. IEEE, New York, NY, USA, 1–6. https://doi.org/10.1109/EUVIP.2014.7018375

[47] Michael J Doughty and Taher Naase. 2006. Further analysis of the human spontaneous eye blink rate by a cluster analysis-based approach to categorize individuals with 'normal'versus 'frequent'eye blink activity. *Eye & contact lens* 32, 6 (2006), 294–299. https://doi.org/10.1097/01.icl.0000224359.32709.4d

[48] Heiko Drewes and Albrecht Schmidt. 2007. Interacting with the Computer Using Gaze Gestures. In *Human-Computer Interaction – INTERACT 2007*. Springer Berlin Heidelberg, Berlin, Heidelberg, 475–488.

[49] Heiko Drewes and Albrecht Schmidt. 2007. Interacting with the Computer Using Gaze Gestures. In *Human-Computer Interaction – INTERACT 2007*. Vol. 4663. Springer Berlin Heidelberg, Berlin, Heidelberg, 475–488. https://doi.org/10.1007/978-3-540-74800-7_43 Series Title: Lecture Notes in Computer Science.

[50] Andrew T. Duchowski, Donald H. House, Jordan Gestring, Robert Congdon, Lech undefinedwirski, Neil A. Dodgson, Krzysztof Krejtz, and Izabela Krejtz. 2014. Comparing Estimated Gaze Depth in Virtual and Physical Environments. In *Proceedings of the Symposium on Eye Tracking Research and Applications* (Safety Harbor, Florida) *(ETRA '14)*. Association for Computing Machinery, New York, NY, USA, 103–110. https://doi.org/10.1145/2578153.2578168

[51] Morten Lund Dybdal, Javier San Agustin, and John Paulin Hansen. 2012. Gaze input for mobile devices by dwell and gestures. In *Proceedings of the Symposium on Eye Tracking Research and Applications*. ACM, Santa Barbara California, 225–228. https://doi.org/10.1145/2168556.2168601

[52] Inger Ekman, Antti Poikola, Meeri Mäkäräinen, Tapio Takala, and Perttu Hämäläinen. 2008. Voluntary Pupil Size Change as Control in Eyes Only Interaction. In *Proceedings of the 2008 Symposium on Eye Tracking Research & Applications* (Savannah, Georgia) *(ETRA '08)*. Association for Computing Machinery, New York, NY, USA, 115–118. https://doi.org/10.1145/1344471.1344501

[53] Julie Epelboim and Patrick Suppes. 2001. A model of eye movements and visual working memory during problem solving in geometry. *Vision research* 41, 12 (2001), 1561–1574. https://doi.org/10.1016/S0042-6989(00)00256-X

[54] Augusto Esteves, Eduardo Velloso, Andreas Bulling, and Hans Gellersen. 2015. Orbits: Gaze Interaction for Smart Watches using Smooth Pursuit Eye Movements. In *Proceedings of the 28th Annual ACM Symposium on User Interface Software & Technology* (Charlotte, NC, USA) *(UIST '15)*. Association for Computing Machinery, New York, NY, USA, 457–466. https://doi.org/10.1145/2807442.2807499

[55] Victor Fajnzylber, Larry González, Pedro Maldonado, Rafael Del Villar, Rodrigo Yáñez, Samuel Madariaga, Milán Magdics, and Mateu Sbert. 2017. Augmented Film Narrative by Use of Non-Photorealistic Rendering. In *2017 International Conference on 3D Immersion (IC3D)*. IEEE, New York, NY, USA, 1–8. https://doi.org/10.1109/IC3D.2017.8251912

[56] Irving Fatt and Barry A Weissman. 2013. *Physiology of the Eye: An Introduction to the Vegetative Functions*. Butterworth-Heinemann, Oxford, United Kingdom. https://books.google.de/books?id=H2OfAgAAQBAJ

[57] Sascha Feder, Alexandra Bendixen, and Wolfgang Einhäuser. 2022. A hybrid control strategy for capturing cognitive processes in virtual reality (VR) in a natural and efficient way. In *2022 IEEE 9th International Conference on Computational Intelligence and Virtual Environments for Measurement Systems and Applications (CIVEMSA)*. IEEE, New York, NY, USA, 1–6. https://doi.org/10.1109/CIVEMSA53371.2022.9853646

[58] Marcela Fejtová, Jan Fejt, and Lenka Lhotská. 2004. Controlling a PC by Eye Movements: The MEMREC Project.. In *ICCHP (Lecture Notes in Computer Science, Vol. 3118)*. Springer, Berlin, Germany, 770–773. https://doi.org/10.1007/978-3-540-27817-7_114

[59] Anna-Maria Felßberg and Isabel Dombrowe. 2018. The effect of different brightness conditions on visually and memory guided saccades. *Vision Research* 142 (2018), 20–26. https://doi.org/10.1016/j.visres.2017.10.004

[60] Mingwang Feng, Rong Fan, Chao Liu, Tianyi Gao, Zheng Wang, and Rencheng Zheng. 2020. Influence of Vehicle Speeds in Curve Driving on Pupil Diameters of Drivers. In *2020 4th CAA International Conference on Vehicular Control and Intelligence (CVCI)*. IEEE, New York, NY, USA, 777–780. https://doi.org/10.1109/CVCI51460.2020.9338528

[61] Yunlong Feng, Gene Cheung, Wai-tian Tan, Patrick Le Callet, and Yusheng Ji. 2013. Low-Cost Eye Gaze Prediction System for Interactive Networked Video Streaming. *IEEE Transactions on Multimedia* 15, 8 (Dec. 2013), 1865–1879. https://doi.org/10.1109/TMM.2013.2272918

[62] Joshua J Foster, David W Sutterer, John T Serences, Edward K Vogel, and Edward Awh. 2017. Alpha-band oscillations enable spatially and temporally resolved tracking of covert spatial attention. *Psychological science* 28, 7 (2017), 929–941. https://doi.org/10.1177/0956797617699167

[63] Javier Galbally, Sebastien Marcel, and Julian Fierrez. 2014. Biometric Antispoofing Methods: A Survey in Face Recognition. *IEEE Access* 2 (2014), 1530–1552. https://doi.org/10.1109/ACCESS.2014.2381273

[64] Rahul Gavas, Debatri Chatterjee, and Aniruddha Sinha. 2017. Estimation of Cognitive Load Based on the Pupil Size Dilation. In *2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*. IEEE, New York, NY, USA, 1499–1504. https://doi.org/10.1109/SMC.2017.8122826

[65] Andrew Gelman and Donald B. Rubin. 1992. Inference from iterative simulation using multiple sequences. *Statistical science* 7, 4 (1992), 457–472. https://doi.org/10.1214/ss/1177011136

[66] Martinho Gonçalves, Tânia Rocha, Luís Magalhães, Emanuel Peres, Maximino Bessa, and Alan Chalmers. 2011. Identifying Different Visual Patterns in Web Users Behaviour. In *Proceedings of the 27th Spring Conference on Computer Graphics* (Viničné, Slovak Republic) *(SCCG '11)*. Association for Computing Machinery, New York, NY, USA, 65–70. https://doi.org/10.1145/2461217.2461231

[67] Lukas Greiter, Christoph Strauch, and Anke Huckauf. 2018. Pupil Responses Signal Less Inhibition for Own Relative to Other Names. In *Proceedings of the 2018 ACM Symposium on Eye Tracking Research & Applications (ETRA '18)*. Association for Computing Machinery, New York, NY, USA, 1–5. https://doi.org/10.1145/3204493.3204576

[68] Jesse W. Grootjen, Henrike Weingärtner, and Sven Mayer. 2023. Highlighting the Challenges of Blinks in Eye Tracking for Interactive Systems. In *Proceedings of the 2023 Symposium on Eye Tracking Research and Applications* (Tubingen, Germany) *(ETRA '23)*. Association for Computing Machinery, New York, NY, USA, Article 63, 7 pages. https://doi.org/10.1145/3588015.3589202

[69] Nishan Gunawardena, Michael Matscheko, Bernhard Anzengruber, Alois Ferscha, Martin Schobesberger, Andreas Shamiyeh, Bettina Klugsberger, and Peter Solleder. 2019. Assessing Surgeons' Skill Level in Laparoscopic Cholecystectomy Using Eye Metrics. In *Proceedings of the 11th ACM Symposium on Eye Tracking Research & Applications (ETRA '19)*. Association for Computing Machinery, New York, NY, USA, 1–8. https://doi.org/10.1145/3314111.3319832

[70] Jacek Gwizdka. 2014. Characterizing Relevance with Eye-Tracking Measures. In *Proceedings of the 5th Information Interaction in Context Symposium (IIiX '14)*. Association for Computing Machinery, New York, NY, USA, 58–67. https://doi.org/10.1145/2637002.2637011

[71] Kanghang He, Cheng Yang, Vladimir Stankovic, and Lina Stankovic. 2017. Graph-based clustering for identifying region of interest in eye tracker data analysis. In *2017 IEEE 19th International Workshop on Multimedia Signal Processing (MMSP)*. IEEE, New York, NY, USA, 1–6. https://doi.org/10.1109/MMSP.2017.8122264

[72] Javier Hernandez-Ortega, Julian Fierrez, Aythami Morales, and Javier Galbally. 2019. Introduction to Face Presentation Attack Detection. In *Handbook of Biometric Anti-Spoofing*. Springer International Publishing, Cham, 187–206. https://doi.org/10.1007/978-3-319-92627-8_9 Series Title: Advances in Computer Vision and Pattern Recognition.

[73] Javier Hernandez-Ortega, Shigenori Nagae, Julian Fierrez, and Aythami Morales. 2019. Quality-based Pulse Estimation from NIR Face Video with Application to Driver Monitoring. http://arxiv.org/abs/1905.06568 arXiv:1905.06568 [cs, eess].

[74] Imali T. Hettiarachchi, Samer Hanoun, Rakesh Veerabhadrappa, Dawei Jia, Simon Hosking, and Asim Bhatti. 2021. Performance Quantification and Heart Rate Analysis in A Repeated-trial Simulation-based Training Task. In *2021 IEEE International Systems Conference (SysCon)*. IEEE, New York, NY, USA, 1–7. https://doi.org/10.1109/SysCon48628.2021.9447147

[75] Linda Hirsch, Jingyi Li, Sven Mayer, and Andreas Butz. 2022. A Survey of Natural Design for Interaction. In *Proceedings of Mensch Und Computer 2022* (Darmstadt, Germany) *(MuC '22)*. Association for Computing Machinery, New York, NY, USA, 240–254. https://doi.org/10.1145/3543758.3543773

[76] Teresa Hirzle, Fabian Fischbach, Julian Karlbauer, Pascal Jansen, Jan Gugenheimer, Enrico Rukzio, and Andreas Bulling. 2022. Understanding, Addressing, and Analysing Digital Eye Strain in Virtual Reality Head-Mounted Displays. *ACM Trans. Comput.-Hum. Interact.* 29, 4, Article 33 (mar 2022), 80 pages. https://doi.org/10.1145/3492802

[77] Kajta Hofmann, Bhaskar Mitra, Filip Radlinski, and Milad Shokouhi. 2014. An Eye-Tracking Study of User Interactions with Query Auto Completion. In *Proceedings of the 23rd ACM International Conference on Conference on Information and Knowledge Management* (Shanghai, China) *(CIKM '14)*. Association for Computing Machinery, New York, NY, USA, 549–558. https://doi.org/10.1145/2661829.2661922

[78] Nora Hollenstein, Maria Barrett, and Marina Björnsdóttir. 2022. The Copenhagen Corpus of Eye Tracking Recordings from Natural Reading of Danish Texts. In *Proceedings of the Thirteenth Language Resources and Evaluation Conference*. European Language Resources Association, Marseille, France, 1712–1720. https://doi.org/10.48550/ARXIV.2204.13311

[79] K. Holmqvist, M. Nyström, R. Andersson, R. Dewhurst, H. Jarodzka, and J. van de Weijer. 2011. *Eye Tracking: A comprehensive guide to methods and measures*. OUP Oxford, Oxford, United Kingdom. https://books.google.de/books?id=5rIDPV1EoLUC

[80] Zhenghao Hu, Hao Zhai, Aomei Li, Zhizhong Xi, Zhaozhen Jiang, and Beiyao Cui. 2020. Blink Detection Algorithm Based on BP Neural Network. In *2020 6th International Conference on Robotics and Artificial Intelligence*. ACM, Singapore Singapore, 35–40. https://doi.org/10.1145/3449301.3449308

[81] Michael Xuelin Huang and Andreas Bulling. 2019. SacCalib: Reducing Calibration Distortion for Stationary Eye Trackers Using Saccadic Eye Movements. In *Proceedings of the 11th ACM Symposium on Eye Tracking Research & Applications (ETRA '19)*. Association for Computing Machinery, New York, NY, USA, 1–10. https://doi.org/10.1145/3317956.3321553

[82] Stephen Hutt, Caitlin Mills, Nigel Bosch, Kristina Krasich, James Brockmole, and Sidney D'Mello. 2017. "Out of the Fr-Eye-ing Pan": Towards Gaze-Based Models of Attention during Learning with Technology in the Classroom. In *Proceedings of the 25th Conference on User Modeling, Adaptation and Personalization (UMAP '17)*. Association for Computing Machinery, New York, NY, USA, 94–103. https://doi.org/10.1145/3079628.3079669

[83] Stephen Hutt, Angela E.B. Stewart, Julie Gregg, Stephen Mattingly, and Sidney K. D'Mello. 2022. Feasibility of Longitudinal Eye-Gaze Tracking in the Workplace. *Proc. ACM Hum.-Comput. Interact.* 6, ETRA, Article 148 (may 2022), 21 pages. https://doi.org/10.1145/3530889

[84] Transparent Statistics in Human–Computer Interaction Working Group. 2019. Transparent Statistics Guidelines. https://doi.org/10.5281/zenodo.2226616

[85] Constantina Ioannou, Per Bækgaard, Ekkart Kindler, and Barbara Weber. 2020. Towards a Tool for Visualizing Pupil Dilation Linked with Source Code Artifacts. In *2020 Working Conference on Software Visualization (VISSOFT)*. IEEE, New York, NY, USA, 105–109. https://doi.org/10.1109/VISSOFT51673.2020.00016

[86] Ryo Ishii, Yukiko I. Nakano, and Toyoaki Nishida. 2013. Gaze Awareness in Conversational Agents: Estimating a User's Conversational Engagement from Eye Gaze. *ACM Trans. Interact. Intell. Syst.* 3, 2, Article 11 (aug 2013), 25 pages. https://doi.org/10.1145/2499474.2499480

[87] Howell Istance and Aulikki I. Hyrskykari. 2017. Supporting Making Fixations and the Effect on Gaze Gesture Performance. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems* (Denver, Colorado, USA) *(CHI '17)*. Association for Computing Machinery, New York, NY, USA, 3022–3033. https://doi.org/10.1145/3025453.3025920

[88] Petar Jerčič, Charlotte Sennersten, and Craig Lindley. 2017. The Effect of Cognitive Load on Physiological Arousal in a Decision-Making Serious Game. In *2017 9th International Conference on Virtual Worlds and Games for Serious Applications (VS-Games)*. IEEE, New York, NY, USA, 153–156. https://doi.org/10.1109/VS-GAMES.2017.8056587

[89] Patrick Jermann and Marc-Antoine Nüssli. 2012. Effects of Sharing Text Selections on Gaze Cross-Recurrence and Interaction Quality in a Pair Programming Task. In *Proceedings of the ACM 2012 Conference on Computer Supported Cooperative Work* (Seattle, Washington, USA) *(CSCW '12)*. Association for Computing Machinery, New York, NY, USA, 1125–1134. https://doi.org/10.1145/2145204.2145371

[90] Shaohua Jia, Do Hyong Koh, Amanda Seccia, Pasha Antonenko, Richard Lamb, Andreas Keil, Matthew Schneps, and Marc Pomplun. 2018. Biometric Recognition Through Eye Movements Using a Recurrent Neural Network. In *2018 IEEE International Conference on Big Knowledge (ICBK)*. IEEE, New York, NY, USA, 57–64. https://doi.org/10.1109/ICBK.2018.00016

[91] Jiang Jun, Boxin Zhao, Peng Zhang, Zhenkun Chen, and Fang Peng. 2021. Research on UAV Control Method Based on Eye Tracking. In *2021 33rd Chinese Control and Decision Conference (CCDC)*. IEEE, New York, NY, USA, 3281–3286. https://doi.org/10.1109/CCDC52312.2021.9602071

[92] G Karthik, J Amudha, and C Jyotsna. 2019. A Custom Implementation of the Velocity Threshold Algorithm for Fixation Identification. In *2019 International Conference on Smart Systems and Inventive Technology (ICSSIT)*. IEEE, New York, NY, USA, 488–492. https://doi.org/10.1109/ICSSIT46314.2019.8987791

[93] Matthew Kay, Steve Haroz, Shion Guha, and Pierre Dragicevic. 2016. Special Interest Group on Transparent Statistics in HCI. In *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems* (San Jose, California, USA) *(CHI EA '16)*. Association for Computing Machinery, New York, NY, USA, 1081–1084. https://doi.org/10.1145/2851581.2886442

[94] Matthew Kay, Gregory L. Nelson, and Eric B. Hekler. 2016. Researcher-Centered Design of Statistics: Why Bayesian Statistics Better Fit the Culture and Incentives of HCI. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing*

Systems (San Jose, California, USA) *(CHI '16)*. Association for Computing Machinery, New York, NY, USA, 4521–4532. https://doi.org/10.1145/2858036.2858465

[95] Ashima Keshava, Anete Aumeistere, Krzysztof Izdebski, and Peter Konig. 2020. Decoding Task From Oculomotor Behavior In Virtual Reality. In *ACM Symposium on Eye Tracking Research and Applications (ETRA '20 Short Papers)*. Association for Computing Machinery, New York, NY, USA, 1–5. https://doi.org/10.1145/3379156.3391338

[96] Ahsan Raza Khan, Syed Mohsin Bokhari, Sara Khosravi, Sajjad Hussain, Rami Ghannam, Muhammad Ali Imran, and Ahmed Zoha. 2022. Feature Selection Mechanism for Attention Classification Using Gaze Tracking Data. In *2022 29th IEEE International Conference on Electronics, Circuits and Systems (ICECS)*. IEEE, New York, NY, USA, 1–4. https://doi.org/10.1109/ICECS202256217.2022.9970936

[97] Tomi Kinnunen, Filip Sedlak, and Roman Bednarik. 2010. Towards Task-Independent Person Authentication Using Eye Movement Signals. In *Proceedings of the 2010 Symposium on Eye-Tracking Research & Applications (ETRA '10)*. Association for Computing Machinery, New York, NY, USA, 187–190. https://doi.org/10.1145/1743666.1743712

[98] Kristopher Kohm, John Porter, and Andrew Robb. 2022. Sensitivity to Hand Offsets and Related Behavior in Virtual Environments over Time. *ACM Trans. Appl. Percept.* 19, 4, Article 17 (nov 2022), 15 pages. https://doi.org/10.1145/3561055

[99] Oleg V. Komogortsev, Young Sam Ryu, Do Hyong Koh, and Sandeep M. Gowda. 2009. Instantaneous saccade driven eye gaze interaction. In *Proceedings of the International Conference on Advances in Computer Enterntainment Technology - ACE '09*. ACM Press, Athens, Greece, 140. https://doi.org/10.1145/1690388.1690412

[100] Dimosthenis Kontogiorgos, Elena Sibirtseva, Andre Pereira, Gabriel Skantze, and Joakim Gustafson. 2018. Multimodal Reference Resolution In Collaborative Assembly Tasks. In *Proceedings of the 4th International Workshop on Multimodal Analyses Enabling Artificial Agents in Human-Machine Interaction* (Boulder, CO, USA) *(MA3HMI'18)*. Association for Computing Machinery, New York, NY, USA, 38–42. https://doi.org/10.1145/3279972.3279976

[101] Fatemeh Koochaki and Laleh Najafizadeh. 2021. A Data-Driven Framework for Intention Prediction via Eye Movement With Applications to Assistive Systems. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 29 (2021), 974–984. https://doi.org/10.1109/TNSRE.2021.3083815

[102] Benthe Kornrumpf, Florian Niefind, Werner Sommer, and Olaf Dimigen. 2016. Neural Correlates of Word Recognition: A Systematic Comparison of Natural Reading and Rapid Serial Visual Presentation. *Journal of Cognitive Neuroscience* 28, 9 (09 2016), 1374–1391. https://doi.org/10.1162/jocn_a_00977 arXiv:https://direct.mit.edu/jocn/article-pdf/28/9/1374/1951600/jocn_a_00977.pdf

[103] Alexander Korotin, Nikita Khromov, Anton Stepanov, Andrey Lange, Evgeny Burnaev, and Andrey Somov. 2019. Towards Understanding of eSports Athletes' Potentialities: The Sensing System for Data Collection and Analysis. In *2019 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI)*. IEEE, New York, NY, USA, 1804–1810. https://doi.org/10.1109/SmartWorld-UIC-ATC-SCALCOM-IOP-SCI.2019.00319

[104] Jani Koskinen and Roman Bednarik. 2020. Gaze - Grabber Distance in Expert and Novice Forest Machine Operators: The Effects of Automatic Boom Control. In *ACM Symposium on Eye Tracking Research and Applications (ETRA '20 Adjunct)*. Association for Computing Machinery, New York, NY, USA, 1–7. https://doi.org/10.1145/3379157.3391414

[105] Luka Krapic, Kristijan Lenac, and Sandi Ljubic. 2015. Integrating Blink Click interaction into a head tracking system: implementation and usability issues. *Universal Access in the Information Society* 14, 2 (June 2015), 247–264. https://doi.org/10.1007/s10209-013-0343-y

[106] Laura Krieger, Gunther Heidemann, and Julius Schöning. 2018. Object of Interest Segmentation in Video Sequences with Gaze Data. In *2018 IEEE International Conference on Image Processing, Applications and Systems (IPAS)*. IEEE, New York, NY, USA, 104–109. https://doi.org/10.1109/IPAS.2018.8708873

[107] Ksenija Krstić, Anđela Šoškić, Vanja Ković, and Kenneth Holmqvist. 2018. All good readers are the same, but every low-skilled reader is different: an eye-tracking study using PISA data. *European Journal of Psychology of Education* 33, 3 (2018), 521–541. https://doi.org/10.1007/s10212-018-0382-0

[108] Jakub Krukar, Panagiotis Mavros, and Christoph Hoelscher. 2020. Towards Capturing Focal/Ambient Attention during Dynamic Wayfinding. In *ACM Symposium on Eye Tracking Research and Applications* (Stuttgart, Germany) *(ETRA '20 Adjunct)*. Association for Computing Machinery, New York, NY, USA, Article 22, 5 pages. https://doi.org/10.1145/3379157.3391417

[109] Aleksandra Królak and Paweł Strumiłło. 2012. Eye-blink detection system for human–computer interaction. *Universal Access in the Information Society* 11, 4 (Nov. 2012), 409–419. https://doi.org/10.1007/s10209-011-0256-6

[110] Aristea Ladas, Christos Frantzidis, Panagiotis Bamidis, and Ana B. Vivas. 2014. Eye Blink Rate as a biological marker of Mild Cognitive Impairment. *International Journal of Psychophysiology* 93, 1 (July 2014), 12–16. https://doi.org/10.1016/j.ijpsycho.2013.07.010

[111] Simon Ladouce, Magda Mustile, Magdalena Ietswaart, and Frédéric Dehais. 2022. Capturing Cognitive Events Embedded in the Real World Using Mobile Electroencephalography and Eye-Tracking. *Journal of Cognitive Neuroscience* 34, 12 (2022), 2237–2255. https://doi.org/10.1162/jocn_a_01903

[112] Kecheng Lai, Yuqi Liu, Qikun He, Ming Yi, and Tsutomu Fujinami. 2021. Saliva Secretion as Indicator of Appetite. In *Proceedings of the 5th International Conference on Medical and Health Informatics* (Kyoto, Japan) *(ICMHI '21)*. Association for Computing Machinery, New York, NY, USA, 249–253. https://doi.org/10.1145/3472813.3473198

[113] Christian Lander and Antonio Krüger. 2018. EyeSense: Towards Information Extraction on Corneal Images. In *Proceedings of the 2018 ACM International Joint Conference and 2018 International Symposium on Pervasive and Ubiquitous Computing and Wearable Computers* (Singapore, Singapore) *(UbiComp '18)*. Association for Computing Machinery, New York, NY, USA, 980–987. https://doi.org/10.1145/3267305.3274121

[114] Sharon Leal and Aldert Vrij. 2008. Blinking During and After Lying. *Journal of Nonverbal Behavior* 32, 4 (Dec. 2008), 187–194. https://doi.org/10.1007/s10919-008-0051-0

[115] Jisoo Lee, Erin Walker, Winslow Burleson, Matthew Kay, Matthew Buman, and Eric B. Hekler. 2017. Self-Experimentation for Behavior Change: Design and Formative Evaluation of Two Approaches. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems* (Denver, Colorado, USA) *(CHI '17)*. Association for Computing Machinery, New York, NY, USA, 6837–6849. https://doi.org/10.1145/3025453.3026038

[116] Jan Leusmann, Carl Oechsner, Johanna Prinz, Robin Welsch, and Sven Mayer. 2023. A Database for Kitchen Objects: Investigating Danger Perception in the Context of Human-Robot Interaction. In *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems* (Hamburg, Germany) *(CHI EA '23)*. Association for Computing Machinery, New York, NY, USA, Article 6, 9 pages. https://doi.org/10.1145/3544549.3585884

[117] Beibin Li, Erin Barney, Caitlin Hudac, Nicholas Nuechterlein, Pamela Ventola, Linda Shapiro, and Frederick Shic. 2020. Selection of Eye-Tracking Stimuli for Prediction by Sparsely Grouped Input Variables for Neural Networks: Towards Biomarker Refinement for Autism. In *ACM Symposium on Eye Tracking Research and Applications (ETRA '20 Full Papers)*. Association for Computing Machinery, New York, NY, USA, 1–8. https://doi.org/10.1145/3379155.3391334

[118] Beibin Li, Nicholas Nuechterlein, Erin Barney, Claire Foster, Minah Kim, Monique Mahony, Adham Atyabi, Li Feng, Quan Wang, Pamela Ventola, Linda Shapiro, and Frederick Shic. 2021. Learning Oculomotor Behaviors from Scanpath. In *Proceedings of the 2021 International Conference on Multimodal Interaction (ICMI '21)*. Association for Computing Machinery, New York, NY, USA, 407–415. https://doi.org/10.1145/3462244.3479923

[119] Fan Li, Chun-Hsien Chen, Gangyan Xu, and Li-Pheng Khoo. 2020. Hierarchical Eye-Tracking Data Analytics for Human Fatigue Detection at a Traffic Control Center. *IEEE Transactions on Human-Machine Systems* 50, 5 (2020), 465–474. https://doi.org/10.1109/THMS.2020.3016088

[120] Weifeng Li, Marc-Antoine Nüssli, and Patrick Jermann. 2010. Gaze Quality Assisted Automatic Recognition of Social Contexts in Collaborative Tetris. In *International Conference on Multimodal Interfaces and the Workshop on Machine Learning for Multimodal Interaction (ICMI-MLMI '10)*. Association for Computing Machinery, New York, NY, USA, 1–8. https://doi.org/10.1145/1891903.1891914

[121] Lars Lischke, Valentin Schwind, Kai Friedrich, Albrecht Schmidt, and Niels Henze. 2016. MAGIC-Pointing on Large High-Resolution Displays. In *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems* (San Jose, California, USA) *(CHI EA '16)*. Association for Computing Machinery, New York, NY, USA, 1706–1712. https://doi.org/10.1145/2851581.2892479

[122] Zaijia Liu, Xianjun Sam Zheng, Mingyang Wu, Rui Dong, and Kaiping Peng. 2013. Culture Influence on Aesthetic Perception of Chinese and Western Paintings: Evidence from Eye Movement Patterns. In *Proceedings of the 6th International Symposium on Visual Information Communication and Interaction* (Tianjin, China) *(VINCI '13)*. Association for Computing Machinery, New York, NY, USA, 72–78. https://doi.org/10.1145/2493102.2493111

[123] Lester C. Loschky and Gary S. Wolverton. 2007. How Late Can You Update Gaze-Contingent Multiresolutional Displays without Detection? *ACM Trans. Multimedia Comput. Commun. Appl.* 3, 4, Article 7 (dec 2007), 10 pages. https://doi.org/10.1145/1314303.1314310

[124] Jean-Luc Lugrin, Dennis Wiebusch, Marc Erich Latoschik, and Alexander Strehler. 2013. Usability benchmarks for motion tracking systems. In *Proceedings of the 19th ACM Symposium on Virtual Reality Software and Technology* (Singapore) *(VRST '13)*. Association for Computing Machinery, New York, NY, USA, 49–58. https://doi.org/10.1145/2503713.2503730

[125] Otto Hans-Martin Lutz and Jörg Krüger. 2017. Assessing visual attention in virtual reality: Automatic one-point calibration for eye-tracking. In *2017 International Conference on Virtual Rehabilitation (ICVR)*. IEEE, New York, NY, USA, 1–2. https://doi.org/10.1109/ICVR.2017.8007455

[126] I. Scott MacKenzie and Colin Ware. 1993. Lag as a determinant of human performance in interactive systems. In *Proceedings of the INTERACT '93 and CHI '93 Conference on Human Factors in Computing Systems* (Amsterdam, The Netherlands) *(CHI '93)*. Association for Computing Machinery, New York, NY, USA, 488–493. https://doi.org/10.1145/169059.169431

[127] Sai Phani Kumar Malladi, Jayanta Mukherjee, Mohamed-Chaker Larabi, and Santanu Chaudhury. 2022. EG-SNIK: A Free Viewing Egocentric Gaze Dataset and Its Applications. *IEEE Access* 10 (2022), 129626–129641. https://doi.org/10.1109/ACCESS.2022.3228484

[128] Samantha Mann, Aldert Vrij, and Ray Bull. 2002. Suspects, lies, and videotape: An analysis of authentic high-stake liars. *Law and Human Behavior* 26, 3 (June 2002), 365–376. https://doi.org/10.1023/A:1015332606792

[129] Sophie Marat, Tien Ho Phuoc, Lionel Granjon, Nathalie Guyader, Denis Pellerin, and Anne Guérin-Dugué. 2009. Modelling Spatio-Temporal Saliency to Predict Gaze Direction for Short Videos. *International Journal of Computer Vision* 82, 3 (May 2009), 231–243. https://doi.org/10.1007/s11263-009-0215-3

[130] Anna Marzecová, Antonio Schettino, Andreas Widmann, Iria SanMiguel, Sonja A Kotz, and Erich Schröger. 2018. Attentional gain is modulated by probabilistic feature expectations in a spatial cueing task: ERP evidence. *Scientific Reports* 8, 1 (2018), 1–14. https://doi.org/10.1038/s41598-017-18347-1

[131] Anna Marzecová, Andreas Widmann, Iria SanMiguel, Sonja A Kotz, and Erich Schröger. 2017. Interrelation of attention and prediction in visual processing: Effects of task-relevance and stimulus probability. *Biological Psychology* 125 (2017), 76–90. https://doi.org/10.1016/j.biopsycho.2017.02.009

[132] Lindsey K. McIntire, John P. McIntire, R. Andy McKinley, and Chuck Goodyear. 2014. Detection of Vigilance Performance with Pupillometry. In *Proceedings of the Symposium on Eye Tracking Research and Applications (ETRA '14)*. Association for Computing Machinery, New York, NY, USA, 167–174. https://doi.org/10.1145/2578153.2578177

[133] Coleman Merenda, Hyungil Kim, Joseph L. Gabbard, Samantha Leong, David R. Large, and Gary Burnett. 2017. Did You See Me? Assessing Perceptual vs. Real Driving Gains Across Multi-Modal Pedestrian Alert Systems. In *Proceedings of the 9th International Conference on Automotive User Interfaces and Interactive Vehicular Applications (AutomotiveUI '17)*. Association for Computing Machinery, New York, NY, USA, 40–49. https://doi.org/10.1145/3122986.3123013

[134] Coleman Merenda, Hyungil Kim, Kyle Tanous, Joseph L. Gabbard, Blake Feichtl, Teruhisa Misu, and Chihiro Suga. 2018. Augmented Reality Interface Design Approaches for Goal-directed and Stimulus-driven Driving Tasks. *IEEE Transactions on Visualization and Computer Graphics* 24, 11 (Nov 2018), 2875–2885. https://doi.org/10.1109/TVCG.2018.2868531

[135] Nadine Marie Moacdieh and Nadine Sarter. 2017. The Effects of Data Density, Display Organization, and Stress on Search Performance: An Eye Tracking Study of Clutter. *IEEE Transactions on Human-Machine Systems* 47, 6 (2017), 886–895. https://doi.org/10.1109/THMS.2017.2717899

[136] Aythami Morales, Francisco M. Costela, Ruben Tolosana, and Russell L. Woods. 2018. Saccade Landing Point Prediction: A Novel Approach Based on Recurrent Neural Networks. In *Proceedings of the 2018 International Conference on Machine Learning Technologies (ICMLT '18)*. Association for Computing Machinery, New York, NY, USA, 1–5. https://doi.org/10.1145/3231884.3231890

[137] Jorge Muñoz, Georgios N. Yannakakis, Fiona Mulvey, Dan Witzner Hansen, German Gutierrez, and Araceli Sanchis. 2011. Towards Gaze-Controlled Platform Games. In *2011 IEEE Conference on Computational Intelligence and Games (CIG'11)*. IEEE, New York, NY, USA, 47–54. https://doi.org/10.1109/CIG.2011.6031988

[138] Yukiko I. Nakano and Ryo Ishii. 2010. Estimating User's Engagement from Eye-Gaze Behaviors in Human-Agent Conversations. In *Proceedings of the 15th International Conference on Intelligent User Interfaces (IUI '10)*. Association for Computing Machinery, New York, NY, USA, 139–148. https://doi.org/10.1145/1719970.1719990

[139] Mojtaba Navvab, Fabio Bisegna, and Franco Gugliermetti. 2015. Dynamic roadways and in-vehicle lighting conditions for determining mesopic adaptation luminance. In *2015 IEEE 15th International Conference on Environment and Electrical Engineering (EEEIC)*. IEEE, New York, NY, USA, 2005–2010. https://doi.org/10.1109/EEEIC.2015.7165482

[140] Amitash Ojha, Francesca Ervas, and Elisabetta Gola. 2017. Emotions as Intrinsic Cognitive Load: An Eye Movement Analysis of High and Low Intelligent Individuals. In *2017 3rd IEEE International Conference on Cybernetics (CYBCONF)*. IEEE, New York, NY, USA, 1–6. https://doi.org/10.1109/CYBConf.2017.7985776

[141] Flavio T.P. Oliveira, Anne Aula, and Daniel M. Russell. 2009. Discriminating the Relevance of Web Search Results with Measures of Pupil Size. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '09)*. Association for Computing Machinery, New York, NY, USA, 2209–2212. https://doi.org/10.1145/1518701.1519038

[142] Wes Olson, Bill Kaliardos, Michael Zuschlag, and Andrew Kendra. 2009. Impact of Traffic Symbol Directional Cues on Pilot Performance during TCAS Events. In *2009 IEEE/AIAA 28th Digital Avionics Systems Conference*. IEEE, New York, NY, USA, 5.D.2–1–5.D.2–10. https://doi.org/10.1109/DASC.2009.5347460

[143] Francesco Onorati, Riccardo Barbieri, Maurizio Mauri, Vincenzo Russo, and Luca Mainardi. 2013. Reconstruction and Analysis of the Pupil Dilation Signal: Application to a Psychophysiological Affective Protocol. In *2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, New York, NY, USA, 5–8. https://doi.org/10.1109/EMBC.2013.6609423

[144] Justin W. Owens, Barbara S. Chaparro, and Evan M. Palmer. 2011. Text Advertising Blindness: The New Banner Blindness? *J. Usability Studies* 6, 3 (may 2011), 172–197.

[145] Matthew J. Page, Joanne E. McKenzie, Patrick M. Bossuyt, Isabelle Boutron, Tammy C. Hoffmann, Cynthia D. Mulrow, Larissa Shamseer, Jennifer M. Tetzlaff, Elie A. Akl, Sue E. Brennan, Roger Chou, Julie Glanville, Jeremy M. Grimshaw, Asbjørn Hróbjartsson, Manoj M. Lalu, Tianjing Li, Elizabeth W. Loder, Evan Mayo-Wilson, Steve McDonald, Luke A. McGuinness, Lesley A. Stewart, James Thomas, Andrea C. Tricco, Vivian A. Welch, Penny Whiting, and David Moher. 2021. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *Systematic Reviews* 10, 1 (Dec. 2021), 89. https://doi.org/10.1186/s13643-021-01626-4

[146] Monalisa Pal, Anwesha Banerjee, Shreyasi Datta, Amit Konar, D. N. Tibarewala, and R. Janarthanan. 2014. Electrooculography based blink detection to prevent Computer Vision Syndrome. In *2014 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT)*. IEEE, Bangalore, India, 1–6. https://doi.org/10.1109/CONECCT.2014.6740337

[147] Almudena Palacios-Ibáñez, Javier Marín-Morales, Manuel Contero, and Mariano Alcañiz. 2023. Predicting Decision-Making in Virtual Environments: An Eye Movement Analysis with Household Products. *Applied Sciences* 13, 12 (2023). https://doi.org/10.3390/app13127124

[148] Gang Pan, Lin Sun, Zhaohui Wu, and Shihong Lao. 2007. Eyeblink-based Anti-Spoofing in Face Recognition from a Generic Webcamera. In *2007 IEEE 11th International Conference on Computer Vision*. IEEE, Rio de Janeiro, Brazil, 1–8. https://doi.org/10.1109/ICCV.2007.4409068

[149] Hyun Soo Park, Eakta Jain, and Yaser Sheikh. 2013. Predicting Primary Gaze Behavior Using Social Saliency Fields. In *2013 IEEE International Conference on Computer Vision*. IEEE, New York, NY, USA, 3503–3510. https://doi.org/10.1109/ICCV.2013.435

[150] Nez Parr and Biao Zeng. 2021. British Sign Language (BSL) User's Gaze Patterns Between Hands and Face During Online Communication. In *Companion Publication of the 13th ACM Web Science Conference 2021* (Virtual Event, United Kingdom) *(WebSci '21 Companion)*. Association for Computing Machinery, New York, NY, USA, 10–14. https://doi.org/10.1145/3462741.3466645

[151] Sudi Patel, Ross Henderson, L Bradley, B Galloway, and L Hunter. 1991. Effect of visual display unit use on blink rate and tear stability. *Optom Vis Sci* 68, 11 (1991), 888–892. https://doi.org/10.1097/00006324-199111000-00010

[152] Alexander R. Payne, Beryl Plimmer, and T. Claire Davies. 2015. Repeatability of Eye-Hand Movement Onset Asynchrony Measurements and Cerebral Palsy: A Case Study. In *Proceedings of the 15th New Zealand Conference on Human-Computer Interaction* (Hamilton, New Zealand) *(CHINZ 2015)*. Association for Computing Machinery, New York, NY, USA, 31–38. https://doi.org/10.1145/2808047.2808058

[153] Xiaoqing Peng. 2022. An Eye-Movement Study of Pronoun Resolutions by Chinese-Speaking Learners. In *Proceedings of the 2022 3rd International Conference on Control, Robotics and Intelligent System* (Virtual Event, China) *(CCRIS '22)*. Association for Computing Machinery, New York, NY, USA, 80–84. https://doi.org/10.1145/3562007.3562023

[154] Xiaoqing Peng. 2022. The Resolution of English Pronoun by Chinese-speaking Learners: Evidence from Eye Movement. In *2022 International Conference on Frontiers of Artificial Intelligence and Machine Learning (FAIML)*. IEEE, New York, NY, USA, 79–82. https://doi.org/10.1109/FAIML57028.2022.00025

[155] Xiaoqing Peng. 2022. The Resolution of English Pronoun by Chinese-speaking Learners: Evidence from Eye Movement. In *2022 International Conference on Frontiers of Artificial Intelligence and Machine Learning (FAIML)*. IEEE, New York, NY, USA, 79–82. https://doi.org/10.1109/FAIML57028.2022.00025

[156] L. Perreault, Bernard Bobée, and Peter Rasmussen. 1999. Halphen Distribution System. I: Mathematical and Statistical Properties. *Journal of Hydrologic Engineering - J HYDROL ENG* 4 (07 1999). https://doi.org/10.1061/(ASCE)1084-0699(1999)4:3(189)

[157] Ken Pfeuffer and Hans Gellersen. 2016. Gaze and Touch Interaction on Tablets. In *Proceedings of the 29th Annual Symposium on User Interface Software and Technology* (Tokyo, Japan) *(UIST '16)*. Association for Computing Machinery, New York, NY, USA, 301–311. https://doi.org/10.1145/2984511.2984514

[158] Bastian Pfleging, Drea K. Fekety, Albrecht Schmidt, and Andrew L. Kun. 2016. A Model Relating Pupil Diameter to Mental Workload and Lighting Conditions. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*. Association for Computing Machinery, New York, NY, USA, 5776–5788.

https://doi.org/10.1145/2858036.2858117

[159] Prarthana Pillai, Balakumar Balasingam, Arunita Jaekel, and Francesco Biondi. 2021. Kalman Filtering to Track Changes in Pupil Size for Automated Driving Systems. In *2021 IEEE 94th Vehicular Technology Conference (VTC2021-Fall)*. IEEE, New York, NY, USA, 1–6. https://doi.org/10.1109/VTC2021-Fall52928.2021.9625045

[160] Jeffrey G. Proudfoot, Jeffrey L. Jenkins, Judee K. Burgoon, and Jay F. Nunamaker. 2015. Deception is in the eye of the communicator: Investigating pupil diameter variations in automated deception detection interviews. In *2015 IEEE International Conference on Intelligence and Security Informatics (ISI)*. IEEE, New York, NY, USA, 97–102. https://doi.org/10.1109/ISI.2015.7165946

[161] I Putu Edy Suardiyana Putra and Rein Vesilo. 2017. Window-size impact on detection rate of wearable-sensor-based fall detection using supervised machine learning. In *2017 IEEE Life Sciences Conference (LSC)*. IEEE, Sydney, Australia, 21–26. https://doi.org/10.1109/LSC.2017.8268134

[162] Ming Qian, Mario Aguilar, Karen N. Zachery, Claudio Privitera, Stanley Klein, Thom Carney, and Loren W. Nolte. 2009. Decision-Level Fusion of EEG and Pupil Features for Single-Trial Visual Detection Analysis. *IEEE Transactions on Biomedical Engineering* 56, 7 (July 2009), 1929–1937. https://doi.org/10.1109/TBME.2009.2016670

[163] Yinuo Qin, Weijia Zhang, Richard Lee, Xiaoxiao Sun, and Paul Sajda. 2022. Predictive Power of Pupil Dynamics in a Team Based Virtual Reality Task. In *2022 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW)*. IEEE, New York, NY, USA, 592–593. https://doi.org/10.1109/VRW55335.2022.00147

[164] Pernilla Qvarfordt and Matthew Lee. 2018. Gaze Patterns during Remote Presentations While Listening and Speaking. In *Proceedings of the 2018 ACM Symposium on Eye Tracking Research & Applications* (Warsaw, Poland) *(ETRA '18)*. Association for Computing Machinery, New York, NY, USA, Article 33, 9 pages. https://doi.org/10.1145/3204493.3204540

[165] Seema F. Al Raisi and Eran Edirisinghe. 2017. A Machine Learning Based Approach to Human Observer Behaviour Analysis in CCTV Video Analytics & Forensics. In *Proceedings of the 1st International Conference on Internet of Things and Machine Learning (IML '17)*. Association for Computing Machinery, New York, NY, USA, 1–10. https://doi.org/10.1145/3109761.3158376

[166] Alexa Romberg, Yayun Zhang, Benjamin Newman, Jochen Triesch, and Chen Yu. 2016. Global and Local Statistical Regularities Control Visual Attention to Object Sequences. In *2016 Joint IEEE International Conference on Development and Learning and Epigenetic Robotics (ICDL-EpiRob)*. IEEE, New York, NY, USA, 262–267. https://doi.org/10.1109/DEVLRN.2016.7846829

[167] Pedro J. Rosa, Francisco Esteves, and Patrícia Arriaga. 2015. Beyond Traditional Clinical Measurements for Screening Fears and Phobias. *IEEE Transactions on Instrumentation and Measurement* 64, 12 (2015), 3396–3404. https://doi.org/10.1109/TIM.2015.2450292

[168] Rabee Rustum and Adebayo J. Adeloye. 2007. Replacing Outliers and Missing Values from Activated Sludge Data Using Kohonen Self-Organizing Map. *Journal of Environmental Engineering* 133, 9 (Sept. 2007), 909–916. https://doi.org/10.1061/(ASCE)0733-9372(2007)133:9(909)

[169] Kamalpreet Singh Saluja, JeevithaShree Dv, Somnath Arjun, Pradipta Biswas, and Teena Paul. 2019. Analyzing Eye Gaze of Users with Learning Disability. In *Proceedings of the 3rd International Conference on Graphics and Signal Processing (ICGSP '19)*. Association for Computing Machinery, New York, NY, USA, 95–99. https://doi.org/10.1145/3338472.3338481

[170] Mirweis Sangin, Gaëlle Molinari, Marc-Antoine Nüssli, and Pierre Dillenbourg. 2008. How Learners Use Awareness Cues about Their Peer's Knowledge? Insights from Synchronized Eye-Tracking Data. In *Proceedings of the 8th International Conference on International Conference for the Learning Sciences - Volume 2* (Utrecht, The Netherlands) *(ICLS'08)*. International Society of the Learning Sciences, Berlin, Germany, 287–294.

[171] Abhraneel Sarma and Matthew Kay. 2020. Prior Setting in Practice: Strategies and Rationales Used in Choosing Prior Distributions for Bayesian Analysis. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3313831.3376377

[172] Christian Schlösser, Andreas Harrer, and Andrea Kienle. 2018. Supporting Dyadic Chat Communication with Eye Tracking Based Reading Awareness. In *2018 IEEE 18th International Conference on Advanced Learning Technologies (ICALT)*. IEEE, New York, NY, USA, 149–151. https://doi.org/10.1109/ICALT.2018.00042

[173] Rebekka S. Schubert, Josephine Hartwig, Mathias Müller, Rainer Groh, and Sebastian Pannasch. 2016. Are Age Differences Missing in Relative and Absolute Distance Perception of Stereoscopically Presented Virtual Objects?. In *Proceedings of the 22nd ACM Conference on Virtual Reality Software and Technology* (Munich, Germany) *(VRST '16)*. Association for Computing Machinery, New York, NY, USA, 307–308. https://doi.org/10.1145/2993369.2996334

[174] Immo Schuetz, T. Scott Murdison, Kevin J. MacKenzie, and Marina Zannoli. 2019. An Explanation of Fitts' Law-like Performance in Gaze-Based Selection Tasks Using a Psychophysics Approach. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. ACM, Glasgow Scotland Uk, 1–13. https://doi.org/10.1145/3290605.3300765

[175] Jun Shao and Bob Zhong. 2003. Last observation carry-forward and last observation analysis. *Statistics in Medicine* 22, 15 (2003), 2429–2441. https://doi.org/10.1002/sim.1519 arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1002/sim.1519

[176] Zohreh Sharafi, Yu Huang, Kevin Leach, and Westley Weimer. 2021. Toward an Objective Measure of Developers' Cognitive Activities. *ACM Trans. Softw. Eng. Methodol.* 30, 3, Article 30 (mar 2021), 40 pages. https://doi.org/10.1145/3434643

[177] Ludwig Sidenmark, Mark Parent, Chi-Hao Wu, Joannes Chan, Michael Glueck, Daniel Wigdor, Tovi Grossman, and Marcello Giordano. 2022. Weighted Pointer: Error-aware Gaze-based Interaction through Fallback Modalities. *IEEE Transactions on Visualization and Computer Graphics* 28, 11 (2022), 3585–3595. https://doi.org/10.1109/TVCG.2022.3203096

[178] Luca Simione, Alisha Vabba, Antonino Raffone, and Marco Mirolli. 2022. Pupil Dilation and Self-Reported Emotional Response to IAPS Pictures: The Role of Emotional Regulation and Trait Mindfulness. In *2022 IEEE International Conference on Metrology for Extended Reality, Artificial Intelligence and Neural Engineering (MetroXRAINE)*. IEEE, New York, NY, USA, 471–476. https://doi.org/10.1109/MetroXRAINE54828.2022.9967538

[179] Aniruddha Sinha, Dibyendu Roy, Rikayan Chaki, Bikram Kumar De, and Sanjoy Kumar Saha. 2019. Readability Analysis Based on Cognitive Assessment Using Physiological Sensing. *IEEE Sensors Journal* 19, 18 (Sep. 2019), 8127–8135. https://doi.org/10.1109/JSEN.2019.2917834

[180] Layth Sliman. 2018. Ocular Guided Robotized Wheelchair for Quadriplegics Users. In *2018 TRON Symposium (TRONSHOW)*. IEEE, New York, NY, USA, 1–7.

[181] Alexis D. Souchet, Mamadou Lamarana Diallo, and Domitile Lourdeaux. 2022. Cognitive Load Classification with a Stroop Task in Virtual Reality Based on Physiological Data. In *2022 IEEE International Symposium on Mixed and Augmented Reality (ISMAR)*. IEEE, New York, NY, USA, 656–666. https://doi.org/10.1109/ISMAR55827.2022.00083

[182] Julian Steil, Inken Hagestedt, Michael Xuelin Huang, and Andreas Bulling. 2019. Privacy-Aware Eye Tracking Using Differential Privacy. In *Proceedings of the 11th ACM Symposium on Eye Tracking Research & Applications*. Association for Computing Machinery, New York, NY, USA, 1–9. https://doi.org/10.1145/3314111.3319915 arXiv:1812.08000 [cs].

[183] Julian Steil, Michael Xuelin Huang, and Andreas Bulling. 2018. Fixation detection for head-mounted eye tracking based on visual similarity of gaze targets. In *Proceedings of the 2018 ACM Symposium on Eye Tracking Research & Applications*. ACM, Warsaw Poland, 1–9. https://doi.org/10.1145/3204493.3204538

[184] Niklas Stein, Gianni Bremer, and Markus Lappe. 2022. Eye Tracking-based LSTM for Locomotion Prediction in VR. In *2022 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*. IEEE, New York, NY, USA, 493–503. https://doi.org/10.1109/VR51125.2022.00069

[185] John A Stern, Donna Boyer, and David Schroeder. 1994. Blink rate: a possible measure of fatigue. *Human factors* 36, 2 (1994), 285–297.

[186] Samuel Stuart, Brook Galna, Sue Lord, Lynn Rochester, and Alan Godfrey. 2014. Quantifying Saccades While Walking: Validity of a Novel Velocity-Based Algorithm for Mobile Eye Tracking. In *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. IEEE, New York, NY, USA, 5739–5742. https://doi.org/10.1109/EMBC.2014.6944931

[187] Shree Krishna Subburaj, Angela E.B. Stewart, Arjun Ramesh Rao, and Sidney K. D'Mello. 2020. Multimodal, Multiparty Modeling of Collaborative Problem Solving Performance. In *Proceedings of the 2020 International Conference on Multimodal Interaction (ICMI '20)*. Association for Computing Machinery, New York, NY, USA, 423–432. https://doi.org/10.1145/3382507.3418877

[188] Hassan Takabi, Yessir Hashem, and Ram Dantu. 2018. Prediction of human error using eye movements patterns for unintentional insider threat detection. In *2018 IEEE 4th International Conference on Identity, Security, and Behavior Analysis (ISBA)*. IEEE, New York, NY, USA, 1–8. https://doi.org/10.1109/ISBA.2018.8311479

[189] Chihiro Tamba, Shoichiro Tomii, and Tomoaki Ohtsuki. 2014. Blink detection using Doppler sensor. In *2014 IEEE 25th Annual International Symposium on Personal, Indoor, and Mobile Radio Communication (PIMRC)*. IEEE, Washington DC, USA, 2119–2124. https://doi.org/10.1109/PIMRC.2014.7136522

[190] Chatpong Tangmanee and Puripant Ruchikachorn. 2018. Online Forms: An Eye Tracking Exploration into Fixation across Three Label Alignments. In *2018 22nd International Computer Science and Engineering Conference (ICSEC)*. IEEE, New York, NY, USA, 1–6. https://doi.org/10.1109/ICSEC.2018.8712777

[191] Kemal Taşkın and Didem Gökçay. 2015. Investigation of Risk Taking Behavior and Outcomes in Decision Making with Modified BART (m-BART). In *2015 International Conference on Affective Computing and Intelligent Interaction (ACII)*. IEEE, New York, NY, USA, 302–307. https://doi.org/10.1109/ACII.2015.7344587

[192] Geoffrey Tien, M. Stella Atkins, Xianta Jiang, Bin Zheng, and Roman Bednarik. 2014. Verbal Gaze Instruction Matches Visual Gaze Guidance in Laparoscopic Skills Training. In *Proceedings of the Symposium on Eye Tracking Research and Applications (ETRA '14)*. Association for Computing Machinery, New York, NY, USA, 331–334. https://doi.org/10.1145/2578153.2578217

[193] Dereck Toker, Cristina Conati, Ben Steichen, and Giuseppe Carenini. 2013. Individual User Characteristics and Information Visualization: Connecting the Dots through Eye Tracking. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Paris, France) *(CHI '13)*. Association for Computing Machinery, New York, NY, USA, 295–304. https://doi.org/10.1145/2470654.2470696

[194] Ryuta Tonomura, Tadamitsu Tadamitsu, Atsushi Manji, Naoyuki Kubota, and Takenori Obo. 2018. Rehabilitation Support System for Attentional Deficits Based on Trail-Making Test. In *2018 Joint 10th International Conference on Soft Computing and Intelligent Systems (SCIS) and 19th International Symposium on Advanced Intelligent Systems (ISIS)*. IEEE, New York, NY, USA, 1127–1132. https://doi.org/10.1109/SCIS-ISIS.2018.00177

[195] Michael Traoré and Christophe Hurter. 2016. Exploratory Study with Eye Tracking Devices to Build Interactive Systems for Air Traffic Controllers. In *Proceedings of the International Conference on Human-Computer Interaction in Aerospace* (Paris, France) *(HCI-Aero '16)*. Association for Computing Machinery, New York, NY, USA, Article 6, 9 pages. https://doi.org/10.1145/2950112.2964584

[196] Yi-Fang Tsai, Erik Viirre, Christopher Strychacz, Bradley Chase, and Tzyy-Ping Jung. 2007. Task performance and eye activity: predicting behavior relating to cognitive workload. *Aviation, space, and environmental medicine* 78, 5 (2007), B176–B185.

[197] Jayson Turner, Andreas Bulling, Jason Alexander, and Hans Gellersen. 2014. Cross-device gaze-supported point-to-point content transfer. In *Proceedings of the Symposium on Eye Tracking Research and Applications* (Safety Harbor, Florida) *(ETRA '14)*. Association for Computing Machinery, New York, NY, USA, 19–26. https://doi.org/10.1145/2578153.2578155

[198] Karl F Van Orden, Tzyy-Ping Jung, and Scott Makeig. 2000. Combined eye activity measures accurately estimate changes in sustained visual task performance. *Biological psychology* 52, 3 (2000), 221–240. https://doi.org/10.1016/S0301-0511(99)00043-5

[199] Giacomo Veneri, Elena Pretegiani, Pamela Federighi, Francesca Rosini, Antonio Federico, and Alessandra Rufa. 2010. Evaluating Human Visual Search Performance by Monte Carlo Methods and Heuristic Model. In *Proceedings of the 10th IEEE International Conference on Information Technology and Applications in Biomedicine*. IEEE, New York, NY, USA, 1–4. https://doi.org/10.1109/ITAB.2010.5687697

[200] Roel Vertegaal. 2008. A Fitts Law comparison of eye tracking and manual input in the selection of visual targets. In *Proceedings of the 10th international conference on Multimodal interfaces - IMCI '08*. ACM Press, Chania, Crete, Greece, 241. https://doi.org/10.1145/1452392.1452443

[201] Hana Vrzakova, Mary Jean Amon, McKenzie Rees, Myrthe Faber, and Sidney D'Mello. 2021. Looking for a Deal? Visual Social Attention during Negotiations via Mixed Media Videoconferencing. *Proc. ACM Hum.-Comput. Interact.* 4, CSCW3, Article 260 (jan 2021), 35 pages. https://doi.org/10.1145/3434169

[202] Hana Vrzakova, Mary Jean Amon, Angela E. B. Stewart, and Sidney K. D'Mello. 2019. Dynamics of Visual Attention in Multiparty Collaborative Problem Solving Using Multidimensional Recurrence Quantification Analysis. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–14. https://doi.org/10.1145/3290605.3300572

[203] Hana Vrzakova, Roman Bednarik, Yukiko I. Nakano, and Fumio Nihei. 2016. Speakers' Head and Gaze Dynamics Weakly Correlate in Group Conversation. In *Proceedings of the Ninth Biennial ACM Symposium on Eye Tracking Research & Applications* (Charleston, South Carolina) *(ETRA '16)*. Association for Computing Machinery, New York, NY, USA, 77–84. https://doi.org/10.1145/2857491.2857522

[204] Manhua Wang, Seul Chan Lee, Harsh Kamalesh Sanghavi, Megan Eskew, Bo Zhou, and Myounghoon Jeon. 2021. In-Vehicle Intelligent Agents in Fully Autonomous Driving: The Effects of Speech Style and Embodiment Together and Separately. In *13th International Conference on Automotive User Interfaces and Interactive Vehicular Applications (AutomotiveUI '21)*. Association for Computing Machinery, New York, NY, USA, 247–254. https://doi.org/10.1145/3409118.3475142

[205] Youmian Wang, Bin Hu, Zhenxiang Chen, Xiaoqing Jiang, Wenjuan Liu, and Peicheng Wang. 2022. INSIDER: A Framework for Assessing Confidence in Psychological Scales Based on Multi-Modal Physiological Signal Fusion. In *2022 IEEE Smartworld, Ubiquitous Intelligence & Computing, Scalable Computing & Communications, Digital Twin, Privacy Computing, Metaverse, Autonomous & Trusted Vehicles (SmartWorld/UIC/ScalCom/DigitalTwin/PriComp/Meta)*. IEEE, New York, NY, USA, 1298–1303. https://doi.org/10.1109/SmartWorld-UIC-ATC-ScalCom-DigitalTwin-PriComp-Metaverse56740.2022.00199

[206] Yixin Wang, Shuang Qiu, Dan Li, Changde Du, Bao-Liang Lu, and Huiguang He. 2022. Multi-Modal Domain Adaptation Variational Autoencoder for EEG-Based Emotion Recognition. *IEEE/CAA Journal of Automatica Sinica* 9, 9 (Sept. 2022), 1612–1626. https://doi.org/10.1109/JAS.2022.105515

[207] Julian Wolf, Quentin Lohmeyer, Christian Holz, and Mirko Meboldt. 2021. Gaze Comes in Handy: Predicting and Preventing Erroneous Hand Actions in AR-Supported Manual Tasks. In *2021 IEEE International Symposium on Mixed and Augmented Reality (ISMAR)*. IEEE, New York, NY, USA, 166–175. https://doi.org/10.1109/ISMAR52148.2021.00031

[208] P Wolkoff, Jacob Klenø Nøjgaard, P Troiano, and B Piccoli. 2005. Eye complaints in the office environment: precorneal tear film integrity influenced by eye blinking efficiency. *Occupational and environmental medicine* 62, 1 (2005), 4–12. https://doi.org/10.1136/oem.2004.016030

[209] Yanyu Xu, Yanbing Dong, Junru Wu, Zhengzhong Sun, Zhiru Shi, Jingyi Yu, and Shenghua Gao. 2018. Gaze Prediction in Dynamic 360° Immersive Videos. In *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*. IEEE, Salt Lake City, UT, USA, 5333–5342. https://doi.org/10.1109/CVPR.2018.00559

[210] Victoria Yaneva, Le An Ha, Sukru Eraslan, Yeliz Yesilada, and Ruslan Mitkov. 2018. Detecting Autism Based on Eye-Tracking Data from Web Searching Tasks. In *Proceedings of the 15th International Web for All Conference* (Lyon, France) *(W4A '18)*. Association for Computing Machinery, New York, NY, USA, Article 16, 10 pages. https://doi.org/10.1145/3192714.3192819

[211] Lora Yekhshatyan and John D. Lee. 2013. Changes in the Correlation Between Eye and Steering Movements Indicate Driver Distraction. *IEEE Transactions on Intelligent Transportation Systems* 14, 1 (March 2013), 136–145. https://doi.org/10.1109/TITS.2012.2208223

[212] Maryam Zahabi, Yinsong Wang, and Shahin Shahrampour. 2021. Classification of Officers' Driving Situations Based on Eye-Tracking and Driver Performance Measures. *IEEE Transactions on Human-Machine Systems* 51, 4 (Aug. 2021), 394–402. https://doi.org/10.1109/THMS.2021.3090787

[213] Ala'a Abu Zaid, Mohammad Sobuh, and Musa Al Yaman. 2017. Development of an Algorithm for Automating Gaze Data Analysis Gathered While Using Upper Limb Prostheses. In *2017 7th International Conference on Modeling, Simulation, and Applied Optimization (ICMSAO)*. IEEE, New York, NY, USA, 1–5. https://doi.org/10.1109/ICMSAO.2017.7934914

[214] Guanhua Zhang, Susanne Hindennach, Jan Leusmann, Felix Bühler, Benedict Steuerlein, Sven Mayer, Mihai Bâce, and Andreas Bulling. 2022. Predicting Next Actions and Latent Intents during Text Formatting. In *Proceedings of the CHI Workshop Computational Approaches for Understanding, Generating, and Adapting User Interfaces* (2022-01-01). Association for Computing Machinery, New York, NY, USA, 1–6. https://sven-mayer.com/wp-content/uploads/2022/08/zhang2022predicting.pdfhttps://perceptualui.org/publications/zhang22_caugaui/

[215] Kun Zhang, Chenxin Liu, Jingying Chen, Xiaodi Liu, Guangshuai Wang, and Rujing Zhang. 2021. Research on the Influence of Target Features on the Visual Tracking of Children with Autism. In *2021 International Symposium on Educational Technology (ISET)*. IEEE, New York, NY, USA, 202–206. https://doi.org/10.1109/ISET52350.2021.00049

[216] Yanxia Zhang, Ken Pfeuffer, Ming Ki Chong, Jason Alexander, Andreas Bulling, and Hans Gellersen. 2017. Look together: using gaze for assisting co-located collaborative search. *Personal and Ubiquitous Computing* 21, 1 (01 Feb 2017), 173–186. https://doi.org/10.1007/s00779-016-0969-x

[217] Rencheng Zheng, Kimihiko Nakano, Hiromitsu Ishiko, Kenji Hagita, Makoto Kihira, and Toshiya Yokozeki. 2016. Eye-Gaze Tracking Analysis of Driver Behavior While Interacting With Navigation Systems in an Urban Area. *IEEE Transactions on Human-Machine Systems* 46, 4 (2016), 546–556. https://doi.org/10.1109/THMS.2015.2504083

[218] Zhaobo Zheng, Kumar Akash, Teruhisa Misu, Vidya Krishnamoorthy, Miaomiao Dong, Yuni Lee, and Gaojian Huang. 2022. Identification of Adaptive Driving Style Preference through Implicit Inputs in SAE L2 Vehicles. In *Proceedings of the 2022 International Conference on Multimodal Interaction* (Bengaluru, India) *(ICMI '22)*. Association for Computing Machinery, New York, NY, USA, 468–475. https://doi.org/10.1145/3536221.3556637

[219] Zhaobo K. Zheng, Kumar Akash, and Teruhisa Misu. 2022. Detection of Perceived Discomfort in SAE L2 Automated Vehicles through Driver Takeovers and Physiological Spikes. In *2022 IEEE 25th International Conference on Intelligent Transportation Systems (ITSC)*. IEEE, New York, NY, USA, 1717–1722. https://doi.org/10.1109/ITSC55140.2022.9922161

[220] Zhiwen Zhou, Jianxiao Ma, Tao Lu, Gen Li, Song Fang, and Ting Tan. 2020. An Evaluation Method for Visual Search Stability in Urban Tunnel Entrance and Exit Sections Based on Markov Chain. *IEEE Access* 8 (2020), 68559–68569. https://doi.org/10.1109/ACCESS.2020.2986272

[221] Huadi Zhu, Wenqiang Jin, Mingyan Xiao, Srinivasan Murali, and Ming Li. 2020. BlinKey: A Two-Factor User Authentication Method for Virtual Reality Devices. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 4, 4 (Dec. 2020), 164:1–164:29. https://doi.org/10.1145/3432217

[222] Jing Zhu, Ying Wang, Rong La, Jiawei Zhan, Junhong Niu, Shuai Zeng, and Xiping Hu. 2019. Multimodal Mild Depression Recognition Based on EEG-EM Synchronization Acquisition Network. In *IEEE Access*, Vol. 7. IEEE, New York, NY, USA, 28196–28210. https://doi.org/10.1109/ACCESS.2019.2901950

[223] Wenchao Zhu, Aaron Kucyi, Arthur F. Kramer, and Yingzi Lin. 2022. Multimodal Physiological Assessment of the Task-related Attentional States in a VR Driving Environment. In *2022 28th International Conference on Mechatronics and Machine Vision in Practice (M2VIP)*. IEEE, New York, NY, USA, 1–5. https://doi.org/10.1109/M2VIP55626.2022.10041103

[224] Vlas Zyrianov, Drew T. Guarnera, Cole S. Peterson, Bonita Sharif, and Jonathan I. Maletic. 2020. Automated Recording and Semantics-Aware Replaying of High-Speed Eye Tracking and Interaction Data to Support Cognitive Studies of Software Engineering Tasks. In *2020 IEEE International Conference on Software Maintenance and Evolution (ICSME)*. IEEE, New York, NY, USA, 464–475. https://doi.org/10.1109/ICSME46990.2020.00051

A APPENDIX

Table 6: Overview of the 81 papers that reported on how they dealt with missing data, listed from the oldest to the newest (and alphabetically for authors from the same year)

	Author(s)	Year	Task	Method	Detector	Additional info
P61	Qian et al. [162]	2009	Visual Search Sequence	Interpolate	Missing Data	
P62	Oliveira et al. [141]	2009	Visual Search	Interpolation	Missing Data	Linear Interpolation
P63	Kinnunen et al. [97]	2010	Video Watching	Interpolation	Tobii Studio	Linear Interpolation
P64	Li et al. [120]	2010	Game	Aggregate	Missing Data	
P65	Nakano and Ishii [138]	2010	Wizard of Oz	Aggregate or Split	Missing Data	Data were combined
P66	Veneri et al. [199]	2010	Visual Search	Interpolate	Missing Data	Linear Interpolation
P67	Muñoz et al. [137]	2011	Game	Remove	Missing Data	
P68	Owens et al. [144]	2011	Semantic Search	Remove	Missing Data	
P69	Broz et al. [32]	2012	Holding a Conversation	Remove	Missing Data	
P70	Babiker et al. [18]	2013	Audio Stimuli	Interpolate	Missing Data	Linear Interpolation
P71	Bekele et al. [21]	2013	Virtual Reality	Remove	Missing Data	
P71	Ishii et al. [86]	2013	Holding a Conversation	Aggregate or split	Missing Data	
P72	Onorati et al. [143]	2013	Holding a Conversation	Reconstruct	Missing Data	Singular Spectral Analysis
P73	Yekhshatyan and Lee [211]	2013	Driving Simulator	Interpolation	Missing Data	
P74	Dechterenko and Lukavsky [46]	2014	Visual Search	Remove	Pupil Size	
P75	Gwizdka [70]	2014	Visual Search	Average	Missing Data	
P76	McIntire et al. [132]	2014	Screen Watching	Imputation	Missing Data	
P77	Stuart et al. [186]	2014	Free Viewing	Interpolate	0, 0 coordintes	Linear Interpolation
P78	Tien et al. [192]	2014	Visual Attention	Interpolation	Missing Data	
P79	Cole et al. [38]	2015	Visual Search	Imputation	Missing Data	
P80	Rosa et al. [167]	2015	Video Watching	Remove / Interpolate	Missing Data	Linear Interpolation
P81	Taşkın and Gökçay [191]	2015	Game	Interpolate	Missing Data	Polynomial Interpolation
P82	Bekele et al. [20]	2016	Social Task	Interpolate	Missing Data	Linear Interpolation
P83	Romberg et al. [166]	2016	Free Viewing	Aggregate	Missing Data	
P84	Bodala et al. [27]	2017	Driving Simulator	Extrapolate	Missing Data	I-CT filter algorithm
P85	Fajnzylber et al. [55]	2017	Video Watching	"filtered"	Missing Data	
P86	Gavas et al. [64]	2017	Memory Task	Interpolate	Missing Data	
P87	Hutt et al. [82]	2017	Learning	WEKA	Missing Data	
P88	Jerčič et al. [88]	2017	Game	Interpolate	Missing Data	Linear Interpolation
P89	Merenda et al. [133]	2017	Driving Simulator	Imputation	Missing Data	Satterthwaite Approx.
P90	Ojha et al. [140]	2017	Reading	Interpolate	Missing Data	Linear Interpolation
P91	Raisi and Edirisinghe [165]	2017	Video Watching	WEKA	Missing Data	
P92	Zaid et al. [213]	2017	Manual Task	Ignore	Missing Data	
P93	Brambilla et al. [28]	2018	Free Viewing	Interpolation / Remove	Missing Data	Linear or Cubic
P94	Greiter et al. [67]	2018	Go/NoGo	Interpolation	Missing Data	
P95	Jia et al. [90]	2018	Free Viewing	Only Clean Data	Noise / Tracking Loss	
P96	Krieger et al. [106]	2018	Watching Video	Remove	Tobii Eye Tracker	
P97	Merenda et al. [134]	2018	Driving Simulator	Imputation	Missing Data	Satterthwaite Approx.
P98	Morales et al. [136]	2018	Video Watching	Interpolation	EyeLink Parser	Cubic Spline Interpolation
P99	Appel et al. [13]	2019	Game	Interpolate / Remove	Missing Data	
P100	Couceiro et al. [42]	2019	Programming / Coding	Resampling	Missing Data	Iterative SSA
P101	Gunawardena et al. [69]	2019	Surgical Intervention	Remove	Missing Data	
P102	Huang and Bulling [81]	2019	Input Method	Interpolation	Missing Data	Linear Interpolation
P103	Karthik et al. [92]	2019	Visual Search	Replace	Missing Data	
P104	Korotin et al. [103]	2019	Game	Interpolation	Missing Data	Linear Interpolation
P105	Saluja et al. [169]	2019	Reading	Interpolation	Missing Data	Linear Interpolation
P106	Sinha et al. [179]	2019	Reading	Interpolation	Missing Data	Cubic Interpolation
P107	Zhu et al. [222]	2019	Free Viewing	Remove / Replace	Missing Data	
P108	Aftab et al. [4]	2020	Input Method	Interpolation	Missing Data	Linear Interpolation
P109	Bafna et al. [19]	2020	Typing Task	Interpolation	Missing Data	Linear Interpolation
P110	Dan et al. [45]	2020	Visual Search	Interpolation	Missing Data	Case by case
P111	Ioannou et al. [85]	2020	Programming / Coding	Interpolation	Missing Data	Linear Interpolation
P112	Keshava et al. [95]	2020	Align Objects in VR	Interpolation	Missing Data	Polynomial Interpolation

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	Author(s)	Year	Task	Method	Detector	Additional info
P113	Koskinen and Bednarik [104]	2020	Operate Joystick	Interpolation	BeGaze Parser	Linear Interpolation
P114	Li et al. [117]	2020	Free Viewing	Imputation	EyeLink Parser	Expectation-Maximization
P115	Li et al. [119]	2020	Target Tracking	Interpolation	Missing Data	Hierarchically Interpolation
P116	Subburaj et al. [187]	2020	Game	Imputation	Missing Data	
P117	Zhou et al. [220]	2020	Driving Simulator	Interpolation	Missing Data	
P118	Zhu et al. [221]	2020	Input Method	Interpolation	Missing Data	Spline Interpolation
P119	Abdrabou et al. [1]	2021	Typing Task	Remove	Missing Data	
P120	Aftab et al. [5]	2021	Driving Simulator	Interpolation	Missing Data	Linear Interpolation
P121	Bixler and D'Mello [25]	2021	Free Viewing	Winsorization	Missing Data	Replace outliers
P122	Hettiarachchi et al. [74]	2021	Game	Interpolation	Missing Data	Cubic Spline Interpolation
P123	Jun et al. [91]	2021	Drone Flying	Remove	Missing Data	
P124	Li et al. [118]	2021	Learning	Interpolation	Missing Data	Billinear
P125	Pillai et al. [159]	2021	Driving Simulator	Moving Window Infilling	Missing Data	
P126	Vrzakova et al. [201]	2021	Video Watching	Remove	Missing Data	
P127	Wang et al. [204]	2021	Driving Simulator	Interpolation	Missing Data	Spline Interpolation
P128	Zahabi et al. [212]	2021	Driving Simulator	Approximated	Missing Data	
P129	Arefin et al. [14]	2022	Visual Discriminaton	Remove	Missing Data	
P130	Hirzle et al. [76]	2022	Virtual Reality	Interpolation	Missing Data	
P131	Khan et al. [96]	2022	Video Watching	Remove	Missing Data	
P132	Malladi et al. [127]	2022	Free Viewing	Interpolation	Missing Data	
P133	Qin et al. [163]	2022	VR Task	Interpolation	Missing Data	Cubic Spline Interpolation
P134	Simione et al. [178]	2022	Free Viewing	Remove / Interpolate	Missing Data	
P135	Souchet et al. [181]	2022	Stroop task	Tobii Pro I-VT software	Missing Data	No Settings Specified
P136	Stein et al. [184]	2022	VR Task	Extrapolate	Missing Data	Linear Interpolation
P137	Wang et al. [205]	2022	Questionaire	Infill with 0	Missing Data	
P138	Zheng et al. [219]	2022	Driving Simulator	Interpolation	Missing Data	Linear Interpolation
P139	Zheng et al. [218]	2022	Input Method	Interpolation	Missing Data	Nearest Neighbours
P140	Zhu et al. [223]	2022	Driving Simulator	Interpolation	Missing Data	