

¹ Language Without Borders: A Step-by-Step Guide to Analyzing
² Webcam Eye-Tracking Data for L2 Research

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⁸ Abstract

Eye-tracking has become a valuable tool for studying cognitive processes in second language (L2) acquisition and bilingualism (Godfroid et al., 2024). While research-grade infrared eye-trackers are commonly used, there are a number of issues that limit its wide-spread adoption. Recently, consumer-based webcam eye-tracking has emerged as an attractive alternative, requiring only internet access and a personal webcam. However, webcam eye-tracking presents unique design and preprocessing challenges that must be addressed for valid results. To help researchers overcome these challenges, we developed a comprehensive tutorial focused on visual world webcam eye-tracking for L2 language research. Our guide will cover all key steps, from experiment design to data preprocessing and analysis, where we highlight the R package `webgazeR`, which is open source and freely available for download and installation: <https://github.com/jgeller112/webgazeR>. We offer best practices for environmental conditions, participant instructions, and tips for designing visual world experiments with webcam eye-tracking. To demonstrate these steps, we analyze data collected through the Gorilla platform (Anwyl-Irvine et al., 2020) using a single word Spanish visual world paradigm (VWP) and show competition within and between L2/L1. This tutorial aims to empower researchers by providing a step-by-step guide to successfully conduct visual world webcam-based eye-tracking studies. To follow along with this tutorial, please download the entire manuscript and its accompanying code with data from here: https://github.com/jgeller112/L2_VWP_Webcam.

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¹ Eye-tracking technology, which has a history spanning over a century, has seen remarkable advancements. In the early days, eye-tracking sometimes required the use of contact lenses fitted with search coils, often requiring anesthesia, or the attachment of suction cups to the sclera of the eyes (Płużyczka, 2018).

4 These methods were not only cumbersome for the researcher, but also uncomfortable and invasive for par-
5 ticipants. Over time, such approaches have been replaced by non-invasive, lightweight, and user-friendly
6 systems. Today, modern eye-tracking technology is widely accessible in laboratories worldwide, enabling
7 researchers to tackle critical questions about cognitive processes . This evolution has had a profound im-
8 pact on fields such as psycholinguistics and bilingualism opening up new possibilities for understanding how
9 language is processed in real time ([Godfroid et al., 2024](#)).

10 Despite its widespread usage, eye-tracking technology faces several obstacles that can limit its acces-
11 sibility. One significant challenge is the specialized expertise required to operate research-grade eye-trackers.
12 Proper usage often demands many hours of training, meaning most research must be conducted in a lab by
13 a trained student or faculty member. Another major limitation is the cost. Eye-trackers can be prohibitively
14 expensive, ranging from a few thousand dollars (e.g., Gazepoint; www.gazept.com) to tens of thousands of
15 dollars (e.g., Tobii (www.tobii.com; SR Research (www.sr-research.com). As a result, not everyone possess
16 the resources, or the time, to incorporate eye-tracking into their research program.

17 In addition, eye-tracking research often requires participants to visit a laboratory, which significantly
18 limits the diversity of the sample or population researchers can recruit. Behavioral science research, in
19 general, frequently suffers from a lack of diversity, relying heavily on participants who are predominantly
20 Western, Educated, Industrialized, Rich, Democratic, and able-bodied (WEIRDA). This focus often excludes
21 individuals from geographically dispersed areas, those from lower socioeconomic backgrounds, and people
22 with disabilities who may face barriers to accessing research facilities. In language research, this issue is
23 particularly evident, as it often prioritizes English-speaking, monolingual, populations ([Blasi et al., 2022](#);
24 [Bylund et al., 2024](#)) and largely includes individuals with normal developing language abilities ([McMurray
et al., 2010](#)). These limitations not only narrow the populations available for study but also compromise the
26 generalizability and applicability of research findings.

27 Eye-tracking outside the lab

28 Methods that allow participants to use their own equipment from anywhere in the world offer a
29 potential solution to the issues outlined above, enabling researchers to recruit more diverse and disadvantaged
30 samples and explore a broader range of questions ([Gosling et al., 2010](#)). The shift toward online behavioral

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31 experiments has been gradually increasing in the behavioral sciences and has become every more important
32 since the 2020 pandemic, which forced many of us to run studies online (Anderson et al., 2019; Rodd, 2024).
33 The *onlineification* of behavioral research has prompted the development of eye-tracking methods that do
34 not rely on traditional lab settings.

35 One method, manual eye-tracking (Trueswell, 2008), involves using video recordings of participants,
36 which can be collected through online teleconferencing platforms such as Zoom (www.zoom.com). Here eye
37 gaze (direction) is manually analyzed posthoc frame by frame from these recordings.

38 Another method, which is the focus of this tutorial, is automated eye-tracking or webcam eye-
39 tracking. Webcam eye-tracking requires three things: 1. A personal computer. 2. An internet connection
40 and 3. A purchased or pre-installed webcam. Gaze information can be collected via a web browser. One
41 common method to perform webcam eye-tracking is through an open source, free, and actively maintained
42 JavaScript library plugin called WebGazer.js (Papoutsaki et al., 2016). This plugin is already incorporated
43 into several popular experimental platforms [e.g., *Gorilla*, *jsPsych*, *PsychoPy*, and *PClrex*; Anwyl-Irvine et
44 al. (2020); Peirce et al. (2019); Leeuw (2015); Zehr and Schwarz (2018)]. A benefit of WebGazer.js is that it
45 does not require users to download any software, and is fully integrated in the browser, making it extremely
46 easy to start webcam eye-tracking.

47 WebGazer.js uses facial feature detection to dynamically estimate gaze positions in real time via
48 webcam. For every time point (based on sampling rate), x and y coordinates are recorded. WebGazer.js
49 leverages machine learning to analyze the relative movement of the eyes and infer gaze location on a screen.
50 To improve accuracy, a calibration process is used in which users interact with visual stimuli, such as
51 looking at and clicking random dots or tracking a moving dot. This mapping process enhances the precision
52 of the gaze-to-screen-coordinate relationship

53 It is important to note that WebGazer.js is not the only method available. Other methods have been
54 implemented by companies like Tobii (www.tobii.com) and Labvanced (Kaduk et al., 2024) . However,
55 because these methods are proprietary, it is unclear what they are doing under the hood.

56 The algorithms underlying webcam-based eye tracking differ significantly from those used in
57 research-grade eye trackers. Research-grade systems employ video-based recording and rely on the pupil-
58 corneal reflection (P-CR) method to track gaze with high precision (Carter & Luke, 2020). This method
59 utilizes infrared light to illuminate the eyes, capturing reflections (known as glints) from the cornea and
60 pupil. High-speed cameras simultaneously capture images at rates of hundreds or thousands of frames per
61 second to measure eye position. By combining data from the corneal reflections and pupil location, these
62 systems calculate gaze direction and position. Proprietary algorithms then map this information to specific
63 locations on the screen.

64 This leads to an important question: how does consumer-grade webcam eye tracking compare to
65 research-grade systems? While validation studies are ongoing, webcam-based eye trackers generally exhibit
66 reduced spatiotemporal accuracy. Studies have reported that these systems achieve spatial accuracy and
67 precision exceeding 1° of visual angle, with latencies ranging from 200 ms to 1000 ms (Kaduk et al., 2024;
68 Semmelmann & Weigelt, 2018; Slim et al., 2024; Slim & Hartsuiker, 2023). Furthermore, the sampling rate

69 of webcam-based systems is much lower, typically capped at 60 Hz, with most studies reporting average or
70 median rates around 30 Hz (Bramlett & Wiener, 2024; Prystauka et al., 2024). Unlike research-grade systems,
71 webcam eye trackers do not use infrared light; instead, they rely on ambient light from the participant's
72 environment. This dependency introduces additional variability in tracking performance.

73 To compare, research-grade systems like the Tobii Pro Spectrum provides spatial precision of 0.03°–
74 0.06° RMS, spatial accuracy of <0.3°, and latency of less than 2.5 ms, with a sampling rate of up to 1200
75 Hz (AB, 2024; Nyström et al., 2021). These advanced metrics make research-grade systems ideal for studies
76 requiring high temporal and spatial resolution.

77 Bringing the visual world paradigm online

78 Despite the differences between research-grade and consumer grade eye-tracking, a number of stud-
79 ies have begun to look at if lab-based results replicate online using webcam eye-tracking. Most relevant to
80 this tutorial are online replications using the VWP (Tanenhaus et al., 1995; cf. Cooper, 1974). For the past
81 25 years, the VWP has been a dominant force in language research, helping researchers tackle a wide range
82 of topics, including sentence processing (Eberhard et al., 1995), word recognition (Allopenna et al., 1998),
83 bilingualism (Ito et al., 2018), and the effects of brain damage on language (Mirman & Graziano, 2012).

84 What makes the widespread use of the VWP even more remarkable is the simplicity of the task. In
85 a typical VWP experiment, participants view a display containing several objects and are asked to select one
86 of them by pointing or clicking. While they listen to a spoken word or phrase that identifies the target object,
87 their eye movements are recorded. Remarkably, looks to each object align very closely—and with precise
88 timing—with the mental activation of the word or concept it represents. This provides a unique and detailed
89 view of how cognitive processes unfold in real time.

90 Most research on visual world eye-tracking has been conducted in laboratory settings using research-
91 grade eye-trackers. However, several attempts have been made to conduct these experiments online using
92 webcam-based eye-tracking. Most online VWP replications have focused on sentence-based language pro-
93 cessing. These studies have looked at effects of set size and determiners (Degen et al., 2021), verb semantic
94 constraint (Prystauka et al., 2024; Slim & Hartsuiker, 2023), grammatical aspect and event comprehension
95 (Vos et al., 2022), and lexical interference (Prystauka et al., 2024).

96 More relevant to the current paper are findings from single-word VWP studies conducted online.
97 To date, only one study has investigated visual world webcam eye-tracking with single words. Slim et al.
98 (2024) examined a phonemic cohort task. In the cohort task, pictures were displayed randomly in one of four
99 quadrants, and participants were instructed to fixate on the target based on the auditory cue. On each trial,
100 one of the pictures was phonemically similar to the target in onset (e.g., *MILK – MITTEN*).

101 They were able to observe significant fixations to the cohort compared to the control condition,
102 replicating lab-based single word VWP experiments with research grade eye-trackers (e.g., Allopenna et al.,
103 1998). However, Slim et al. (2024) only observed these competition effects in a later time window compared
104 to remote eye-tracking.

105 It is important to note, however, that while these studies represent successful replication attempts,
106 there is an important caveat. Most notably, some studies (Degen et al., 2021; Slim et al., 2024; e.g., Slim
107 & Hartsuiker, 2023) reported considerable delays in the temporal onset of effects. Several factors likely
108 contribute to these delays, including reduced spatial precision, computational demands, the size of areas of
109 interest (AOIs), and the number of calibrations performed (Degen et al., 2021).

110 More recent work has addressed these limitations by utilizing an updated version of WebGazer.js
111 and using different experimental platforms.¹ For instance, Vos et al. (2022) demonstrated a significant
112 reduction in delays—approximately 50 ms—when comparing lab-based and online versions of the VWP
113 using an updated version of WebGazer within the jsPsych framework (Leeuw, 2015). Furthermore, studies
114 by Prystauka et al. (2024) and Bramlett and Wiener (2024), which leveraged the Gorilla platform alongside
115 the improved WebGazer algorithm, reported effects comparable to those observed in traditional lab-based
116 VWP studies.

117 These findings underscore the potential of the online version of the VWP, powered by webcam eye-
118 tracking, to achieve results similar to those of traditional lab-based methods. Importantly, they demonstrate
119 that this approach can effectively be used to study competition effects in single-word speech perception

120 Tutorial

121 Taken together, it seems that webcam eye-tracking is viable alternative to lab-based eye-tracking.
122 Given this, we aimed to support researchers in their efforts to conduct high-quality webcam eye-tracking
123 studies with the VWP. While a valuable tutorial on webcam eye-tracking in the VWP already exists (Bramlett
124 & Wiener, 2024), we believe there is value in having multiple resources available to researchers. To this end,
125 we sought to expand on the tutorial by Bramlett and Wiener (2024) by incorporating many of their useful
126 recommendations, but also offering an R package to help streamline data pre-processing.

127 The purpose of this tutorial is to provide an overview of the basic set-up and design features of an
128 online VWP task using the Gorilla platform (Anwyl-Irvine et al., 2020) and to highlight the pre-processing
129 steps needed to analyze webcam eye-tracking data. Here we use the popular open source programming
130 language R and introduce the webgazeR package (Geller & Prystauka, 2024) to facilitate pre-processing of
131 webcam data. To highlight the steps needed to process webcam eye-tracking data we present data from a
132 Spanish spoken word VWP with L2 Spanish speakers. To our knowledge, L2 processing and competitor
133 effects have not been looked at in the online version of the VWP.

134 The structure of the tutorial will be as follows. We first outline the general methods used to conduct
135 a visual world webcam eye-tracking experiment. Next, we detail the data preprocessing steps required to
136 prepare the data for analysis. Finally, we demonstrate one statistical approach for analyzing our preprocessed
137 data, highlighting its application and implications.

¹Studies showing this delay used IPCbex

138

L2 VWP Webcam Eye-tracking

139 To highlight the preprocessing steps required to analyze webcam eye-tracking data, we examined
140 the competitive dynamics of second-language (L2) learners of Spanish during spoken word recognition.
141 Specifically, we investigated both within-language and cross-language (L2/L1) competition using webcam-
142 based eye-tracking.

143 It is well established that competition plays a critical role in language processing (Magnuson et al.,
144 2007). In speech perception, as the auditory signal unfolds over time, competitors (or cohorts)—phonological
145 neighbors that differ from the target by an initial phoneme—become activated. To successfully recognize the
146 spoken word, these competitors must be inhibited or suppressed. For example, as the word *wizard* is spoken,
147 cohorts like *whistle* might also be briefly activated and in order for wizard to be recognized, *whistle* must be
148 suppressed.

149 A key question in the L2 literature is whether competition can occur cross-linguistically, with in-
150 teractions between a speaker’s first language (L1) and second language (L2). A recent study by Sarrett et
151 al. (2022) explored this question using carefully designed stimuli to examine within- and between linguistic
152 (L2/L1) competition in adult L2 Spanish speakers learners using a Spanish VWP. Their study included two
153 key conditions:

- 154 1. Spanish-Spanish condition: A Spanish competitor was presented alongside the target word. For ex-
155 ample, if the target word spoken was “cielo” (sky), the Spanish competitor was “ciencia” (science).
- 156 2. Spanish-English (cross-linguistic) condition: An English competitor was presented for the Spanish
157 target word. For example, if the target word spoken was “botas” (boots), the English competitor was
158 “border.”

159 Sarrett et al. (2022) also included a no competition condition where the Spanish-English pairs were
160 not cross-linguistic competitors (e.g., *frontera* as the target word and *botas/boots* as an unrelated item in the
161 pair). They observed competition effects in both of the critical conditions: within-Spanish competition (e.g.,
162 *cielo - ciencia*) and cross-linguistic competition (e.g., *botas - border*). For this tutorial, we collected data to
163 conceptually replicate their pattern of findings.

164 There are two key differences between our dataset and the original study by Sarrett et al. (2022)
165 worth noting. First, Sarrett et al. (2022) focused on adult L2 Spanish speakers and posed more fine-grained
166 questions about the time course of competition and resolution and its relationship with L2 language acquisi-
167 tion. Second, unlike McCall et al., who measured Spanish proficiency objectively (e.g., using LexTALE-esp;
168 Izura et al. (2014)), we relied on Prolific’s filters to recruit L2 Spanish speakers.

169 Our primary goal here was to demonstrate the pre-processing steps required to analyze webcam-
170 based eye-tracking data. A secondary goal was to provide evidence of L2 competition within and between
171 or cross-linguistically using this methodology. To our knowledge, no papers have looked at spoken word
172 recognition and competition using online methods. It is our hope that researchers can use this to test more
173 detailed questions about L2 processing using webcam-based eye-tracking.

174 Method

175 All tasks herein can be previewed here (<https://app.gorilla.sc/openmaterials/953693>). The
176 manuscript, data, and R code can be found on Github (https://github.com/jgeller112/webcam_gazeR_VWP).

177 Participants

178 We recruited participants from Prolific, a participant recruitment platform, who were: (1) between
179 the ages of 18 and 36 years old, (2) native English speakers, (3) were also fluent in Spanish, and (4) residents of
180 the US. All participants were taken to the Gorilla hosting and experiment platform (www.gorilla.sc; (Anwyl-
181 [Irvine et al., 2020](#)). The participant flow is shown in Figure 1. A total of 187 participants consented to
182 participate in the study. Of these, 111 passed the headphone screener checkpoint and proceeded to the VWP.
183 Among these, 32 participants successfully completed the Visual World Paradigm (VWP) task with at least
184 100 trials, while 79 participants failed calibration. Ninety-one participants completed the entire experiment,
185 including the final questionnaires. Table 1 provides basic demographic information about the participants
186 who completed the full experiment. After applying additional exclusion criteria (low accuracy (< 80%) and
187 excessive missing eye-data (> 30%)), the final sample consisted of 28 participants with usable eye-tracking
188 data.

189 Materials**VWP..**

191 **Items.** We adapted materials from Sarrett et al. (2022). In their cross-linguistic VWP, participants
192 were presented with four pictures and a spoken Spanish word and had to select the image that matched the
193 spoken word by clicking on it. The word stimuli for the experiment were chosen from textbooks used by
194 students in their first and second year college Spanish courses.

195 The item sets consisted of two types of phonologically-related word pairs: one pair of Spanish-
196 Spanish words and another of Spanish-English words. The Spanish-Spanish pairs were unrelated to the
197 Spanish-English pairs. All the word pairs were carefully controlled on a number of dimensions (see (Sarrett
198 et al., 2022)).

199 There were three experimental conditions: (1) the Spanish-Spanish condition, where one of the
200 Spanish words was the target and the other was the competitor; (2) the Spanish-English condition, where a
201 Spanish word was the target and its English phonological cohort served as the competitor; and (3) the No
202 Competitor condition, where the Spanish word did not overlap with any other word in the set. The Spanish-
203 Spanish condition had twice as many trials as the other conditions due to the interchangeable nature of the
204 target and competitor words in that pair.

205 There were 15 sets of 4 items (half the number of sets used in (Sarrett et al., 2022)). Each item within
206 a set was repeated 4 times as the target word. This yielded 240 trials (15 sets × 4 items per set × 4 repetitions).
207 Each item set consisted of one Spanish-Spanish cohort pair and one Spanish-English cohort pair. Both

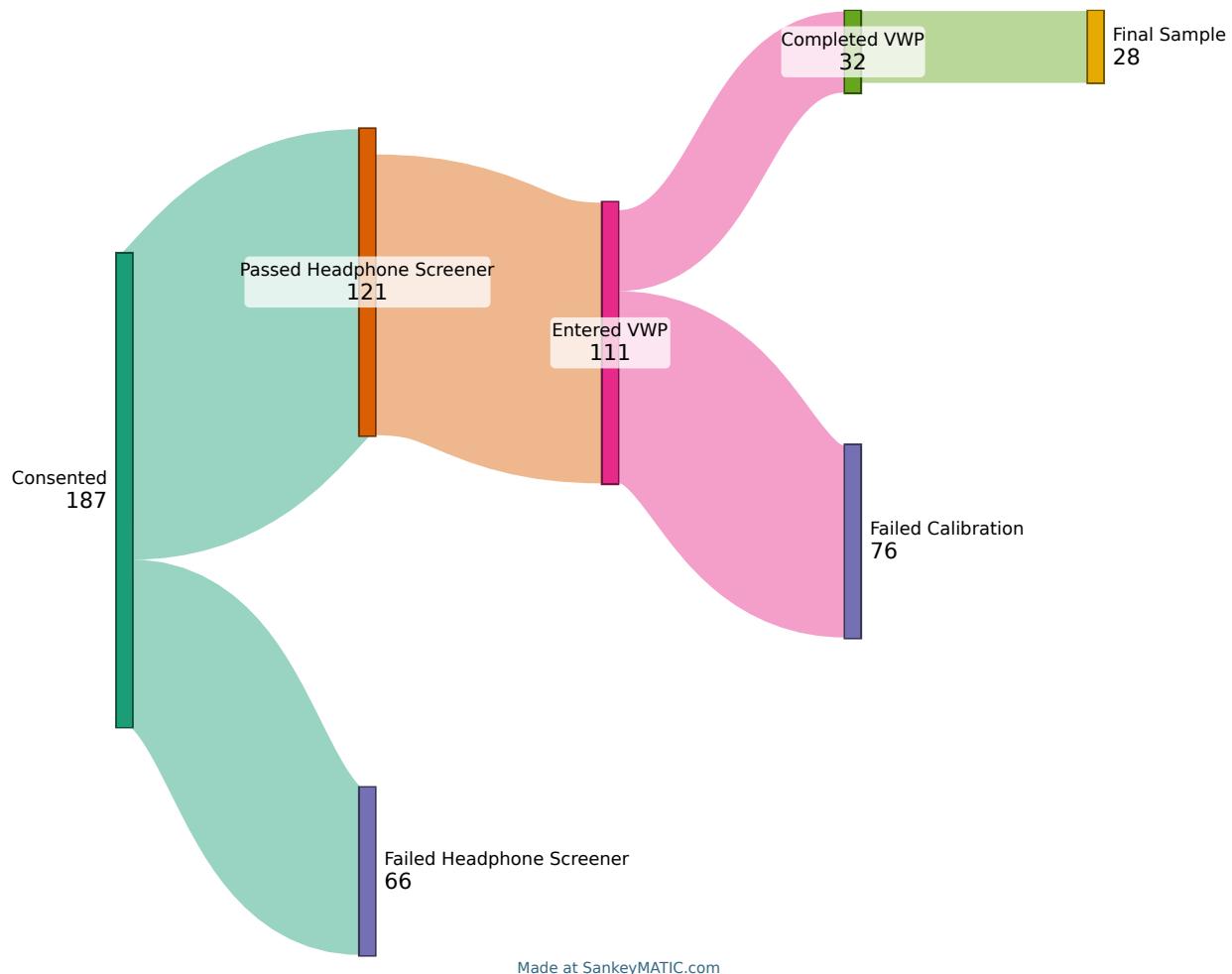
Table 1*Participant demographic variables*

Characteristic	N = 91¹
Age	(20.0, 35.0), 28.2(4.4)
Gender	
Female	42 / 91 (46%)
Male	49 / 91 (54%)
Spoken dialect	
Do not know	11 / 91 (12%)
Midwestern	19 / 91 (21%)
New England	11 / 91 (12%)
Other (please specify)	7 / 91 (7.7%)
Pacific northwest	7 / 91 (7.7%)
Pacific southwest	7 / 91 (7.7%)
Southern	21 / 91 (23%)
Southwestern	8 / 91 (8.8%)
Race	
Decline to state	1 / 91 (1.1%)
Hispanic or Latino	38 / 91 (42%)
Not Hispanic or Latino	52 / 91 (57%)
Browser	
Chrome	77 / 91 (85%)
Edge	3 / 91 (3.3%)
Firefox	7 / 91 (7.7%)
Safari	4 / 91 (4.4%)
Years Speaking Spanish	(0, 35), 15(10)
Percentage Time Speaking Spanish	25(23)

¹ (Min, Max), Mean(SD); n / N (%); Mean(SD)

Figure 1

Participant flow through the experiment



208 items in a Spanish-Spanish pair had a “reciprocal” competitor relationship (that is, we could test activation
 209 for *cielo* given *ciencia*, and for *ciencia* given *cielo*). Consequently, there were 120 trials in the Spanish-
 210 Spanish condition. In contrast, only one item from the Spanish-English pair had the specified competitor
 211 relationship (we could test activation for *frontera border*, given *botas*, but when hearing *frontera*, there was
 212 no competitor). Thus, there were only 60 trials for each the Spanish-English competition as well as the No
 213 Competitor condition. Items occurred in each of the four corners of the screen on an equal numbers of trials.

214 **Stimuli.** In Sarrett et al. (2022) all auditory stimuli were recorded by a female bilingual speaker
 215 whose native language was Mexican Spanish and also spoke English. Stimuli were recorded in a sound-
 216 attenuated room sampled at 44.1 kHz. Auditory tokens were edited to reduce noise and remove clicks. The
 217 auditory tokens were then amplitude normalized to 70 dB SPL. For each target word, there were four separate
 218 recordings so each instance was unique.

219 Visual stimuli were images from a commercial clipart database that were selected by a consensus

220 method involving a small group of students. All .wav files were converted to .mp3 for online data collection.
221 All stimuli can be found here: <https://osf.io/mgkd2/>.

222 **Headphone screener.** Headphones were required for all participants. To ensure this, we used a six-
223 trial task taken from Woods et al. (2017). On each trial, three tones of the same frequency and duration were
224 presented sequentially. One tone had a lower amplitude than the other two tones. Tones were presented in
225 stereo, but the tones in the left and right channels were 180 out of phase across stereo channels—in free field,
226 these sounds should cancel out or create distortion, whereas they will be perfectly clear over headphones.
227 The listener picked which of the three tones was the quietest. Performance is generally at the ceiling when
228 wearing headphones but poor when listening in the free field (due to phase cancellation).

229 **Demographics questionnaire.** Participants completed a demographic questionnaire as part of the
230 study. The questions covered basic demographic information, including age, gender, spoken dialect, ethnicity,
231 and race.

232 Participants also answered a series of questions related to their personal health and environmental
233 conditions during the experiment. These questions addressed any history of vision problems (e.g., corrected
234 vision, eye disease, or drooping eyelids) and whether they were currently taking medications that might impair
235 judgment. Participants also indicated if they were wearing eyeglasses, contacts, makeup, false eyelashes, or
236 hats.

237 The questionnaire inquired about their environment, asking if there was natural light in the room, if
238 they were using a built-in camera or an external one (with an option to specify the brand), and their estimated
239 distance from the camera. Participants were asked to estimate how many times they looked at their phone or
240 got up during the experiment and whether their environment was distraction-free.

241 Additional questions assessed the clarity of calibration instructions, allowing participants to suggest
242 improvements, and asked if they were wearing a mask during the session. These questions aimed to gather
243 insights into personal and environmental factors that could impact data quality and participant comfort during
244 the experiment.

245 To gauge L2 experience, we asked participants when they started speaking Spanish, how many years
246 of Spanish speaking experience they had, and to provide, on a scale between 0-100, how often they use
247 Spanish in their daily lives.

248 **Procedure**

249 All tasks were completed in a single session, lasting approximately 45 minutes. The tasks were
250 presented in a fixed order: consent, headphone screener, spoken word VWP, and questionnaire items.

251 The experiment was programmed in the Gorilla Experiment Platform (Anwyl-Irvine et al., 2019),
252 with personal computers as the only permitted device type. Upon entering the online study, participants
253 received general information to decide if they wished to participate, after which they provided informed
254 consent. Participants were then instructed to adjust the volume to a comfortable level while noise played.

255 Next, participants completed a headphone screening test. They had three attempts to pass this test.

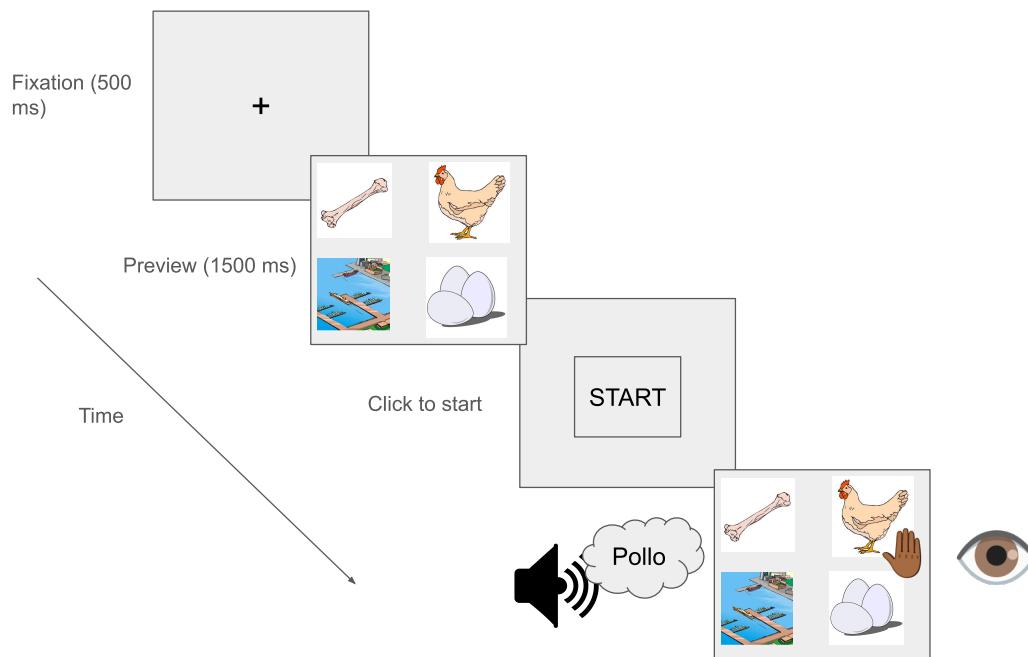
256 If unsuccessful by the third attempt, participants were directed to an early exit screen, followed by the ques-
 257 tionnaire.

258 For those who passed the screening, the next task was the VWP. This began with instructional videos
 259 providing specific guidance on the ideal experiment setup for eye-tracking and calibration procedures. Par-
 260 ticipants were then required to enter full-screen mode before calibration. A 9 point calibration procedure
 261 was used. Calibration occurred every 60 trials for a total of 3 calibrations. Participants had three attempts to
 262 successfully complete each calibration phase. If calibration was unsuccessful, participants were directed to
 263 an early exit screen, followed by the questionnaire.

264 In the main VWP task, each trial began with a 500 ms fixation cross at the center of the screen. This
 265 was followed by a preview screen displaying four images, each positioned in a corner of the screen. After
 266 1500 ms, a start button appeared in the center. Participants clicked the button to confirm they were focused
 267 on the center before the audio played. Once clicked, the audio was played, and the images remained visible.
 268 Participants were instructed to click the image that best matched the spoken target word, while their eye
 269 movements were recorded. Eye movements were only recorded on that screen. Figure 2 displays the VWP
 270 trial sequence.

Figure 2

VWP trial schematic



271 After completing the main VWP task, participants proceeded to the final questionnaire, which in-
 272 cluded questions about the eye-tracking task and basic demographic information. Participants were then
 273 thanked for their participation.

274 **Preprocessing data**

275 After the data is collected you can begin preprocessing your data. Below we highlight the steps
 276 needed to preprocess your webcam eye-tracking data and get it ready for analysis. For some of this pre-
 277 processing we will use the newly created `webgazeR` package (v. 0.1.0) which is an extension of the `gazeR`
 278 package (Geller et al., 2020) which was created to analyze VWP data in lab-based studies.

279 For preprocessing visual world webcam eye data, we follow six general steps:

- 280 1. Reading in data
- 281 2. Data Exclusion
- 282 3. Combining trial- and eye-level data
- 283 4. Assigning areas of interest
- 284 5. Time Binning
- 285 6. Aggregating (optional)

286 For each of these steps, we will display R code chunks demonstrating how to perform each step with
 287 helper functions (if applicable) from the `webgazeR` (Geller & Prystauka, 2024) package in R.

288 **Load packages**

289 **Package Installation and Setup.** Before turning to the pre-processing code below, we will need to
 290 make sure all the necessary packages are installed. The code will not run if the packages are not installed
 291 properly. If you have already installed the packages mentioned below, then you can skip ahead and ignore this
 292 section. To install the necessary packages, simply run the following code - it may take some time (between
 293 1 and 5 minutes to install all of the libraries so you do not need to worry if it takes some time).

294 **webgazeR installation.** The `webgazeR` package is installed from the Github repository using the
 295 `remotes` package.

```
library(remotes) # install github repo

remotes::install_github("jgeller112/webgazeR")
```

296 Once this is installed, `webgazeR` can be loaded along with additional useful packages. The following
 297 code will load the required packages or install them if you do not have them on your system.

```
options(stringsAsFactors = FALSE) # no automatic data transformation
options("scipen" = 100, "digits" = 10) # suppress math annotation

# List of required packages
```

```

required_packages <- c(
  "tidyverse",      # data wrangling
  "here",          # relative paths instead of absolute aids in reproducibility
  "tinytable",     # nice tables
  "janitor",       # functions for cleaning up your column names
  "webgazeR",      # has webcam functions
  "readxl",        # read in Excel files
  "ggokabeito",   # color-blind friendly palettes
  "flextable",     # Word tables
  "permuco",       # permutation analysis
  "foreach",       # permutation analysis
  "geomtextpath",  # for plotting labels on lines of ggplot figures
  "cowplot"        # combine ggplot figures
)

# Install and load each package
for (pkg in required_packages) {
  if (!require(pkg, character.only = TRUE)) {
    install.packages(pkg, dependencies = TRUE)
    library(pkg, character.only = TRUE)
  }
}

```

298 Once `webgazeR` and other helper packages have been installed and loaded the user is ready to start
 299 cleaning your data.

300 ***Reading in data***

301 **Behavioral, trial-level, data.** To process eye-tracking data you will need to make sure you have
 302 both the behavioral data and the eye-tracking data files. We have all the data needed in the repository by
 303 navigating to the L2 subfolder in the data folder (data -> L2). For the behavioral data, Gorilla produces a
 304 .csv file that includes trial-level information (here contained in the object `L2_data`). The files needed are
 305 called `data_exp_196386-v5_task-scf6.csv` and `data_exp_196386-v6_task-scf6.csv`. We have
 306 two files because we ran a modified version of the experiment.

307 The .csv files contain meta-data for each trial, such as what picture were presented on each
 308 trial, which object was the target, reaction times, audio presentation times, what object was clicked on,
 309 etc. To load our data files into our R environment, we use the `here` package to set a relative rather
 310 than an absolute path to our files. We read in the data files from the repository for both versions of the
 311 task and merge the files together. `L2_data` merges both `data_exp_196386-v5_task-scf6.csv` and

312 data_exp_196386-v6_task-scf6.csv into one object.

```
# load in trial level data
# combine data from version 5 and 6 of the task
L2_1 <- read_csv(here("data", "L2", "data_exp_196386-v5_task-scf6.csv"))
L2_2 <- read_csv(here("data", "L2", "data_exp_196386-v6_task-scf6.csv"))
L2_data <- rbind(L2_1, L2_2) # bind the two objects together
```

313 **Eye-tracking data.** Gorilla currently saves each participant's eye-tracking data trial by trial. The
 314 raw subfolder in the data folder in the project repository contains the eye-tracking files by participant for each
 315 trial individually. Contained in those files, we have information pertaining to each trial such as participant
 316 id, time since trial started, x and y coordinates of looks, convergence (the model's confidence in finding
 317 a face (and accurately predicting eye movements), face confidence (represents the support vector machine
 318 (SVM) classifier score for the face model fit), and information pertaining to the the AOI screen coordinates
 319 (standardized and user-specific). The vwp_files_L2 object below contains a list of all the files contained in
 320 the folder. Because vwp_files_L2 contains trial data as well as calibration data, we remove the calibration
 321 trials and save the files to vwp_paths_filtered_L2.

```
# Get the list of all files in the folder
vwp_files_L2 <- list.files(here::here("data", "L2", "raw"), pattern =
  "\\.xlsx$", full.names = TRUE)
# Exclude files that contain "calibration" in their filename
vwp_paths_filtered_L2 <- vwp_files_L2[!grepl("calibration", vwp_files_L2)]
```

322 When data is generated from Gorilla, each trial in your experiment is saved as an individual
 323 file. Because of this, we need some way to take all the individual files and merge them together. The
 324 merge_webcam_files() function merges each trial from each participant into a single tibble or data frame.
 325 Before running the merge_webcam_files() function, ensure that your working directory is set to where
 326 the files are stored. merge_webcam_files() reads in all the .xlsx files from the raw subfolder, binds them
 327 together into one dataframe, and cleans up the column names. The function then filters the data to include
 328 only rows where the type is “prediction” and the screen_index matches the specified value (in our case,
 329 screen 4 is where we collected eye-tracking data). If you recorded across multiple screens the screen_index
 330 argument can take multiple values (e.g., screen_index= c(1, 4, 5), will take eye-tacking information from
 331 screens, 1, 4, and 5)). merge_webcam_files() also renames the spreadsheet_row column to trial and
 332 sets both trial and subject as factors for further analysis in our pipeline. As a note, all steps should be
 333 followed in order due to the renaming of column names. If you encounter an error it might be because column
 334 names have not been changed.

```
setwd(here::here("data", "L2", "raw")) # set working directory to raw data folder
edat_L2 <- merge_webcam_files(vwp_paths_filtered_L2, screen_index=4) # eye
  ↳ tracking occurred on screen index 4
```

335 *Subject and trial level data removal*

336 To ensure high-quality data, it is essential to filter out unreliable data based on both behavioral and
 337 eye-tracking criteria before merging datasets. In our dataset, participants will be excluded if they meet any
 338 of the following conditions: failure to successfully calibrate throughout the experiment (less than 100 trials),
 339 low accuracy ($< 80\%$), low sampling rates (< 5), and a high proportion of gaze data outside the screen
 340 coordinates ($> 30\%$). Successful calibration is crucial for capturing accurate eye-tracking measurements,
 341 so participants who could not maintain proper calibration may have inaccurate gaze data. Similarly, low
 342 accuracy may indicate poor engagement or task difficulty, which can reduce the reliability of the behavioral
 343 data and suggest that eye-tracking data may be less precise.

344 First, we will create a cleaned up version of our behavioral, trial-level, data L2_data by
 345 creating an object named eye_behav_L2 that selects useful columns from that file and renames stimuli to
 346 make them more intuitive. Because most of this will be user-specific, no function is called here. Below we
 347 describe the preprocessing done on the behavioral data file. The below code processes and transforms the
 348 L2_data dataset into a cleaned and structured format for further analysis. First, the code renames several
 349 columns for easier access using janitor::clean_names() (Firke, 2023) function. We then select only the
 350 columns we need and filter the dataset to include only rows where zone_type is “response_button_image”,
 351 representing the picture selected for that trial. Afterward, the function renames additional columns (tlpic
 352 to TL, trpic to TR, etc.). We also renamed participant_private_id to subject, spreadsheet_row
 353 to trial, and reaction_time to RT. This makes our columns consistent with the edat above for merging
 354 later on. Lastly, reaction_time (RT) is converted to a numeric format for further numerical analysis.

355 It is important to note here that what the behavioral spreadsheet denotes as trial is not in fact the trial
 356 number used in the eye-tracking files. Thus it is imperative you use spreadsheet_row as trial number to
 357 merge the two files successfully.

```
eye_behav_L2 <- L2_data %>%
  janitor::clean_names() %>%
  # Select specific columns to keep in the dataset
  dplyr::select(participant_private_id, correct, tlpic, trpic, blpic, brpic,
    ↳ condition,
    eng_targetword, targetword, typetl, typetr, typebl, typebr,
    ↳ zone_name,
```

```

    zone_type, reaction_time, spreadsheet_row, response) %>%
    # Filter the rows where 'Zone.Type' equals "response_button_image"
    dplyr::filter(zone_type == "response_button_image") %>%
    # Rename columns for easier use and readability
    dplyr::rename(
      TL = tlpic,                      # Rename 'tlpic' to 'TL'
      TR = trpic,                      # Rename 'trpic' to 'TR'
      BL = blpic,                      # Rename 'blpic' to 'BL'
      BR = brpic,                      # Rename 'brpic' to 'BR'
      targ_loc = zone_name,           # Rename 'zone_name' to 'targ_loc'
      subject = participant_private_id, # Rename 'participant_private_id' to
      ↪ 'subject'
      trial = spreadsheet_row,        # Rename 'spreadsheet_row' to 'trial'
      acc = correct,                  # Rename 'correct' to 'acc' (accuracy)
      RT = reaction_time            # Rename 'reaction_time' to 'RT'
    ) %>%
    # Convert the 'RT' (Reaction Time) column to numeric type
    dplyr::mutate(RT = as.numeric(RT),
      subject = as.factor(subject),
      trial = as.factor(trial))
  
```

358 **Audio onset.** Because we are using spoken audio on each trial and running this experiment from
 359 the browser, audio onset is never going to be consistent across participants. In Gorilla there is an option
 360 to collect advanced audio features (you must make sure you select this when designing the study) such as
 361 when the audio play was requested, fired (played) and when the audio ended. To do so you must click on
 362 advanced settings and select 1 (see Figure 3). We will want to incorporate this timing information into our
 363 analysis pipeline. Gorilla records the onset of the audio which varies by participant. We are extracting that
 364 in the `audio_rt_L2` object by filtering `zone_type` to `content_web_audio` and `response` equal to “AUDIO
 365 PLAY EVENT FIRED”. This will tell us when the audio was triggered in the experiment. We are creating a
 366 column called (`RT_audio`) which we will use later on to correct for audio delays.

```

audio_rt_L2 <- L2_data %>%
  janitor::clean_names() %>%
  select(participant_private_id, zone_type, spreadsheet_row, reaction_time,
  ↪ response) %>%
  
```

Figure 3*Advanced audio settings in Gorilla*

Web Audio ?

If 0 allow participant to start media manually. Choose 1 (start manually) or 0. Default: 1

Media can be played up to times. Default: 1

If (setting) advance when media is finished. Choose 1 (advance when finished) or 0. Default: 0

Advanced Settings + Show

If 1 , provide additional metrics on audio events Choose 1 for on or 0/unset for off. Default: 0/unset.

Audio format: mp3 . When playing audio files specified by embedded data, manually specify the format (usually wav or mp3) here. Default: mp3

Show Stop Button: . When playing audio, show a stop button allowing the audio file to be stopped. Choose 1 for on (show stop button), or 0/unset for off. Default: 0/unset

Show full audio controls: . Show a full set of controls for the audio file, allowing participants to play, pause, rewind etc. Choose 1 for on (show full controls), or 0/unset for off. Default: 0/unset

Localisation Settings ? Docs + Show

```

filter(zone_type=="content_web_audio", response=="AUDIO PLAY EVENT FIRED")%>%
  distinct() %>%
dplyr::rename("subject" = "participant_private_id",
  "trial" = "spreadsheet_row",
  "RT_audio" = "reaction_time") %>%
select(-zone_type) %>%
mutate(RT_audio=as.numeric(RT_audio))

```

367 We then merge this information with eye_behav_L2.

```

# merge the audio Rt data to the trial level object
trial_data_rt_L2 <- merge(eye_behav_L2, audio_rt_L2, by=c("subject", "trial"))

```

368 **Trial removal.** As stated above, participants who did not successfully calibrate 3 times or less
 369 were rejected from the experiment. Let's take a look at how many trials each participant had using the
 370 trial_data_rt_L2 object. Deciding to remove trials is ultimately up to the researcher. In our case, we
 371 removed participants with less than 100 trials. In Table 2 we can see several participants failed some of the
 372 calibration attempts and do not have an adequate number of trials. Again we make no strong recommendations here.
 373 If you to decide to do this, we recommend pre-registering this decision.

```

# find out how many trials each participant had
edatntrials_L2 <- trial_data_rt_L2 %>%
  dplyr::group_by(subject)%>%
  dplyr::summarise(ntrials=length(unique(trial)))

```

374 Let's remove them from the analysis using the below code.

```

trial_data_rt_L2 <- trial_data_rt_L2 %>%
  filter(subject %in% edatntrials_bad_L2$subject)

```

375 **Low accuracy.** In our experiment, we want to make sure accuracy is high (> 80%). Again, we want
 376 participants that are fully attentive in the experiment. In the below code, we keep participants with accuracy
 377 equal to or above 80% and only include correct trials and save it to trial_data_acc_clean_L2.

```

# Step 1: Calculate mean accuracy per subject and filter out subjects with mean
  ↳ accuracy < 0.8
subject_mean_acc_L2 <- trial_data_rt_L2 %>%

```

Table 2

Participants with less than 100 trials

subject	ntrials
12102265	2
12110638	55
12110829	59
12110878	59
12110897	60
12111234	57
12111244	58
12111363	58
12111663	57
12111703	58
12111869	60
12111960	46
12112152	59
12212113	56
12213826	99
12213965	59

```

group_by(subject) %>%
  dplyr::summarise(mean_acc = mean(acc, na.rm = TRUE)) %>%
  filter(mean_acc > 0.8)

# Step 2: Join the mean accuracy back to the main dataset and exclude trials with
# accuracy < 0.8
trial_data_acc_clean_L2 <- trial_data_rt_L2 %>%
  inner_join(subject_mean_acc_L2, by = "subject") %>%
  filter(acc==1) # only use accurate responses for fixation analysis

```

³⁷⁸ **RTs.** There is much debate on how to handle RT data (see [Miller, 2023](#)). Because of this. we leave
³⁷⁹ it up to the reader and researcher to decide what to do with RTs. In the current example we ignore RTs.

380 **Sampling rate.** While most commercial eye-trackers sample at a constant rate, data captured by we-
 381 bcams are widely inconsistent. Below is some code to calculate the sampling rate of each participant. Ideally,
 382 you should not have a sampling rate less than 5 Hz. It has been recommended you drop those values ([Bramlett
 383 & Wiener, 2024](#)) The below function `analyze_sample_rate()` calculates calculates the sampling rate for
 384 each subject and each trial in our eye-tracking dataset (`edat_L2`). The function provides overall statistics,
 385 including the median (used by ([Bramlett & Wiener, 2024](#))) and standard deviation of sampling rates in your
 386 experiment, and also generates a histogram of median sampling rates by subject. Looking at Figure 4, the
 387 sampling rate ranges from 5 to 35 Hz with a median sampling rate of 21.56. This corresponds to previous
 388 webcam eye-tracking work (e.g., ([Bramlett & Wiener, 2024](#); [Prystauka et al., 2024](#)))

```
samp_rate_L2 <- analyze_sampling_rate(edat_L2)
```

```
389 Overall Median Sampling Rate (Hz): 21.56171771
390 Overall Standard Deviation of Sampling Rate (Hz): 7.399937723
391
392 Sampling Rate by Trial:
393 # A tibble: 10,665 x 5
394 # Groups:   subject [60]
395   subject trial max_time n_times     SR
396   <fct>    <fct>    <dbl>    <int>  <dbl>
397  1 12102265  8        4895     108   22.1
398  2 12102265 11       4920.    112   22.8
399  3 12102265 15       4911.    79    16.1
400  4 12102265 17       4916.    113   23.0
401  5 12102265 20       4903.    112   22.8
402  6 12102265 21       1826.    40    21.9
403  7 12102265 28       4917.    114   23.2
404  8 12102265 31       4913.    79    16.1
405  9 12102265 34       4948.    88    17.8
406 10 12102265 35       4901.    93    19.0
407 # i 10,655 more rows
408
409 Median Sampling Rate by Subject:
410 # A tibble: 60 x 2
411   subject med_SR
412   <fct>    <dbl>
413  1 12102265  21.9
414  2 12102286  30.6
415  3 12102530  19.9
416  4 12110559  29.3
```

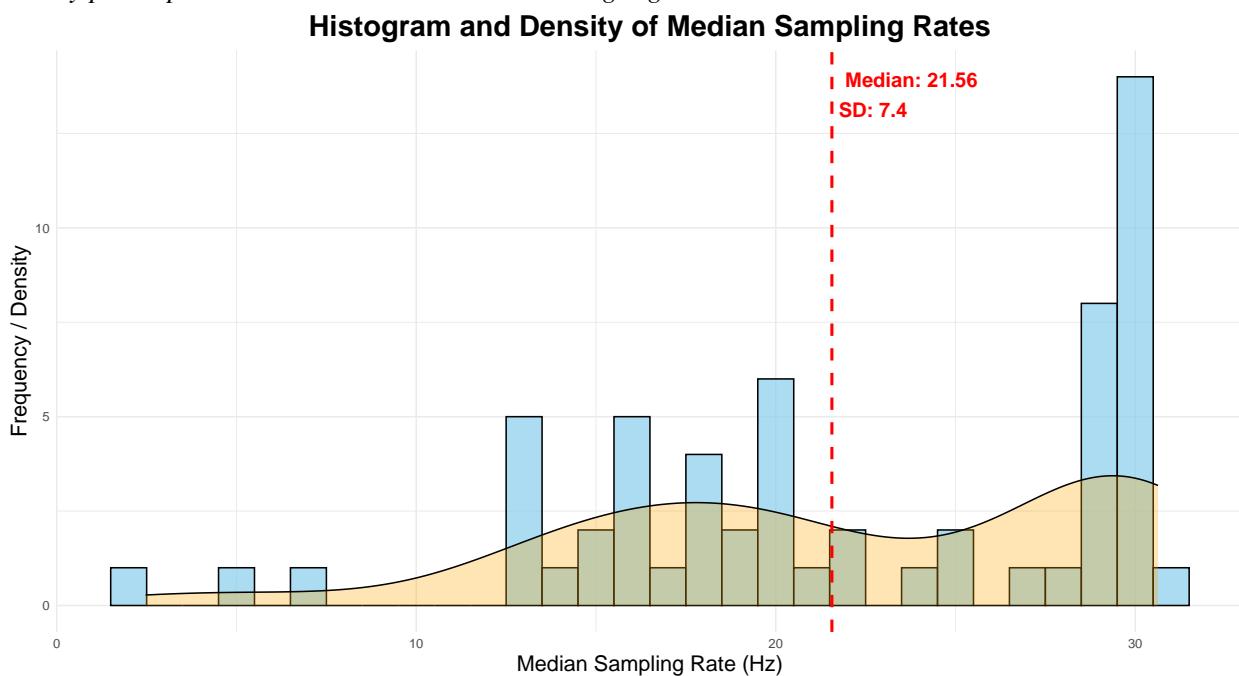
```

417 5 12110579 13.3
418 6 12110585 30.1
419 7 12110586 14.8
420 8 12110600 2.47
421 9 12110638 29.0
422 10 12110685 19.5
423 # i 50 more rows

```

Figure 4

Participant sampling-rate for L2 experiment. A histogram and overlayed density plot shows median sampling rate by participant. the overall median and SD is highlighted in red.



424 When using the above function, separate dataframes are produced by-participants and by-trial. These
425 can be added to the behavioral dataframe using the below code.

```

# Extract by-subject and by-trial sampling rates from the result
subject_sampling_rate_L2 <- samp_rate_L2$median_SR_by_subject # Sampling rate by
# subject
trial_sampling_rate_L2 <- samp_rate_L2$SR_by_trial # Sampling rate by trial
trial_sampling_rate_L2$subject<-as.factor(trial_sampling_rate_L2$subject)

# Assuming target_data is your other dataset that contains subject and trial
# information
# Append the by-subject sampling rate to target_data (based on subject)

```

```

subject_sampling_rate_L2$subject <- as.factor(subject_sampling_rate_L2$subject)

# Assuming target_data is your other dataset that contains subject and trial
# information
# Append the by-subject sampling rate to target_data (based on subject)
trial_sampling_rate_L2$subject<-as.factor(trial_sampling_rate_L2$subject)

# Assuming target_data is your other dataset that contains subject and trial
# information
# Append the by-subject sampling rate to target_data (based on subject)
subject_sampling_rate_L2$subject <- as.factor(subject_sampling_rate_L2$subject)
trial_data_acc_clean_L2$subject <- as.factor(trial_data_acc_clean_L2$subject)

target_data_with_subject_SR_L2 <- trial_data_acc_clean_L2 %>%
  left_join(subject_sampling_rate_L2, by = "subject")

target_data_with_subject_SR_L2$trial <-
  as.factor(target_data_with_subject_SR_L2$trial)

# Append the by-trial sampling rate to target_data (based on subject and trial)
target_data_with_full_SR_L2 <- target_data_with_subject_SR_L2 %>%
  select(subject, trial, med_SR)%>%
  full_join(trial_sampling_rate_L2, by = c("subject", "trial"))

trial_data_L2 <- left_join(trial_data_acc_clean_L2, target_data_with_full_SR_L2,
  by=c("subject", "trial"))

```

426 Now we can use this information to filter out data with poor sampling rates. Users can use the
 427 `filter_sampling_rate()` function to either (1) throw out data, by-participant, by-trial, or both, or (2) label
 428 sampling rates below a certain threshold as bad (TRUE or FALSE). Let's use the `filter_sampling_rate()`
 429 function to do this. We will use our `trial_data_L2` object.

430 We leave it up to the user to decide what to do with low sampling rates and make no specific rec-
 431 ommendations here. In our case we are going to remove the data by-participant and by-trial (setting `action`
 432 = "both") if sampling frequency is below 5hz (`threshold=5`). The `filter_sampling_rate()` function
 433 is designed to process a dataset containing participant-level and trial-level sampling rates. It allows the user
 434 to either filter out data that falls below a certain sampling rate threshold or simply label it as "bad". The
 435 function gives flexibility by allowing the threshold to be applied at the participant-level, trial-level, or both.
 436 It also lets the user decide whether to remove the data or flag it as below the threshold without removing it. If
 437 `action = remove`, the function will output how many subjects and trials were removed by on the threshold.

```
filter_edat_L2 <- filter_sampling_rate(trial_data_L2, threshold = 5,
                                         action = "remove",
                                         by = "both")
```

438 The message produced states that 1 subject is thrown out along with 107 trials (trials associated with
 439 the 1 subject).

440 **Out-of-bounds (outside of screen).** It is important that we do not include points that fall outside
 441 the standardized coordinates (0,1). The `gaze_oob()` function calculates how many of the data points fall
 442 outside the standardized range. Here we need our eye-tracking data (`edat_L2`). Running the `gaze_oob()`
 443 function returns a table listing how many data points fall outside this range (total, X and Y), and also provides
 444 percentages (see Table 3). This information would be useful to include in the final paper.

```
oob_data_L2 <- gaze_oob(edat_L2)
```

445 [1] "/home/runner/work/L2_VWP_Webcam/L2_VWP_Webcam/_manuscript/Figures/oob_data_L2.png"

446 We can also add add by-participant and by-trial out of bounds data to our behavioral, trial-level, data
 447 (`filter_edat_L2`) and finally exclude participants and trials with more than 30% missing data. The value
 448 of 30 is just a suggestion and should not be used as a rule of thumb for all studies nor are we endorsing this
 449 value.

```
remove_missing <- oob_data_L2 %>%
  # Start with the
  `oob_data` dataset and assign the result to `remove_missing`
  select(subject, total_missing_percentage) %>%
  # Select only the
  `subject` and `total_missing_percentage` columns from `oob_data`
  left_join(filter_edat_L2, by = "subject") %>%
  # Perform a left
  `join with `filter_edat` on the `subject` column, keeping all rows from
  `oob_data`
  filter(total_missing_percentage < 30) %>%
  # Filter the data
  `to keep only rows where `total_missing_percentage` is less than 30 %>%
  na.omit()
```

450 ***Eye-tracking data***

451 **Convergence and confidence.** In the eye-tracking data we need to remove rows with poor conver-
 452 gence and confidence scores in our eye-tracking data. The convergence column refers to WebGazer.js
 453 confidence in finding a face (and accurately predicting eye movements). Confidence values vary from 0 to 1,
 454 and numbers less than 0.5 suggest that the model has probably converged. `face_conf` represents the support

Table 3*Out of bounds gaze statistics*

subject	total_points	outside_count	total_missing_percentage	x_outside_count	y_outside_count	x_outside_percentage	y_outside_percentage
12102265	6,197	1,132	18.27	202	947	3.26	15.28
12102286	11,765	354	3.01	267	181	2.27	1.54
12102530	9,025	385	4.27	244	147	2.70	1.63
12110559	11,890	416	3.50	194	222	1.63	1.87
12110579	5,822	1,063	18.26	697	436	11.97	7.49
12110585	13,974	776	5.55	83	694	0.59	4.97
12110586	5,281	216	4.09	176	77	3.33	1.46
12110600	731	1	0.14	1	0	0.14	0.00
12110638	4,647	1,056	22.72	996	159	21.43	3.42
12110685	6,356	1,099	17.29	1,006	241	15.83	3.79
12110713	12,647	1,107	8.75	787	538	6.22	4.25
12110751	10,028	995	9.92	475	570	4.74	5.68
12110829	4,016	671	16.71	510	223	12.70	5.55
12110878	847	27	3.19	13	16	1.53	1.89
12110890	7,683	454	5.91	204	251	2.66	3.27
12110891	8,746	2,277	26.03	867	1,579	9.91	18.05
12110897	295	0	0.00	0	0	0.00	0.00
12111092	5,039	1,053	20.90	556	606	11.03	12.03
12111234	4,018	524	13.04	90	440	2.24	10.95
12111244	3,136	104	3.32	74	30	2.36	0.96
12111363	3,648	1,020	27.96	382	753	10.47	20.64
12111367	10,325	337	3.26	259	90	2.51	0.87
12111379	11,410	2,832	24.82	2,083	1,104	18.26	9.68
12111410	6,480	135	2.08	82	53	1.27	0.82
12111423	9,877	891	9.02	684	207	6.93	2.10
12111501	32,569	3,712	11.40	2,003	1,800	6.15	5.53
12111514	12,729	2,495	19.60	2,111	666	16.58	5.23
12111624	6,761	197	2.91	139	67	2.06	0.99
12111663	5,598	1,354	24.19	233	1,153	4.16	20.60
12111703	3,577	1,572	43.95	527	1,507	14.73	42.13
12111795	9,129	1,465	16.05	1,408	201	15.42	2.20
12111866	4,627	550	11.89	360	284	7.78	6.14
12111869	1,485	55	3.70	54	1	3.64	0.07
12111910	6,221	653	10.50	486	211	7.81	3.39
12111960	5,902	1,780	30.16	705	1,121	11.95	18.99
12112152	4,062	1,289	31.73	448	1,172	11.03	28.85
12210934	11,338	2,472	21.80	1,021	1,709	9.01	15.07
12210955	4,229	1,744	41.24	142	1,668	3.36	39.44
12211266	7,552	880	11.65	313	654	4.14	8.66
12211290	11,740	592	5.04	336	361	2.86	3.07
12211353	9,337	1,218	13.04	414	1,008	4.43	10.80
12211956	2,467	349	14.15	256	101	10.38	4.09
12212098	6,278	2,812	44.79	315	2,586	5.02	41.19
12212113	4,321	434	10.04	384	72	8.89	1.67
12212204	8,321	657	7.90	406	291	4.88	3.50
12212388	6,771	810	11.96	695	128	10.26	1.89
12212716	8,013	516	6.44	303	216	3.78	2.70
12212723	7,748	747	9.64	60	717	0.77	9.25
12212808	7,011	593	8.46	422	191	6.02	2.72
12213162	13,211	1,060	8.02	674	428	5.10	3.24
12213496	14,536	4,540	31.23	2,052	3,270	14.12	22.50
12213685	2,329	1	0.04	1	0	0.04	0.00
12213754	9,463	927	9.80	79	848	0.83	8.96
12213794	7,515	501	6.67	336	228	4.47	3.03
12213826	4,518	698	15.45	356	414	7.88	9.16
12213892	7,293	375	5.14	248	133	3.40	1.82
12213965	1,646	194	11.79	60	145	3.65	8.81
12213971	10,532	2,210	20.98	1,872	457	17.77	4.34
12214172	9,006	1,178	13.08	921	336	10.23	3.73
12214281	5,457	678	12.42	373	339	6.84	6.21

455 vector machine (SVM) classifier score for the face model fit. This score indicates how strongly the image
 456 under the model resembles a face. Values vary from 0 to 1, and here numbers greater than 0.5 are indicative
 457 of a good model fit. In our `edat_L2` object we filter out convergence less than 0.5 and face confidence greater
 458 than 0.5 and save it to `edat_1_L2`

```
455 edat_1_L2 <- edat_L2 %>%
  dplyr::filter(convergence <= .5, face_conf >= .5) # remove poor convergnce and
  ↵   face confidence
```

459 **Combining eye and trial-level data.** Next, we will combine the eye-tracking data and behavioral
 460 data. In this case, we'll use `right_join` to add the behavioral data to the eye-tracking data. This ensures that
 461 all rows from the eye-tracking data are preserved, even if there isn't a matching entry in the behavioral data
 462 (missing values will be filled with NA). The resulting object is called `dat_L2`. We use the `distinct()`
 463 function afterward to remove any duplicate rows that may arise during the join

```
459 dat_L2 <- right_join(edat_1_L2,remove_missing, by = c("subject","trial"))

460 dat_L2 <- dat_L2 %>%
  ↵   distinct() # make sure to remove duplicate rows
```

464 Areas of Interest

465 Zone coordinates

466 In the lab, we can control every aspect of the experiment. Online we cant do this. Participants are
 467 going to be completing the experiment under a variety of conditions. This includes using different computers,
 468 with very different screen dimensions. To control for this, Gorilla outputs standardized zone coordinates
 469 (labeled as `x_pred_normalised` and `y_pred_normalised` in the eye-tracking file) . As discussed in the
 470 Gorilla documentation, the Gorilla lays everything out in a 4:3 frame and makes that frame as big as possible.
 471 The normalized coordinates are then expressed relative to this frame; for example, the coordinate 0.5, 0.5 will
 472 always be the center of the screen, regardless of the size of the participant's screen. We used the normalized
 473 coordinates in our analysis (in general, you should always use normalized coordinates). However, there are
 474 a few different ways to specify the four coordinates of the screen, which I think are worth highlighting here.

475 **Quadrant approach.** One way is to make the AOIs as big as possible, dividing the screen into four
 476 quadrants. This approach has been used in several studies (e.g., (Bramlett & Wiener, 2024; Prystauka et
 477 al., 2024)).@tbl-quadcor lists coordinates for the quadrant approach and Figure 5 shows how each quadrant
 478 looks in standardized space.

479 [1] "/home/runner/work/L2_VWP_Webcam/L2_VWP_Webcam/_manuscript/Figures/aoi-quad.png"

Table 4

Quadrant coordinates in standardized space

loc	x_normalized	y_normalized	width_normalized	height_normalized	xmin	ymin	xmax	ymax
TL	0.0	0.5	0.5	0.5	0.0	0.5	0.5	1.0
TR	0.5	0.5	0.5	0.5	0.5	0.5	1.0	1.0
BL	0.0	0.0	0.5	0.5	0.0	0.0	0.5	0.5
BR	0.5	0.0	0.5	0.5	0.5	0.0	1.0	0.5

480 We plot all the fixations in each of the quadrants highlighted in different colors (Figure 5), removing
 481 points outside the standardized screen space.

482 We plot all the fixations in each of the quadrants highlighted in different colors (Figure 5), removing
 483 points outside the standardized screen space. As a note, we have decided to use an outer edge approach
 484 here (eliminating eye fixations that extend beyond the screen coordinates). Bramlett and Wiener (2024) have
 485 suggested an inner-edge approach and we may add this functionality once more testing is done. For now, we
 486 believe that the outer edge approach leads to the least amount of bias in the eye-tracking pipeline.

487 **Matching conditions with screen locations.** The goal of the provided code is to assign condition
 488 codes (e.g., Target, Unrelated, Unrelated2, and Cohort) to each image in the dataset based on the screen
 489 location where the image is displayed (e.g., TL, TR, BL, BR).

490 For each trial, the images are dynamically placed at different screen locations, and the code maps
 491 each image to its corresponding condition based on these locations.

```
# Assuming your data is in a data frame called dat_L2
dat_L2 <- dat_L2 %>%
  mutate(
    Target = case_when(
      typetl == "target" ~ TL,
      typetr == "target" ~ TR,
      typebl == "target" ~ BL,
      typebr == "target" ~ BR,
      TRUE ~ NA_character_ # Default to NA if no match
    ),
    Unrelated = case_when(
      typetl == "unrelated1" ~ TL,
      typetr == "unrelated1" ~ TR,
      typebl == "unrelated1" ~ BL,
      typebr == "unrelated1" ~ BR,
      TRUE ~ NA_character_
    ),
    Unrelated2 = case_when(
```

Figure 5

AOI coordinates in standardized space using the quadrant approach

Quadrants with Width Annotations

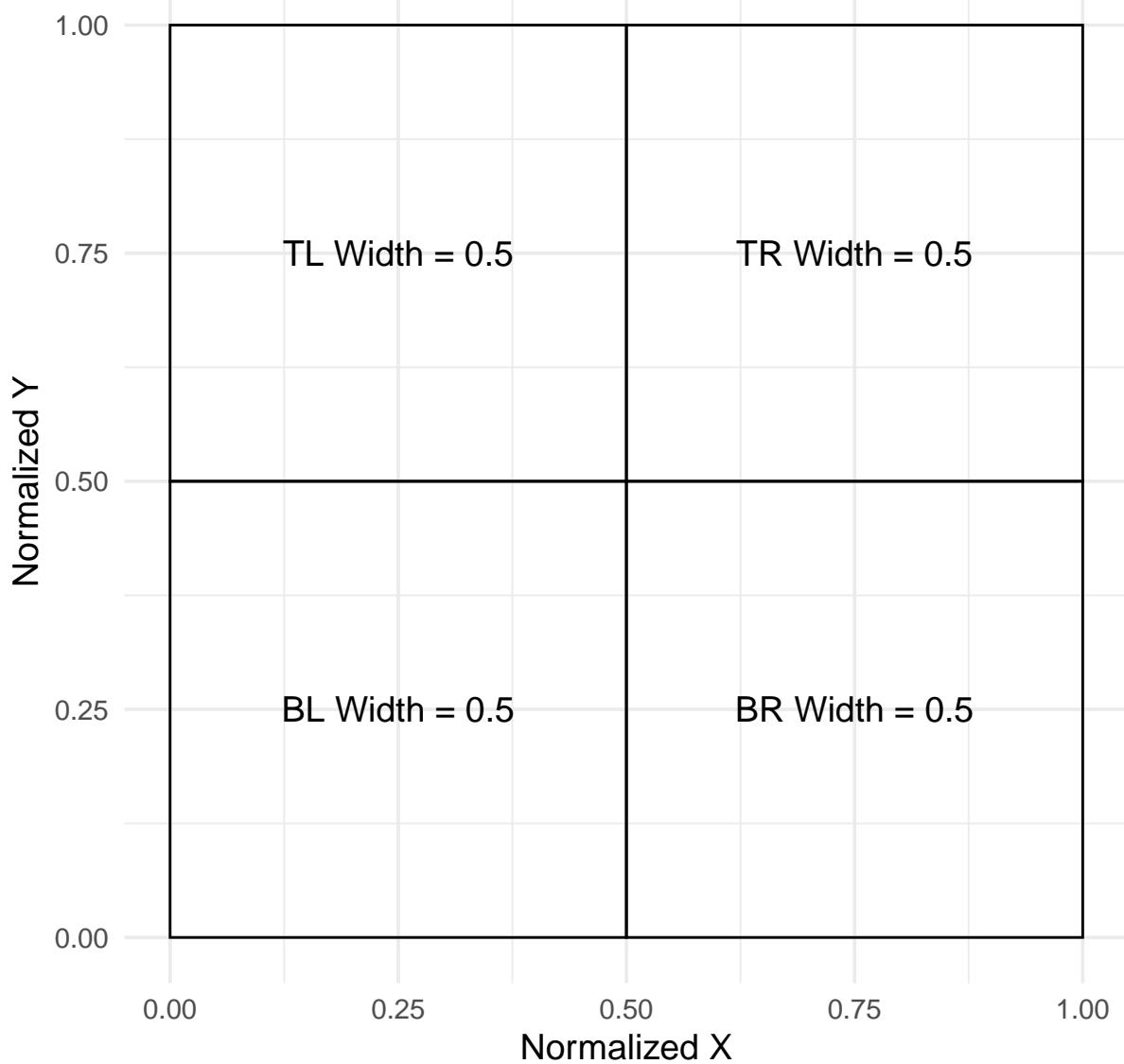
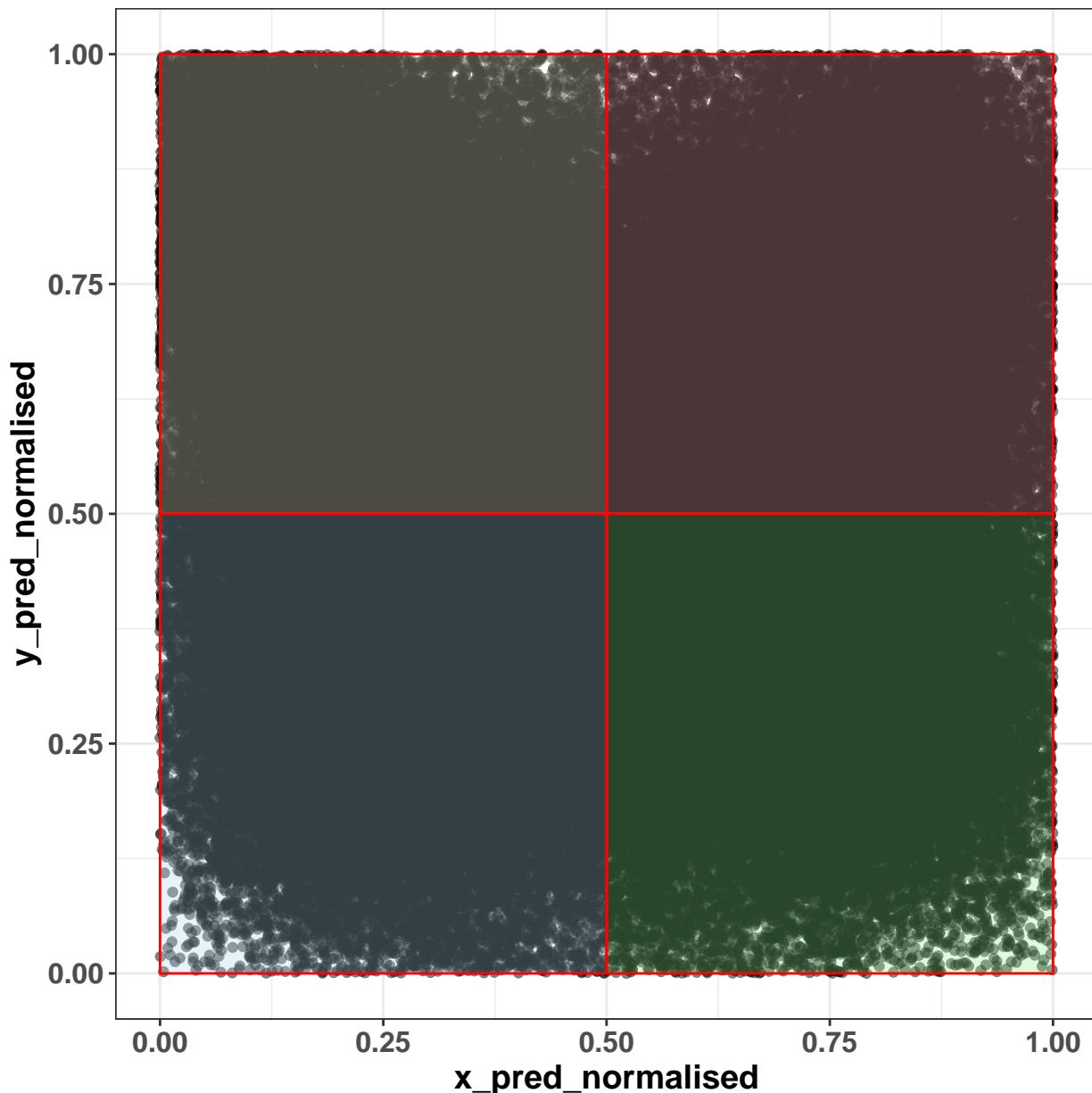


Figure 6

All looks in each of the screen quadrants



```
    typetl == "unrelated2" ~ TL,
    typetr == "unrelated2" ~ TR,
    typebl == "unrelated2" ~ BL,
    typebr == "unrelated2" ~ BR,
    TRUE ~ NA_character_
),
Cohort = case_when(
    typetl == "cohort" ~ TL,
    typetr == "cohort" ~ TR,
    typebl == "cohort" ~ BL,
    typebr == "cohort" ~ BR,
    TRUE ~ NA_character_
)
```

In addition to tracking the condition of each image during randomized trials, a custom function, `find_location()`, determines the specific screen location of each image by comparing it against the list of possible locations. This function ensures that the appropriate location is identified or returns NA if no match exists. Specifically, `find_location()` first checks if the image is NA (missing). If the image is NA, the function returns NA, meaning that there's no location to find for this image. If the image is not NA, the function creates a vector called `loc_names` that lists the names of the possible locations. It then attempts to match the given image with the locations. If a match is found, it returns the name of the location (e.g., TL, TR, BL, or BR) of the image.

```
# Apply the function to each of the targ, cohort, rhyme, and unrelated columns
dat_colnames_L2 <- dat_L2 %>%
  rowwise() %>%
  mutate(
    targ_loc = find_location(c(TL, TR, BL, BR), Target),
    cohort_loc = find_location(c(TL, TR, BL, BR), Cohort),
    unrelated_loc = find_location(c(TL, TR, BL, BR), Unrelated),
    unrealted2_loc= find_location(c(TL, TR, BL, BR), Unrelated2),
  ) %>%
  ungroup()
```

Once we do this we can use `assign_aoi()` to loop through our object called `dat_colnames_L2` and assign locations (i.e., TR, TL, BL, BR) to where participants looked at on the screen. This requires the x and y coordinates and the location of our aois `aoi_loc`. Here we are using the quadrant approach. This function will label non-looks and off screen coordinates with NA. To make it easier to read we change the

504 numerals assigned by the function to actual screen locations (e.g., TL, TR, BL, BR).

```
assign_L2 <- webgazeR::assign_aoi(dat_colnames_L2,X="x_pred_normalised",
→ Y="y_pred_normalised",aoi_loc = aoi_loc)

AOI_L2 <- assign_L2 %>%
  mutate(loc1 = case_when(
    AOI==1 ~ "TL",
    AOI==2 ~ "TR",
    AOI==3 ~ "BL",
    AOI==4 ~ "BR"
  ))

```

505 In AOI_L2 we label looks to Targets, Unrelated, and Cohort items with 1 (looked) and 0 (no look).

```
AOI_L2$target <- ifelse(AOI_L2$loc1==AOI_L2$targ_loc, 1, 0) # if in coordinates
→ 1, if not 0.

AOI_L2$unrelated <- ifelse(AOI_L2$loc1 == AOI_L2$unrelated_loc, 1, 0) # if in
→ coordinates 1, if not 0.

AOI_L2$unrelated2 <- ifelse(AOI_L2$loc1 == AOI_L2$unrealted2_loc, 1, 0) # if in
→ coordinates 1, if not 0.

AOI_L2$cohort <- ifelse(AOI_L2$loc1 == AOI_L2$cohort_loc, 1, 0) # if in
→ coordinates 1, if not 0.
```

506 The locations of looks need to be “gathered” or pivoted into long format—that is, converted from
 507 separate columns into a single column. This transformation makes the data easier to visualize and analyze.
 508 We use the `pivot_longer()` function from the `tidyverse` to combine the columns (Target, Unrelated,
 509 Unrelated2, and Cohort) into a single column called `condition1`. Additionally, we create another column
 510 called `Looks`, which contains the values from the original columns (e.g., 0 or 1 for whether the area was
 511 looked at).

```

dat_long_aoi_me_L2 <- AOI_L2 %>%
  select(subject, trial, condition, target, cohort, unrelated, unrelated2, time,
  ~ x_pred_normalised, y_pred_normalised, RT_audio) %>%
  pivot_longer(
    cols = c(target, unrelated, unrelated2, cohort),
    names_to = "condition1",
    values_to = "Looks"
)

```

512 We further clean up the object by first cleaning up the condition codes. They have a numeral ap-
 513 pended to them and that should be removed. We then adjust the timing in the gaze_sub_L2_comp object by
 514 aligning time to the actual audio onset. To achieve this, we subtract RT_audio from time for each trial. In
 515 addition, we subtract 300 ms from this to account for the 100 ms of silence at the beginning of each audio
 516 clip and 200 ms to account for the oculomotor delay when planning an eye movement Viviani (1990). Addi-
 517 tionally, we set our interest period between 0 ms (audio onset) and 2000 ms. This was chosen based on the
 518 time course figures in Sarrett et al. (2022) . It is important that you choose your interest area carefully and
 519 preferably you preregister it. The interest period you choose can have drastic We also filter out gaze coordi-
 520 nates that fall outside the standardized window, ensuring only valid data points are retained. The resulting
 521 object gaze_sub_long_L2 provides the corrected time column spanning from -200 ms to 2000 ms relative
 522 to stimulus onset with looks outside the screen removed.

```

# repalce the numbers appended to conditions that somehow got added
dat_long_aoi_me_comp <- dat_long_aoi_me_L2 %>%
  mutate(condition = str_replace(condition, "TCUU-SPENG\\d*", "TCUU-SPENG")) %>%
  mutate(condition = str_replace(condition, "TCUU-SPSP\\d*", "TCUU-SPSP"))%>%
  na.omit()

```

```

# dat_long_aoi_me_comp has condition corrected

gaze_sub_L2_long <-dat_long_aoi_me_comp%>%
  group_by(subject, trial, condition) %>%
  mutate(time = (time-RT_audio)-300) %>% # subtract audio rt onset and account
  ~ for occ motor planning and silence in audio
  filter(time >= -200, time < 2000) %>%
  dplyr::filter(x_pred_normalised > 0,
                x_pred_normalised < 1,
                y_pred_normalised > 0,
                y_pred_normalised < 1)

```

Table 5

Aggregated proportion looks for each condition in each 100 ms time bin

condition	condition1	time_bin	Fix
TCUU-ENGSP	cohort	-200	0.2615870787
TCUU-ENGSP	cohort	-100	0.2588888889
TCUU-ENGSP	cohort	0	0.2508226691
TCUU-ENGSP	cohort	100	0.2574108818
TCUU-ENGSP	cohort	200	0.2298850575
TCUU-ENGSP	cohort	300	0.2244212099

523 **Samples to bins**

524 **Downsampling**

525 Downampling into smaller time bins is a common practice in gaze data analysis, as it helps create a
 526 more manageable dataset and reduces noise. When using research grade eye-trackers, downampling is often
 527 not needed. However, with consumer-based webcam eye-tracking it is recommended you downsample your
 528 data so participants have consistent bin sizes (e.g., ([Slim & Hartsuiker, 2023](#))). In `webgazeR` we included the
 529 `downsample_gaze()` function to assist with this process. We apply this function to the `gaze_sub_L2_long`
 530 object, and set the `bin.length` argument to 100, which groups the data into 100-millisecond intervals. This
 531 adjustment means that each bin now represents a 100 ms passage of time. We specify time as the variable
 532 to base these bins on, allowing us to focus on broader patterns over time rather than individual millisecond
 533 fluctuations. There is no agreed upon downampling value, but with webcam data larger bins are preferred
 534 ([Slim & Hartsuiker, 2023](#)).

535 In addition, the `downsample_gaze()` allows you to aggregate across other variables, such as condition,
 536 condition1, and use the newly created `timebins` variable, which represents the time intervals over which
 537 we aggregate data. The resulting downsampled dataset, output as Table 5, provides a simplified and more
 538 concise view of gaze patterns, making it easier to analyze and interpret broader trends.

```
gaze_sub_L2 <- webgazeR::downsample_gaze(gaze_sub_L2_long, bin.length=100,
                                         timevar="time", aggvars=c("condition", "condition1", "time_bin"))
```

539 [1] "/home/runner/work/L2_VWP_Webcam/L2_VWP_Webcam/_manuscript/Figures/downsample_table.png"

540 To simplify the analysis, we combine the two unrelated conditions and average them (this is for the
 541 proportional plots).

```
# Average Fix for unrelated and unrelated2, then combine with the rest
gaze_sub_L2_avg <- gaze_sub_L2 %>%
  group_by(condition, time_bin) %>%
  summarise(
    Fix = mean(Fix[condition1 %in% c("unrelated", "unrelated2")], na.rm =
      TRUE),
    condition1 = "unrelated", # Assign the combined label
    .groups = "drop"
  ) %>%
  # Combine with rows that do not include unrelated or unrelated2
  bind_rows(gaze_sub_L2 %>% filter(!condition1 %in% c("unrelated",
  "unrelated2")))
```

542 The above will not include the subject variable. If you want to keep participant-level data we need
 543 to add `subject` to the `aggvars` argument.

```
# add subject-level data
gaze_sub_L2_id <- webgazeR::downsample_gaze(gaze_sub_L2_long, bin.length=100,
  timevar="time", aggvars=c("subject", "condition", "condition1", "time_bin"))
```

544 Aggregation is an optional step. If you do not plan to analyze proportion data, and instead what time
 545 binned data with binary outcomes preserved please set the `aggvars` argument to “none.” This will return a
 546 time binned column, but will not aggregate over other variables.

```
# get back trial level data with no aggregation
gaze_sub_id <- downsample_gaze(gaze_sub_L2_long, bin.length=100, timevar="time",
  aggvars="none")
```

547 We need to make sure we only have one unrelated value.

```
gaze_sub_id <- gaze_sub_id %>%
  mutate(condition1 = ifelse(condition1=="unrelated2", "unrelated", condition1))
```

548 Visualizing time course data

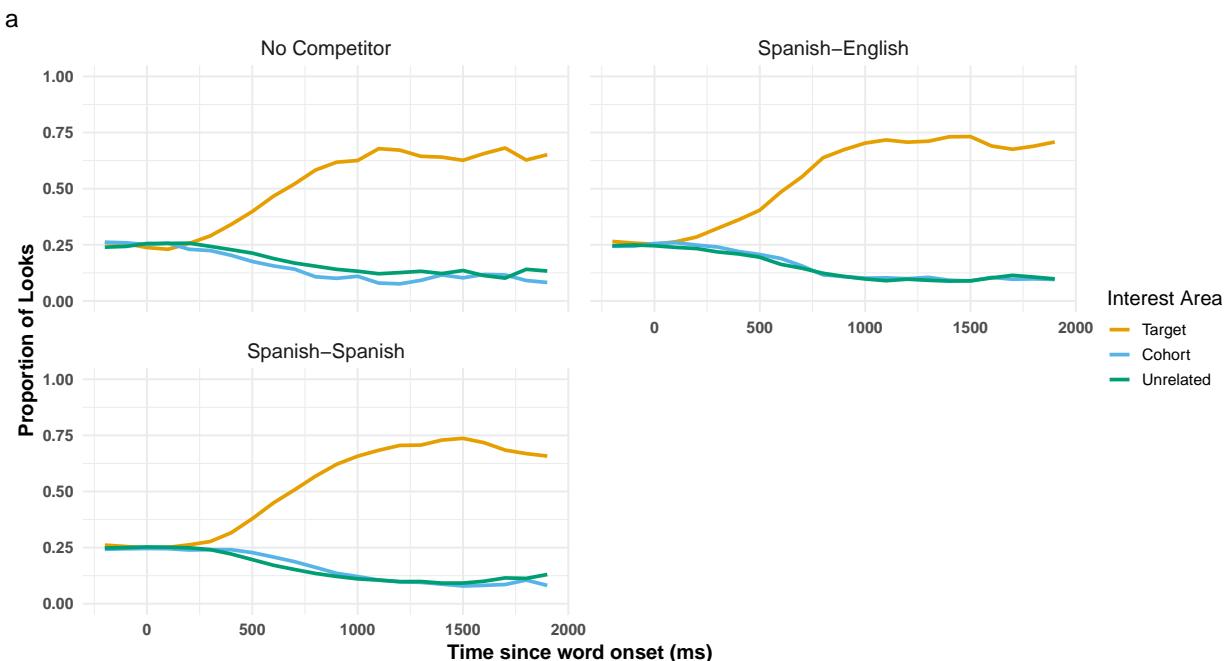
549 To simplify plotting your time-course data, we have created the `plot_IA_proportions()` func-
 550 tion. This function takes several arguments. The `ia_column` argument specifies the column containing your
 551 Interest Area (IA) labels. The `time_column` argument requires the name of your time bin column, and the

552 proportion_column argument specifies the column containing fixation or look proportions. Additional
 553 arguments allow you to specify custom names for each IA in the ia_mapping argument, enabling you to
 554 label them as desired. In order to use this function, you must use the downsample_gaze() function.

555 Below we have plotted the time course data in Figure 7 for each condition. By default the graphs
 556 are using a color-blind friendly palette from the ggokabeito package (Barrett, 2021). Because these are
 557 ggplot objects, you can further modify if you choose.

Figure 7

Comparison of L2 competition effect in the Spanish-Spanish condition, the Spanish-English condition, and the no competition condition.



558 **Gorilla provided coordinates**

559 Thus far, we have used the coordinates representing the four quadrants of the screen. However,
 560 Gorilla provides their own quadrants representing image location on the screen. To the authors' knowledge,
 561 these quadrants have not been looked at in any studies reporting eye-tracking results. Let's examine how
 562 reasonable our results are with the Gorilla provided coordinates.

563 We will use the function extract_aois() to get the standardized coordinates for each quadrant on
 564 screen. You can use the zone_names argument to get the zones you want to use. In our example, we want the
 565 TL, BR, BL, TR coordinates. We input the object from above vwp_paths_filtered_L2 that contains all our
 566 eye-tracking files and extract the coordinates we want. These are labeled in Table 6. In Figure 8 we can see
 567 that the AOIs are a bit smaller than when using the quadrant approach. We can take these coordinates
 568 and use them in our analysis.

Table 6

Gorilla provided gaze coordinates

loc	x_normalized	y_normalized	width_normalized	height_normalized	xmin	ymin	xmax	ymax
BL	0.03	0.04	0.26	0.25	0.03	0.04	0.29	0.29
TL	0.02	0.74	0.26	0.25	0.02	0.74	0.28	0.99
TR	0.73	0.75	0.24	0.24	0.73	0.75	0.97	0.99
BR	0.73	0.06	0.23	0.25	0.73	0.06	0.96	0.31

569 We are not going to highlight the steps here as they are the same as above. we are just replacing the
 570 coordinates.

```
# apply the extract_aois fucntion
aois_L2 <- extract_aois(vwp_paths_filtered_L2, zone_names = c("TL", "BR", "TR",
  ↵ "BL"))
```

```
assign_L2_gor <- webgazeR::assign_aoi(dat_colnames_L2,X="x_pred_normalised",
  ↵ Y="y_pred_normalised",aoi_loc = aois_L2)
```

571 Visualizing time course data with Gorilla coordinates

572 The Gorilla provided coordinates show a similar pattern to the quadrant approach. However, the
 573 time course looks a bit nosier given the smaller AOIs.

574 Modeling data

575 When analyzing VWP data there are many analytic approaches to choose from (e.g., growth curve
 576 analysis (GCA), cluster permutation tests (CPT), generalized additive mixed models (GAMMS), logistic
 577 multilevel models, divergent point analysis, etc.), and a lot has already been written describing these methods
 578 and applying them to visual world fixation data from the lab (see ([Ito & Knoeferle, 2023](#); [McMurray &](#)
 579 [Kutlu, n.d.](#); [Stone et al., 2021](#)) and online ([Bramlett & Wiener, 2024](#)). This tutorial's goal, however, is to
 580 not evaluate different analytic approaches and tell readers what they should use. All methods have their
 581 strengths and weaknesses (see [Ito & Knoeferle, 2023](#)). Nevertheless, statistical modeling should be guided
 582 by the questions researchers have and thus serious thought needs to be given to the proper analysis. In the
 583 VWP, there are two general questions one might be interested in: (1) Are there any overall difference in
 584 fixations between conditions and (2) Are there any time course differences in fixations between conditions.

Figure 8

Gorilla provided standardized coordinates for the four quadrants on the screen

Quadrants with Width Annotations

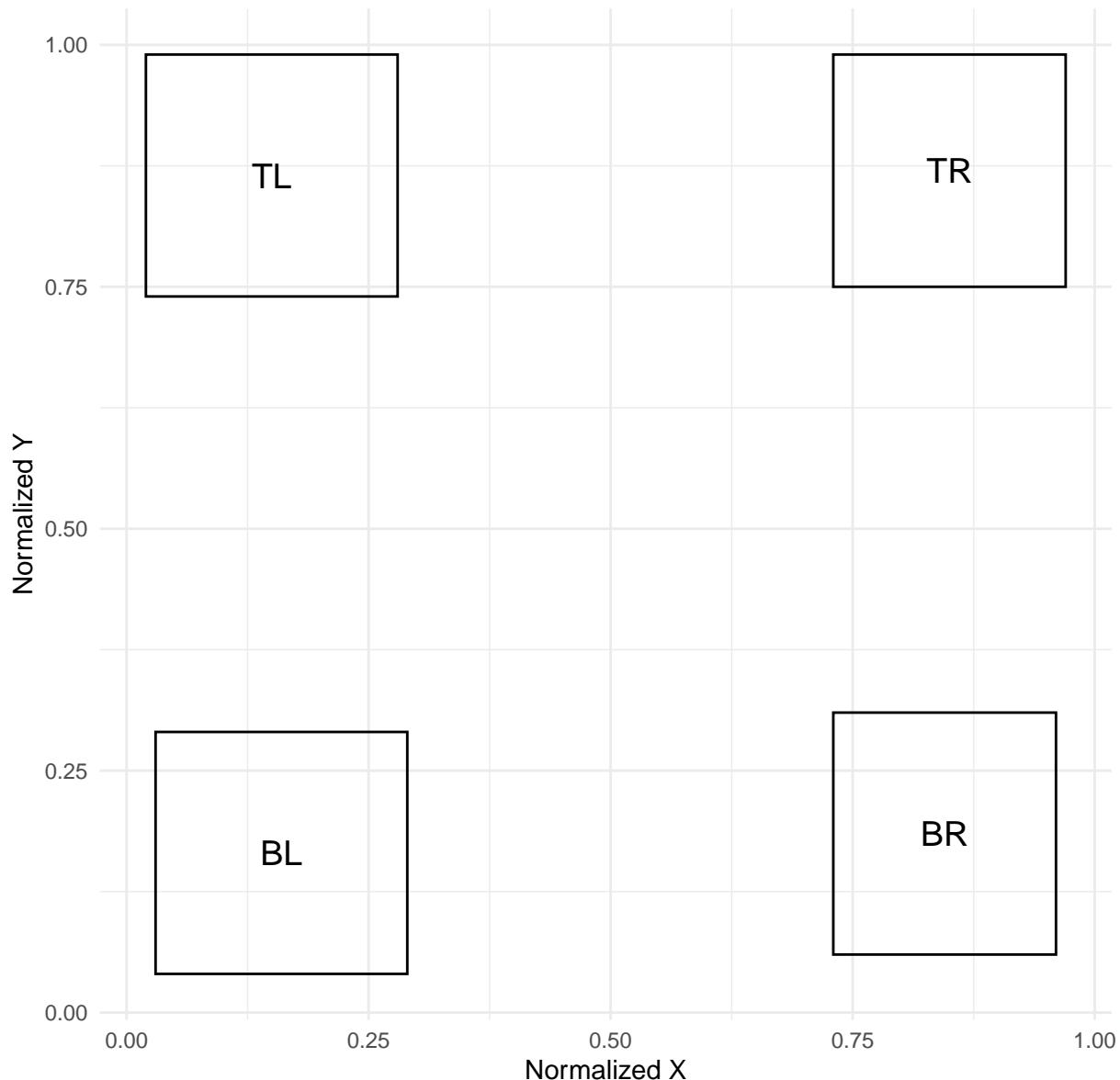
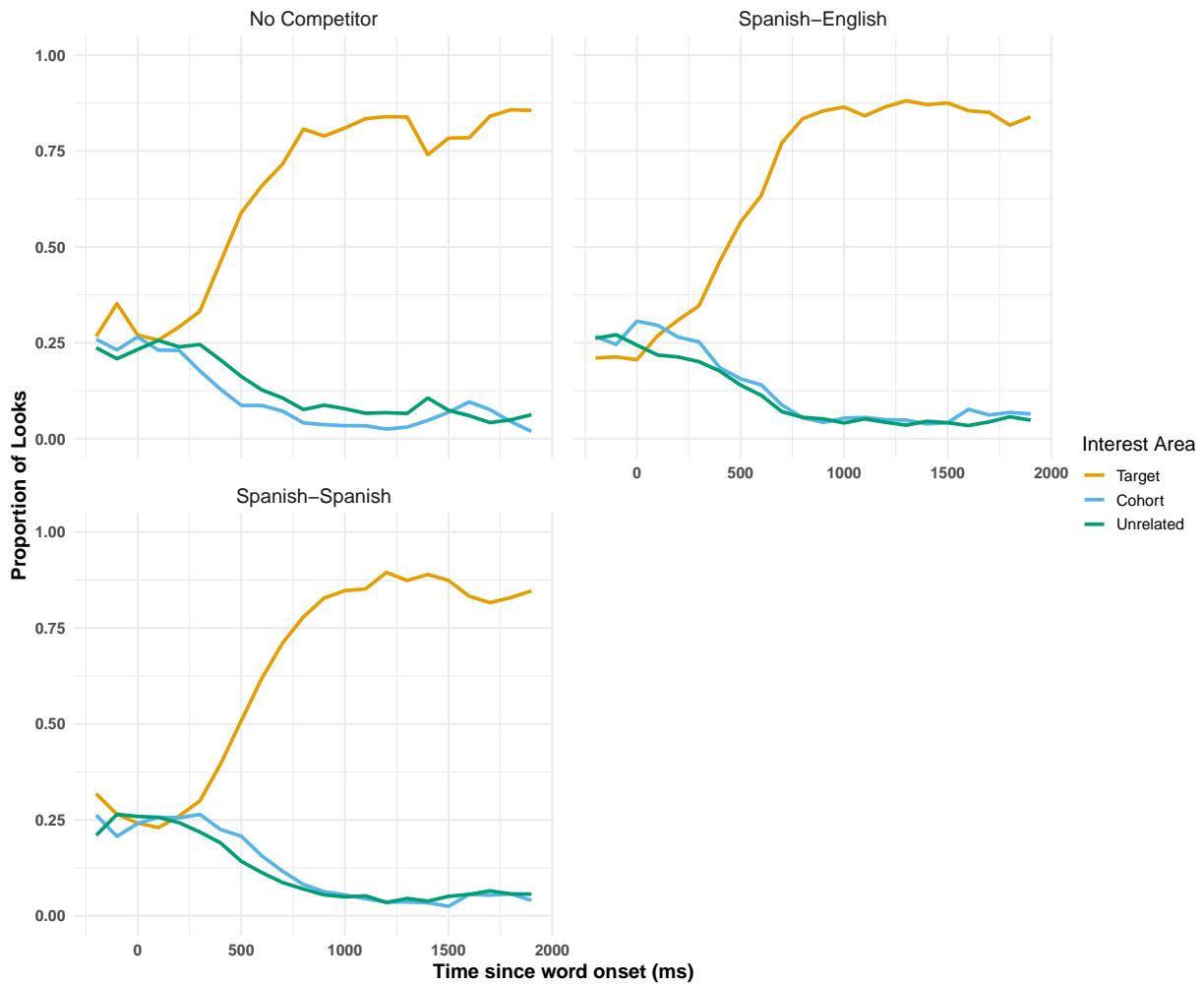


Figure 9

Comparison of competition effects with Gorilla standardized coordinates

a



585 With our data, one question we might want to answer is if there are any fixation differences between
 586 the cohort and unrelated conditions across the time course. One statistical approach we chose to highlight
 587 to answer this question is a cluster permutation analysis (CPA). The CPA is suitable for testing differences
 588 between two conditions or groups over an interest period while controlling for multiple comparisons and
 589 autocorrelation.

590 **CPT**

591 CPA is a technique that has become increasingly popular, particularly in the field of cognitive neu-
 592 ropsychology, for analyzing MEG and EEG data (Maris & Oostenveld, 2007). While its adoption in VWP
 593 studies has been relatively slow, it is now beginning to appear more frequently (Huang & Snedeker, 2020;
 594 Ito & Knoeferle, 2023). Notably, its use is growing in online eye-tracking studies (see (Slim et al., 2024;

595 Slim & Hartsuiker, 2023; Vos et al., 2022)).

596 Before I show you how to apply this method to the current dataset, I want to briefly explain what
597 CPT is. The CPT is a data-driven approach that increases statistical power while controlling for Type I errors
598 across multiple comparisons—exactly what we need when analyzing fixations across the time course.

599 The clustering procedure involves three main steps:

600 1. Cluster Formation: With our data, a multilevel logistic models is conducted for every data point
601 (condition by time). Adjacent data points that surpass the mass univariate significance threshold (e.g., $p < .05$)
602 are combined into clusters. The cluster-level statistic, typically the sum of the t-values (or F-values) within
603 the cluster, is computed. By clustering adjacent significant data points, this step accounts for autocorrelation
604 by considering temporal dependencies rather than treating each data point as independent.

605 2. Null Distribution Creation: A surrogate null distribution is generated by randomly permuting the
606 conditions within subjects. This randomization is repeated n times (here 1000), and the cluster-level statistic
607 is computed for each permutation. This step addresses multiple comparisons by constructing a distribution
608 of cluster statistics under the null hypothesis, ensuring that family-wise error rates (FWER) are controlled.

609 3. Significance Testing: The cluster-level statistic from the observed (real) comparison is compared
610 to the null distribution. Clusters with statistics falling in the highest or lowest 2.5% of the null distribution
611 are considered significant (e.g., $p < 0.05$).

612 To preform CPT, we will load in the `permutes` (Voeten, 2023), `permuco` (Frossard & Renaud,
613 2021), and `foreach` (& Weston, 2022) packages in R so we can use the `cluster.glmer()` function to run
614 a cluster permutation model with our `gaze_sub_id` dataset where each row in Looks denotes whether the
615 AOI was fixated, with values of zero (not fixated) or one (fixated).

616 Below you find sample code to perform multilevel CPA in R (please see the Github repository for
617 further code).

```
library(permutes) # cpa
library(permuco) # cpa
library(foreach) # for par processing
library(doParallel)

# Step 1: Set up parallel backend
num_cores <- detectCores() - 1 # Use all available cores minus one for system
  ↳ stability
cl <- makeCluster(num_cores)
registerDoParallel(cl)

# Step 2: Define the total number of permutations
total_perms <- 1000
```

Table 7

Clustermass statistics for the Spanish-Spanish condition

cluster	cluster_mass	p.cluster_mass	bin_start	bin_end	t	si
1.00	210.03	0.00	7.00	13.00	5.14	

```
# Step 3: Split the permutations across available cores
perms_per_core <- total_perms / num_cores

# Step 4: Use foreach to run the function in parallel
cpa.lme <- foreach(i = 1:num_cores, .combine = 'rbind', .packages = 'permutes')
  %dopar% {
    permutes::clusterperm.glmer(Looks~ condition1_code + (1|subject) + (1|trial),
    data=gaze_sub_L2_cp1, series.var=~time_bin, nperm = perms_per_core)
  }

# Step 5: Stop the parallel backend
stopCluster(cl)
```

618 For the Spanish-Spanish condition, we observed one significant cluster from 500-1000 ms (see Ta-
 619 ble 7). Figure 10 highlights the significant cluster (shaded) for both the Spanish-Spanish and Spanish-English
 620 conditions. We see there is one significant cluster in both conditions.

621

Discussion

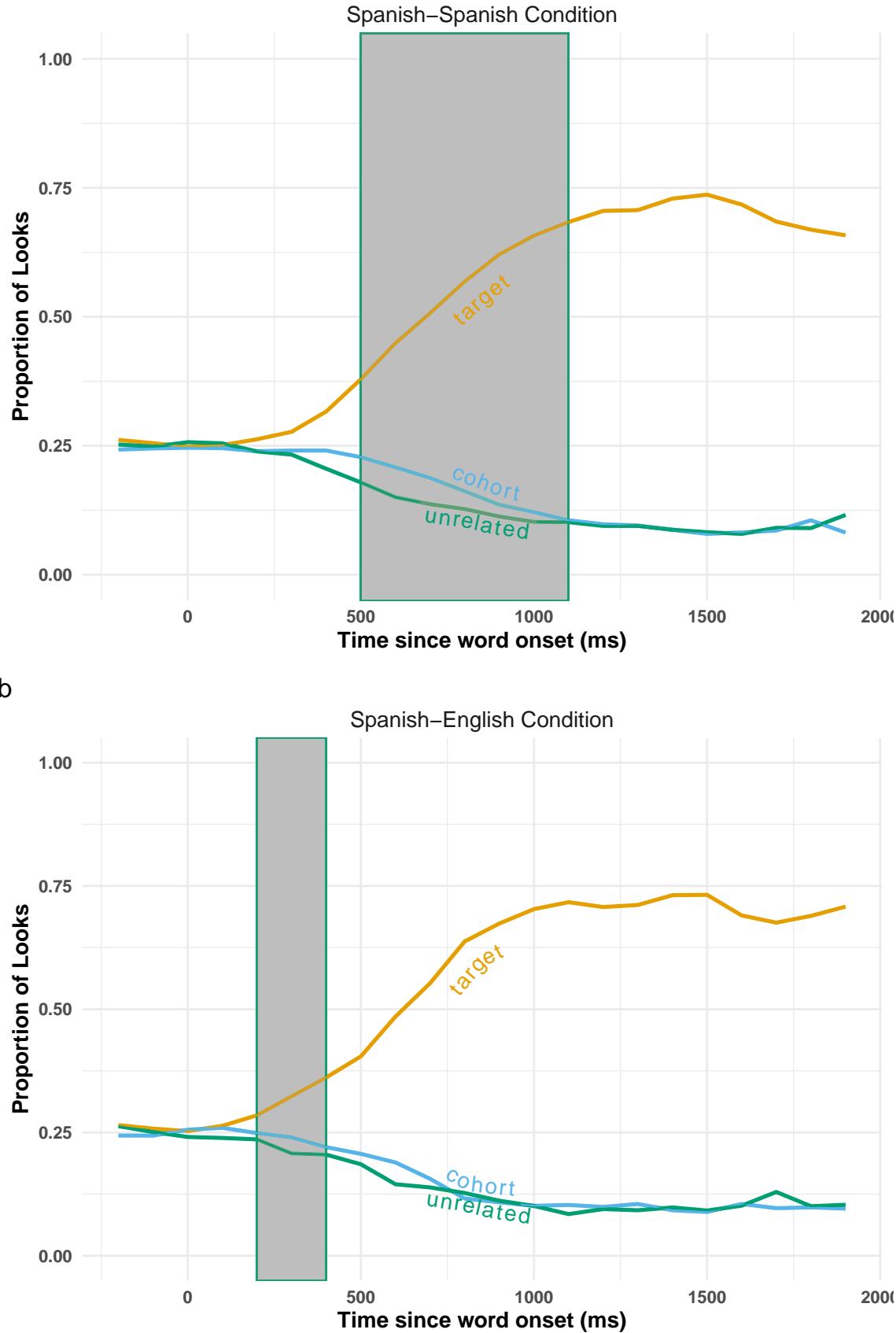
622 Webcam eye-tracking is a relatively nascent technology, and as such, there is limited guidance avail-
 623 able for researchers. To ameliorate this, we created a tutorial to assist new users of visual world webcam
 624 eye-tracking, using some of the best practices available [e.g., Bramlett and Wiener (2024)]. To further facil-
 625 itate this process, we created the `webgazeR` package, which contains several helper functions designed to
 626 streamline data preprocessing, analysis, and visualization.

627 In this tutorial, we covered the basic steps of running a visual world webcam-based eye-tracking
 628 experiment. We highlighted these steps by using data from a cross-linguistic VWP looking at competitive
 629 processes in L2 speakers of Spanish. Specifically, we attempted to replicate the experiment by Sarrett et al.
 630 (2022) where they observed within- and between L2/L1 competition using carefully crafted materials.

631 While the main purpose of this tutorial was to highlight the steps needed to analyze webcam eye-
 632 tracking data, replicating Sarrett et al. (2022) allowed us to not only assess whether within and between L2/L1

Figure 10

Average looks in the cross-linguistic VWP task over time for the Spanish-Spanish condition (a) and the Spanish-English condition (b). The shaded rectangles indicate when cohort looks were greater than chance based on the CPA.



633 competition can be found in a spoken word recognition VWP experiment online (one of the first studies to
634 do so), but also provide insight in how to run VWP studies online and the issues associated with it.

635 Our conceptual replication findings are highly encouraging, demonstrating competition effects both
636 within (Spanish-Spanish condition) and across languages (Spanish-English condition), closely paralleling the
637 results reported by Sarrett et al. (2022). However, several important methodological and sample differences
638 warrant discussion.

639 A key methodological difference between our study and Sarrett et al. (2022) lies in the approach used
640 to analyze the time course of competition. While Sarrett et al. (2022) employed a non-linear curve-fitting
641 method (McMurray et al., 2010), we used CPA. This methodological distinction limits our ability to address
642 similar temporal questions. Nonetheless, the overall temporal patterns are strikingly similar. For instance,
643 our CPA revealed a significant cluster starting at 500 ms, whereas Sarrett et al. (2022) identified competition
644 effects emerging at approximately 400 ms. This indicates a delay of about 100 ms in competition onset
645 between lab-based and online eye-tracking data. This delay, while notable, reflects a significant improvement
646 over previous webcam-based studies (Slim et al., 2024; e.g., Slim & Hartsuiker, 2023). It is important
647 to emphasize, however, that CPA clusters cannot reliably be used to make temporal inferences about the
648 onset/offset of effects (Fields & Kuperberg, 2019; Ito & Knoeferle, 2023).

649 Our study also employed a truncated stimulus set, with only 250 trials compared to the 450 trials
650 in Sarrett et al. (2022). Despite this reduction, the number of trials in our study remains larger than most
651 existing webcam-based studies. Even with the smaller set, we observed a similar pattern of competition
652 effects in both the Spanish-Spanish and Spanish-English conditions, demonstrating the robustness of our
653 findings.

654 Another notable difference is the recruitment strategy and participant screening. Sarrett et al. (2022)
655 recruited participants from a Spanish college course and used the LexTALE-Spanish assessment (Izura et al.,
656 2014) to evaluate Spanish proficiency. In contrast, our data were collected via Prolific with limited filters,
657 which only allowed us to screen for native language and experience with another language. This constraint
658 limited our ability to refine participant selection further and likely contributed to differences in participant
659 profiles. While Sarrett et al. (2022) focused on adult L2 learners with known language proficiency levels,
660 our sample included a broader range of L2 speakers with limited checks on their language abilities. This
661 may help explain why we did not observe a cohort competition effect that persisted across the time course as
662 reported by Sarrett et al. (2022).

663 Overall, while the methodological and sample differences between the two studies are notable, the
664 similarities in the competition effects observed within and across languages reinforce the robustness of these
665 findings across different research settings. While we do not wish to downplay our findings, a more systematic
666 study is needed to ensure there generalizability.

667 Limitations

668 While the above suggests that webcam eye-tracking is a promising avenue for language research,
669 there are some issues that we ran into that need to be addressed. One issue is data loss due to poor calibration.
670 In our study, we had to throw out ~40% of our data due to poor calibration. Other studies have shown numbers
671 much higher [e.g., 73%; Slim and Hartsuiker (2023)] and lower [e.g., 20%; Prystauka et al. (2024)]. Given
672 this, it is still an open question as to what contributes to better vs. poor data quality in webcam eye-tracking. To
673 this end, we included an assessment after the VWP that included questions on the participants' experimental
674 set-ups and overall experiences with the eye-tracking experiment. All questions are included Table 8.

675 *Poor vs. good calibrators*

676 In our experimental design, participants were branched based on whether they successfully com-
677 pleted the experiment or failed calibration at any point. Table 2 highlights the comparisons between good
678 and poor calibrators. For the sake of brevity, we do not include responses to all questions. You can look
679 at all the responses at our repo. However, two key differences emerge that may provide insight into factors
680 influencing successful calibration.

681 One notable difference is the type of webcam used. Participants who failed calibration predomi-
682 nantly reported using built-in webcams, whereas those who successfully calibrated reported using a variety
683 of external webcams. This suggests that built-in webcams may not provide sufficient resolution for calibra-
684 tion in the experiment. Slim and Hartsuiker (2023) performed some correlations looking at calibration score
685 and webcam quality and noticed that high frame rate correlated with a calibration scores.

686 Another difference lies in the participants' environmental setup. Individuals who failed calibration
687 were more likely to be in environments with natural light. Since natural light is known to interfere with
688 eye-tracking, it may have contributed to their inability to calibrate successfully.

689 We did not notice any other differences between those that successful calibrated vs. those who did
690 not. For researchers wanting to use webcam eye-tracking, they should try to make sure participants are in
691 rooms without natural light, and use good web cameras. While we tried to emphasize this in our instructional
692 videos, more explicit instruction may be needed. An avenue for research research would be to compare lab
693 based webcam eye-tracking to online based webcam eye tracking to see if control of the environment can
694 produce better results.

695 It is important to note here that Gorilla uses WebGazer.js (Papoutsaki et al., 2016) to perform it's
696 eye tracking. It is unclear if poor calibration results from the noise introduced by participants' environ-
697 ments/equipments or if it is a function of the method itself, or both. We have listed some equipment and
698 environmental factors that may contribute to the poor performance; however it could be the algorithm itself
699 that is poor. There are other experimental platforms out there that use different eye-tracking ML algorithms
700 to perform webcam eye-tracking (e.g., labvanced; (Kaduk et al., 2024)). In labvanced, compared to Gorilla
701 they use head motion tracking that measures the distance of the participant in front the screen to ensure head
702 movement is restricted to an acceptable range. Together this might make for a better eye-tracking experience

Table 8*Eye-tracking questionnaire items*

Question
1. Do you have a history of vision problems (e.g., corrected vision, eye disease, or drooping eyelids)?
2. Are you on any medications currently that can impair your judgement?
If yes, please list below:
4. Does your room currently have natural light?
5. Are you using the built in camera?
If no, what brand of camera are you using?
6. Please estimate how far you think you were sitting from the camera during the experiment (an arm's length from your monitor is about 20 inches (51 cm).
7. Approximately how many times did you look at your phone during the experiment?
8. Approximately how many times did you get up during the experiment?
9. Was the environment you took the experiment in distraction free?
10. When you had to calibrate, were the instructions clear?
11. What additional information would you add to help make things easier to understand?
12. Are you wearing a mask?

Table 9*Responses to eye-tracking questions for participants who successfully calibrated vs. participants who had trouble calibratrin*

Question	Response	percentage_good	percentage_bad
1. Do you have a history of vision problems (e.g., corrected vision, eye disease, or drooping eyelids)?	No	65.714	64.286
1. Do you have a history of vision problems (e.g., corrected vision, eye disease, or drooping eyelids)?	Yes	34.286	35.714
2. Are you on any medications currently that can impair your judgement?	No	100.000	98.214
2. Are you on any medications currently that can impair your judgement?	Yes	0.000	1.786
4. Does your room currently have natural light?	No	40.000	26.786
4. Does your room currently have natural light?	Yes	60.000	73.214
5. Are you using the built in camera?	No	14.286	8.929
5. Are you using the built in camera?	Yes	85.714	91.071
9. Was the environment you took the experiment in distraction free?	No	11.429	3.571
9. Was the environment you took the experiment in distraction free?	Yes	88.571	96.429

703 with less data thrown out. This should be investigated further.

704 **Generalizability to other platforms**

705 We demonstrated how to analyze webcam eye-tracking data from a Gorilla experiment using We-
 706 bGazer.js. While we were unable to validate this pipeline on other experimental platforms using WebGazer.js,
 707 such as PCIbex (Zehr & Schwarz, 2018) or jsPsych (Leeuw, 2015), we believe that this basic pipeline will
 708 generalize to those platforms, as WebGazer.js underlies them all and provides consistent output. We encour-
 709 age researchers to test this pipeline in their own studies and report any issues on our GitHub repository. We
 710 are committed to continuing improvements to webgazeR, ensuring that users can effectively analyze webcam
 711 eye-tracking data with our package.

712 **Power**

713 While we successfully demonstrated competition effects similar to Garrett's study, we did not conduct
 714 an a priori power analysis. With webcam eye-tracking, it has been recommended running twice the number

715 of participants from the original sample, or powering the study to detect an effect size half as large as the
716 original ([Slim & Hartsuiker, 2023](#); also see [Simonsohn, 2015](#)) . We did attempt to increase our sample size
717 2x, but were unable to recruit enough participants through Prolific. However, our sample size is similar to
718 the lab based studies.

719 We strongly urge researchers to perform power analyses and justify their sample sizes ([Lakens, n.d.](#)).
720 While tools like G*Power ([Faul et al., 2007](#)) are available for this purpose, we recommend power simulations
721 using Monte Carlo or resampling methods on pilot or sample data ([Prystauka et al., 2024](#); see [Slim & Hart-
722 suiker, 2023](#)). Several excellent R packages, such as `mixedpower` ([Kumle et al., 2021](#)) and SIMR ([Green &
723 MacLeod, 2016](#)) make such simulations straightforward and accessible.

724 **Recommendations**

725 Based on our findings and limitations, we propose the following recommendations for researchers
726 conducting visual world webcam eye-tracking experiments.

727 **1. Prioritize external webcams**

728 Our questionnaire suggested that participants using external webcams had significantly better calibra-
729 tion success compared to those relying on built-in webcams. External webcams generally provide
730 higher resolution and frame rates, which are critical for accurate eye-tracking. Researchers should
731 encourage participants to use external webcams whenever possible.

732 **2. Optimize environmental conditions**

733 Natural light was a common factor in environments where calibration failed. Researchers should advise
734 participants to conduct experiments in rooms with controlled lighting—ideally, artificial lighting with
735 minimal glare or shadows—to reduce interference with eye-tracking accuracy.

736 **3. Conduct a priori power analysis**

737 To ensure adequate statistical power, researchers should conduct a priori power analyses either via GUI
738 like GPower or perform Monte Carlo simulations/resampling on pilot data. This step is particularly
739 important for online studies, where sample variability can be higher than in controlled lab environ-
740 ments.

741 **4. Collect detailed post-experiment feedback**

742 Including post-experiment questionnaires about participants' setups (e.g., webcam type, browser, light-
743 ing conditions) can provide valuable insights into calibration success factors. These data can help refine
744 participant instructions and inclusion criteria for future studies.

745 By adhering to these recommendations, researchers can enhance the reliability and generalizability
746 of their webcam eye-tracking studies, ensuring the potential of this technology is fully realized.

747 **Conclusions**

748 This work highlighted the steps required to process webcam eye-tracking data collected via Gorilla,
749 showcasing the potential of webcam-based eye-tracking for robust psycholinguistic experimentation. With a
750 standardized pipeline for processing eye-tracking data we hope we have given researchers a clear path forward
751 when collecting and analyzing visual word webcam eye-tracking data.

752 Moreover, our findings demonstrate the feasibility of conducting high-quality online experiments,
753 paving the way for future research to address more nuanced questions about L2 processing and language
754 comprehension more broadly. Additionally, further refinement of webcam eye-tracking methodologies could
755 enhance data precision and extend their applicability to more complex experimental designs. This is an
756 exciting time for eye-tracking research, with its boundaries continuously expanding. We eagerly anticipate
757 the advancements and possibilities that the future of webcam eye-tracking will bring.

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