

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

³ Jason Geller¹, Yanina Prystauka², Sarah E. Colby³, and Julia R. Drouin⁴

⁴ ¹Department of Psychology and Neuroscience, Boston College

⁵ ²Department of Linguistic, Literary and Aesthetic Studies, University of Bergen

⁶ ³Department of Linguistics, University of Ottawa

⁷ ⁴Division of Speech and Hearing Sciences, University of North Carolina at Chapel Hill

⁸ Abstract

Eye-tracking has become a valuable tool for studying cognitive processes in second language acquisition and bilingualism (Godfroid et al., 2024). While research-grade infrared eye-trackers are commonly used, several factors limit their widespread adoption. Recently, consumer-based webcam eye-tracking has emerged as an attractive alternative, requiring only a personal webcam and internet access. However, webcam-based eye-tracking introduces unique design and preprocessing challenges that must be addressed to ensure valid results. To help researchers navigate these challenges, we developed a comprehensive tutorial focused on visual world webcam eye-tracking for second language research. This guide covers key preprocessing steps—from reading in raw data to visualization and analysis—highlighting the open-source R package `webgazeR`, freely available at: <https://github.com/jgeller112/webgazer>. To demonstrate these steps, we analyze data collected via the Gorilla platform (Anwyl-Irvine et al., 2020) using a single-word Spanish visual world paradigm (VWP), showcasing evidence of competition both within and between Spanish and English. This tutorial aims to empower researchers by providing a step-by-step guide to successfully conduct webcam-based visual world eye-tracking studies. To follow along, please download the complete manuscript, code, and data from: https://github.com/jgeller112/L2_VWP_Webcam.

Keywords: VWP, Tutorial, Webcam eye-tracking, R, Gorilla, Spoken word recognition, L2 processing

¹ Eye-tracking technology, which has a history spanning over a century, has seen remarkable advancements. In the early days, eye-tracking often required the use of contact lenses fitted with search coils—sometimes necessitating anesthesia—or the attachment of suction cups to the sclera of the eyes (Płużyczka, 2018). These methods were not only cumbersome for researchers, but also uncomfortable and invasive for

5 participants. Over time, such approaches have been replaced by non-invasive, lightweight, and user-friendly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 impact
8 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 In the last decade, there has been a gradual shift towards conducting more behavioral experiments
11 online (Anderson et al., 2019; Rodd, 2024). This “onlineification” of behavioral research has driven the
12 development of remote eye-tracking methods that do not rely on traditional laboratory settings. Allowing
13 participants to use their own equipment from anywhere in the world opens the door to recruiting more diverse
14 and historically underrepresented populations (Gosling et al., 2010). Behavioral research has long struggled
15 with a lack of diverse and representative samples, relying heavily on participants who are predominantly
16 Western, Educated, Industrialized, Rich, and Democratic (WEIRD) (Henrich et al., 2010). Additionally,
17 we propose adding able-bodied to this acronym (WEIRD-A) (Peterson, 2021), to highlight the exclusion of
18 individuals with disabilities who may face barriers to accessing research facilities. In language research, this
19 issue is especially pronounced, as studies often focus on “modal” listeners and speakers—typically young,
20 monolingual, and neurotypical (Blasi et al., 2022; Bylund et al., 2024; McMurray et al., 2010).

21 In this paper, we contribute to the growing body of research suggesting that webcam-based eye-
22 tracking, which is administered remotely and requires access to only a computer webcam, can increase in-
23 clusivity and representation of the participant samples we include in research studies. Namely, by minimizing
24 the requirements for participants to travel to a lab, use specialized equipment, or meet strict scheduling de-
25 mands, webcam-based approaches can facilitate participation from individuals in rural or geographically
26 isolated areas and people with disabilities that make getting to a lab difficult. This approach also promotes
27 inclusion of broader sociodemographic groups that have been historically underrepresented in cognitive and
28 developmental research. We illustrate this by replicating a visual world eye-tracking study with bilingual
29 English-Spanish speaking participants (Garrett et al., 2022) using online methods (i.e., recruitment via Pro-
30 lific.co and webcam-based eye-tracking). To facilitate broader adoption of this approach, we also introduce
31 our R package, webgazeR (Geller, 2025), and present a step-by-step tutorial for analyzing webcam-based
32 VWP data.

Jason Geller  <https://orcid.org/0000-0002-7459-4505>
Yanina Prystauka  <https://orcid.org/0000-0001-8258-2339>
Sarah E. Colby  <https://orcid.org/0000-0002-2956-3072>
Julia R. Drouin  <https://orcid.org/0000-0003-0798-3268>

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Correspondence concerning this article should be addressed to Jason Geller, Department of Psychology and Neuroscience, Boston College, McGuinn Hall 405, Chestnut Hill, MA 02467-9991, USA, drjasongeller@gmail.com: jason.geller@bc.edu

33 This paper is divided into three parts. First, we introduce automated webcam-based eye-tracking.
34 Second, we review the viability of conducting VWP studies using online eye-tracking methods. Third, we
35 present a detailed tutorial for analyzing webcam-based VWP data with the webgazeR package, using our
36 replication experiment to highlight the steps needed for preprocessing.

37 Webcam Eye-Tracking with WebGazer.js

38 There are two popular methods for online eye-tracking. One method, manual eye-tracking
39 (Trueswell, 2008), involves using video recordings of participants, which can be collected through online
40 teleconferencing platforms such as Zoom (www.zoom.com). Here eye gaze (direction) is manually analyzed
41 post-hoc frame by frame from these recordings. However, this method raises ethical and privacy concerns,
42 as not all participants may be comfortable having their videos recorded and stored for analysis.

43 Another method, which is the focus of this paper, is automated eye-tracking or webcam eye-tracking.
44 Webcam eye-tracking generally has three requirements for the participant: (1) a personal computer, tablet, or
45 smartphone (see Chen-Sankey et al., 2023), (2) an internet connection, and (3) a built-in or external camera.
46 Gaze data is collected directly through a web browser without requiring any additional software installation,
47 making it highly accessible.

48 A popular tool for enabling webcam-based eye-tracking is WebGazer.js (Papoutsaki et al., 2016)¹,
49 an open-source, freely available, and actively maintained JavaScript library. WebGazer.js has already been
50 integrated into several popular experimental platforms, including Gorilla, jsPsych, PsychoPy, Labvanced, and
51 PCIbex (Anwyl-Irvine et al., 2020; Kaduk et al., 2024; Leeuw, 2015; Peirce et al., 2019; Zehr & Schwarz,
52 2018). Because WebGazer.js runs locally on the participant's machine, it does not store webcam video
53 recordings, helping alleviate ethical and privacy concerns associated with online eye-tracking.

54 Under the hood, WebGazer.js uses machine learning to estimate gaze position in real time by fitting
55 a facial mesh to the participant and detecting the location of the eyes. At each sampling point—determined
56 by the participant's device and webcam capabilities—x and y gaze coordinates are recorded. To improve
57 accuracy, participants complete calibration and validation routines in which they fixate on targets in specific
58 locations on the screen (in some cases a manual approach is used where users click on targets).

59 Eye-tracking in the Lab vs. Online

60 Several studies in psychology and psycholinguistics have evaluated the viability of WebGazer.js for
61 online research. Generally, lab-based effects can be successfully replicated in online environments using
62 WebGazer.js (Bogdan et al., 2024; Bramlett & Wiener, 2024, 2025; Özsoy et al., 2023; Prystauka et al.,
63 2024; Slim et al., 2024; Slim & Hartsuiker, 2023; Van der Cruyssen et al., 2024; Vos et al., 2022). However,
64 a critical finding across online replication studies is that effect sizes are often smaller and more variable than

¹It is important to note that WebGazer.js is not the only method available. Other methods have been implemented by companies like Tobii (www.tobii.com) and Labvanced (Kaduk et al., 2024). However, because these methods are proprietary, they are less accessible and difficult to reproduce.

65 those observed in laboratory settings (Bogdan et al., 2024; Slim et al., 2024; Slim & Hartsuiker, 2023; Van
66 der Cruyssen et al., 2024).

67 These attenuated effects likely stem from several technical limitations inherent to webcam-based
68 eye-tracking. Unlike research-grade trackers that use infrared illumination and pupil–corneal reflection
69 techniques—and can sample at rates up to 2,000 Hz with sub-degree spatial precision (0.1° to 0.35°) (Carter
70 & Luke, 2020; Hooge et al., 2024)—WebGazer.js typically operates at lower frame rates, around 30 Hz
71 (Bramlett & Wiener, 2024; Prystauka et al., 2024). Moreover, the performance of the algorithm is highly de-
72 pendent on ambient lighting conditions, making it more susceptible to variability introduced by differences
73 in head position, screen brightness, and background contrast.

74 There are also notable issues with the spatial and temporal accuracy of webcam-based eye-tracking
75 using WebGazer.js. Spatial precision is often lower, with average errors frequently exceeding 1° of visual
76 angle (Papoutsaki et al., 2016). Temporal delays are also substantially larger, ranging from 200 ms to over
77 1000 ms (Semmelmann & Weigelt, 2018; Slim et al., 2024; Slim & Hartsuiker, 2023). Additionally, recent
78 work by Bogdan et al. (2024) has documented a systematic bias in gaze estimates favoring centrally located
79 stimuli.

80 Bringing the Visual World Paradigm (VWP) Online

81 Despite these technical challenges, webcam-based eye-tracking has proven particularly well-suited
82 for adapting VWP (Tanenhaus et al., 1995; cf. Cooper, 1974) to online environments.

83 In the field of language research, few methods have had as enduring an impact as the VWP. Over
84 the past 25 years, the VWP has enabled researchers to address a broad range of topics, including sentence
85 processing (Altmann & Kamide, 1999; Huettig et al., 2011; Kamide et al., 2003), spoken word recognition
86 (Allopenna et al., 1998; Dahan et al., 2001; Huettig & McQueen, 2007; McMurray et al., 2002), bilingual
87 language processing (Hopp, 2013; Ito et al., 2018; Rossi et al., 2019), the effects of brain damage on language
88 (Mirman & Graziano, 2012; Yee et al., 2008), and the impact of hearing loss on lexical access (McMurray
89 et al., 2017).

90 What makes the widespread use of the VWP particularly remarkable is the simplicity of the task.
91 In a typical VWP experiment, participants view a display of several objects, each represented by a picture,
92 while their eye movements are recorded in real time as they listen to a spoken word or phrase. Researchers are
93 commonly interested in the proportion of fixations directed to each image on the screen. Although variations
94 of the task exist—and implementations may differ depending on specific research goals or design choices—
95 the core finding remains consistent: as the speech signal unfolds, listeners initially distribute fixations across
96 phonologically related images (e.g., cohort or rhyme competitors) before ultimately fixating on the image
97 that matches the spoken word. This robust effect provides compelling evidence for anticipatory or predictive
98 processing during language comprehension.

99 While eye movements are often time-locked to linguistic input, the relationship between eye move-
100 ments and lexical processing is not one-to-one. Lexical activation interacts with non-lexical factors such as

101 selective attention, visual salience, task demands, working memory, and prior expectations—all of which
102 can shape where and when participants look (Bramlett & Wiener, 2025; Eberhard et al., 1995; Huettig et
103 al., 2011; Kamide et al., 2003). Nonetheless, the VWP remains a powerful and flexible tool for studying
104 online language processing, offering fine-grained insights into how linguistic and cognitive processes unfold
105 moment by moment.

106 Several attempts have been made to conduct these experiments online using webcam-based eye-
107 tracking. Most online VWP replications have focused on sentence-based language processing. These studies
108 have looked at effects of set size and determiners (Degen et al., 2021), verb semantic constraint (Prystauka
109 et al., 2024; Slim & Hartsuiker, 2023), grammatical aspect and event comprehension (Vos et al., 2022), and
110 lexical interference (Prystauka et al., 2024).

111 More relevant to the current tutorial are findings from single-word VWP studies conducted online.
112 Recent research examined single-word speech perception online using a phonemic cohort task (Bramlett
113 & Wiener, 2025; Slim et al., 2024). In the cohort task, pictures were displayed randomly in one of four
114 quadrants, and participants were instructed to fixate on the target based on the auditory cue. On each trial,
115 one of the pictures was phonemically similar to the target in onset (e.g., *MILK – MITTEN*). Slim et al. (2024)
116 were able to observe significant fixations to the cohort compared to the control condition, replicating lab-
117 based single word VWP experiments with research grade eye-trackers (e.g., Allopenna et al., 1998). However,
118 time course differences were observed in the webcam-based setting such that competition effects occurred
119 later in processing compared to traditional, lab-based eye-tracking.

120 Several factors have been proposed to explain the poor temporal performance in the VWP. These
121 include reduced spatial precision, computational demands introduced by the WebGazer.js algorithm, slower
122 internet connections, smaller areas of interest (AOIs), and calibration quality (Boxtel et al., 2024; Degen et
123 al., 2021; Slim et al., 2024).

124 Importantly, temporal issues are not observed in every case. Work has begun to address many of these
125 challenges by leveraging updated versions of WebGazer.js and adopting different experimental platforms. For
126 instance, Vos et al. (2022) reported a substantial reduction in temporal delays—approximately 50 ms—when
127 using a newer version of WebGazer.js embedded within the jsPsych framework (Leeuw, 2015). Similarly,
128 studies by Prystauka et al. (2024) and Bramlett and Wiener (2024), which utilized the Gorilla Experiment
129 Builder in combination with the improved WebGazer algorithm, found timing and competition effects closely
130 aligned with those observed in traditional lab-based VWP studies.

131 While these temporal delays do present a challenge, and are at present an open issue, the general
132 findings that WebGazer.js can approximate looks to areas on the screen and replicate lab-based findings
133 underscore the potential of adapting the VWP to online environments using webcam-based eye-tracking.
134 Importantly, recent studies demonstrate that this approach can successfully capture key psycholinguistic
135 effects—such as lexical competition during single-word speech recognition—in a manner comparable to
136 traditional lab-based methods (Slim et al., 2024).

137 **Bilingual Competition: A Visual World Webcam Eye-Tracking Replication**

138 A goal of the present study was to conceptually replicate a study by Sarrett et al. (2022) wherein
139 they examined the competitive dynamics of second-language (L2) learners of Spanish, whose first language
140 (L1) is English, during spoken word recognition. Specifically, we investigated both within-language and
141 cross-language (L2/L1) competition using webcam-based eye-tracking.

142 It is well established that lexical competition plays a central role in language processing (Magnuson
143 et al., 2007). During spoken word recognition, as the auditory signal unfolds over time, multiple lexical
144 candidates—or competitors—can become partially activated. Successful recognition depends on resolving
145 this competition by inhibiting or suppressing mismatching candidates. For example, upon hearing the initial
146 segments of the word *wizard*, phonologically similar words such as *whistle* (cohort competitor) may be briefly
147 activated. As the word continues to unfold, additional competitors like *blizzard* (a rhyme competitor) might
148 also become active. For *wizard* to be accurately recognized, activation of competitors such as *whistle* and
149 *blizzard* must ultimately be suppressed.

150 One important area of exploration concerns lexical competition across languages. There is growing
151 evidence that lexical competition can occur cross-linguistically (see Ju & Luce, 2004; Spivey & Marian,
152 1999). In a recent study, Sarrett et al. (2022) investigated whether cross-linguistic competition arises in
153 unbalanced L2 Spanish speakers—that is, individuals who acquired Spanish later in life. They used carefully
154 controlled stimuli to examine both within-language and cross-language competition in adult L2 Spanish
155 learners. Using a Spanish-language visual world paradigm, their study included two critical conditions:

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

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

165 There are two key differences between our dataset and the original study by Sarrett et al. (2022) worth
166 noting. First, Sarrett et al. (2022) focused on adult unbalanced L2 Spanish speakers and posed more fine-
167 grained questions about the time course of competition and resolution and its relationship with L2 language
168 acquisition. Second, unlike Sarrett et al. (2022), who measured Spanish proficiency objectively using
169 LexTALE-esp (Izura et al., 2014)) and ran this study using participants from a Spanish college course, we
170 relied on participant filtering on Prolific (www.prolific.co) to recruit L2 Spanish speakers.

171 To conduct our online webcam replication, we used the experimental platform Gorilla (Anwyl-Irvine
172 et al., 2020), which integrates WebGazer.js for gaze tracking. We selected Gorilla because it offers robust

173 WebGazer.js integration and seems to address several temporal accuracy concerns identified in other plat-
174 forms (Slim et al., 2024; Slim & Hartsuiker, 2023).

175 **Tutorial Overview**

176 This paper has two aims. First, we aim to provide evidence for lexical competition within and across
177 languages in L2 Spanish speakers, using webcam-based eye-tracking with WebGazer.js. While there is grow-
178 ing interest in using VWP using webcam-based methods, lexical competition in single-word L2 processing
179 has not yet been investigated using the online version of the VWP, making this a novel application. We
180 hope that this work encourages researchers to explore more detailed questions about L2 processing using
181 webcam-based eye-tracking.

182 Second, we offer a tutorial that outlines key preprocessing steps for analyzing webcam-based eye-
183 tracking data. Building on recommendations proposed by Bramlett and Wiener (2024), our contribution
184 focuses on data preprocessing—transforming raw gaze data into a format suitable for visualization and anal-
185 ysis. Here we introduce a new R package—`webgazeR`(Geller, 2025)—designed to streamline and standardize
186 preprocessing for webcam-based eye-tracking studies. We believe that offering multiple, complementary re-
187 sources enhances methodological transparency and supports broader adoption of webcam-based eye-tracking
188 methods. For in-depth guidance on experimental design considerations, we refer readers to Bramlett and
189 Wiener (2024).

190 Although Bramlett and Wiener (2024)'s tutorial provides a lot of useful code, the experiment-specific
191 nature of the code may pose challenges for newcomers. In contrast, the `webgazeR` package offers a modular,
192 generalizable approach. It includes functions for importing raw data, filtering and visualizing sampling rates,
193 extracting and assigning areas of interest (AOIs), downsampling and upsampling gaze data, interpolating
194 and smoothing time series, and performing non-AOI-based analyses such as intersubject correlation (ISC),
195 a method increasingly used to explore gaze synchrony in naturalistic paradigms (i.e., online learning) with
196 webcam-based eye-tracking (Madsen et al., 2021).

197 We first begin by outlining the general methods used to conduct our webcam-based visual world
198 experiment. Second, we detail the data preprocessing steps needed to prepare the data for analysis using
199 `webgazeR`. Third, we demonstrate a statistical approach for analyzing the preprocessed data, highlighting its
200 application and implications.

201 To promote transparency and reproducibility, all analyses were conducted in R (R Core Team, 2024)
202 using Quarto (Allaire et al., 2024), an open-source publishing system that enables dynamic and repro-
203 ducible documents. Figures, tables, and text are generated programmatically and embedded directly in the
204 manuscript, ensuring seamless integration of results. To further enhance computational reproducibility, we
205 employed the `nix` package (Rodrigues & Baumann, 2025), which leverages the Nix ecosystem (Dolstra &
206 contributors, 2023). This approach captures not only the R package versions but also system dependencies
207 at runtime. Researchers can reproduce the exact computational environment by installing the Nix package
208 manager and using the provided `default.nix` file. Detailed setup instructions are included in the README
209 file of the accompanying GitHub repository. A video tutorial is also provided.

210

Method

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

213 **Participants**

214 Participants were recruited through Prolific (www.prolific.co, 2024), an online participant recruitment
215 platform. Our goal was to approximately double the sample size of Sarrett et al. (2022) to enhance
216 statistical power and ensure greater generalizability of the findings. However, due to practical constraints
217 and the challenges associated with online webcam eye-tracking (e.g., calibration failures) and also the lim-
218 ited pool of bilingual Spanish speakers, we were unable to achieve the targeted usable sample size. Therefore,
219 we report the final sample based on all participants who met our predefined inclusion criteria.

220 Inclusion criteria required participants to: (1) be between 18 and 36 years old, (2) be native English
221 speakers, (3) also be fluent in Spanish, and (4) reside in the United States. Criterion 1 was based on findings
222 from Colby and McMurray (2023), which suggest that age-related changes in spoken word recognition begin
223 to emerge in individuals in their 40s; thus, we limited our sample to participants younger than 36. Criteria 2
224 and 3 ensured that we were recruiting native English speakers and those fluent in Spanish to test L1 and L2
225 interactions. Criterion 4 matched the population of the original study, which was conducted with university
226 students in Iowa, and therefore we restricted recruitment to U.S. residents.

227 After agreeing to participate, individuals were redirected to the Gorilla experiment platform
228 (www.gorilla.sc; (Anwyl-Irvine et al., 2020)). A flow diagram of participant progression through the ex-
229 periment is shown in Figure 1. In total, 187 participants assessed the experimental platform and consented
230 to be in the study. Of these, 121 passed the headphone screener checkpoint, and 111 proceeded to the VWP
231 task. Out of the 111 participants who entered the VWP, 91 completed the final surveys at the end of the ex-
232 periment. Among these, 32 participants successfully completed the VWP task with at least 100 trials, while
233 79 participants did not provide adequate data for inclusion, primarily due to failed calibration attempts. After
234 applying additional exclusion criteria—namely, overall VWP task accuracy below 80%, excessive missing
235 eye-tracking data (>30%), and sampling rate < 5hz—the final analytic sample consisted of 28 participants
236 with usable eye-tracking data. Descriptive demographic information for the full sample that made it to the
237 final survey is provided in Table 1.

238 **Materials**

239 **VWP**

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

Figure 1

This sankey plot illustrates the flow of participants from initial consent ($N = 187$) through each stage of the study to the final analyzed sample ($N = 28$). The width of each stream is proportional to the number of participants. Detours indicate points of attrition, including failures in the headphone screener ($N = 66$) and calibration ($N = 76$). Only participants who passed all screening and calibration stages, and completed the Visual World Paradigm (VWP), were included in the final sample.

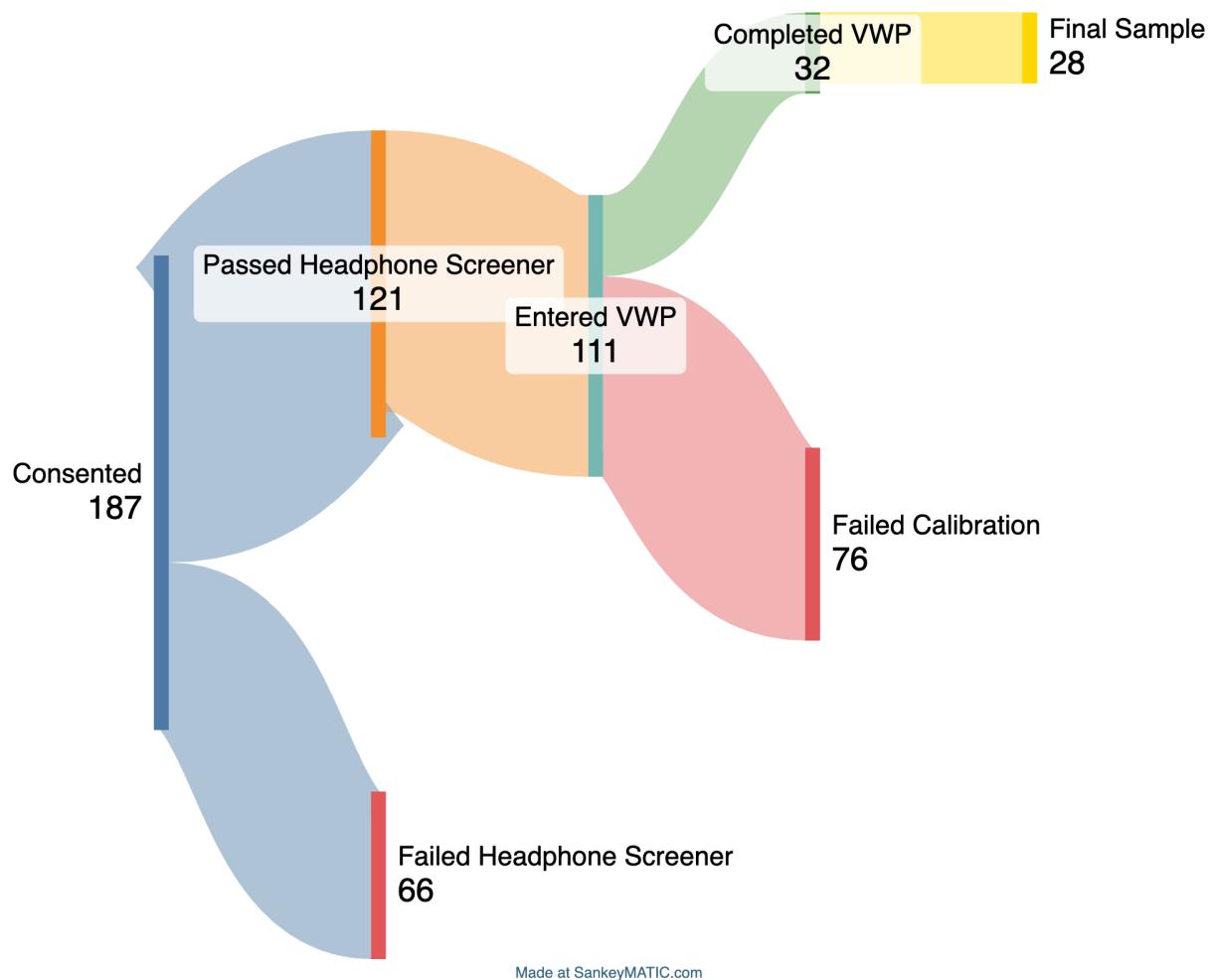


Table 1*Participant demographic variables*

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%)
Ethnicity	
Decline to state	1 / 91 (1.1%)
Hispanic or Latino	38 / 91 (42%)
Not Hispanic or Latino	52 / 91 (57%)
Race	
American Indian/Alaska Native	2 / 91 (2.2%)
Asian	13 / 91 (14%)
Black or African American	10 / 91 (11%)
Decline to state	7 / 91 (7.7%)
More than one race	4 / 91 (4.4%)
White	55 / 91 (60%)
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)
% Experience Using Spanish Daily Life	25(23)

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

The item sets consisted of two types of phonologically-related word pairs: one pair of Spanish-Spanish words and another of Spanish-English words. The Spanish-Spanish pairs were unrelated to the Spanish-English pairs. All the word pairs were carefully controlled on a number of dimensions (see Sarrett et al., 2022). There were three experimental conditions: (1) the Spanish-Spanish (within) condition, where one of the Spanish words was the target and the other was the competitor; (2) the Spanish-English (cross-linguistic) condition, where a Spanish word was the target and its English phonological cohort served as the competitor; and (3) the No Competitor condition, where the Spanish word did not overlap with any other word in the set. The Spanish-Spanish condition had twice as many trials as the other conditions due to the interchangeable nature of the target and competitor words in that pair.

Each item within a set appeared four times as the target word, resulting in a total of 240 trials (15 sets × 4 items per set × 4 repetitions). Each set included one Spanish–Spanish cohort pair and one Spanish–English cohort pair. In the Spanish–Spanish condition, both words in the pair served as mutual competitors—for example, *cielo* activated *ciencia*, and vice versa. This bidirectional relationship yielded 120 trials for the Spanish–Spanish condition.

In contrast, the Spanish–English pairs had an asymmetrical relationship: only one item in each pair functioned as a competitor (e.g., *botas* could activate *frontera*, but *frontera* did not have a corresponding competitor). As a result, there were 60 trials each for the Spanish–English and No Competitor conditions. Across all trials, target items were equally distributed among the four screen quadrants to ensure balanced visual presentation

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

Visual stimuli were images from a commercial clipart database that were selected by a consensus method involving a small group of students. All .wav files were converted to .mp3 for online data collection. All stimuli can be found here: <https://osf.io/mgkd2/>.

Headphone Screener

Headphones were required for all participants. To ensure compliance, we administered a six-trial headphone screening task adapted from Milne et al. (2021), which is available for implementation on the Gorilla platform. On each trial, three tones of the same frequency and duration were presented sequentially. One tone had a lower amplitude than the other two tones. Tones were presented in stereo, but the tones in the left and right channels were 180 out of phase across stereo channels—in free field, these sounds should cancel out or create distortion, whereas they will be perfectly clear over headphones. The listener picked which of the three tones was the quietest. Performance is generally at the ceiling when wearing headphones but poor when listening in the free field (due to phase cancellation).

280 ***Participant Background and Experiment Conditions Questionnaire***

281 We had participants complete a demographic questionnaire as part of the study. The questions cov-
282 ered basic demographic information, including age, gender, spoken dialect, ethnicity, and race. To gauge L2
283 experience, we asked participants when they started speaking Spanish, how many years of Spanish speaking
284 experience they had, and to provide, on a scale between 0-100, how often they use Spanish in their daily
285 lives.

286 To further probe into data quality issues and get a better sense of why participants could not make
287 it through the experiment, participants answered a series of questions at the end of the experiment related to
288 their personal health and environmental conditions during the experiment. These questions addressed any
289 history of vision problems (e.g., corrected vision, eye disease, or drooping eyelids) and whether they were
290 currently taking medications that might impair judgment. Participants also indicated if they were wearing
291 eyeglasses, contacts, makeup, false eyelashes, or hats.

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

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

300 ***Procedure***

301 All tasks and questionnaires were developed using the Gorilla Experiment Builder's graphical user
302 interface (GUI) and integrated coding tools (Anwyl-Irvine et al., 2020). Each participant completed the study
303 in a single session lasting approximately 45 minutes. Tasks were presented in a fixed order: informed consent,
304 headphone screening, the spoken word Visual World Paradigm (VWP) task, and a set of questionnaire items.
305 These are available to view here: <https://app.gorilla.sc/openmaterials/953693>.

306 Only personal computers were permitted for participation. Upon entering the study from Prolific,
307 participants were presented with a consent form. Once consent was given, participants completed a head-
308 phone screening test. They had three attempts to pass this test. If unsuccessful by the third attempt, partic-
309 ipants were directed to an early exit screen, followed by the questionnaire. They had three attempts to pass
310 this test. If unsuccessful by the third attempt, participants were directed to an early exit screen, followed by
311 the questionnaire.

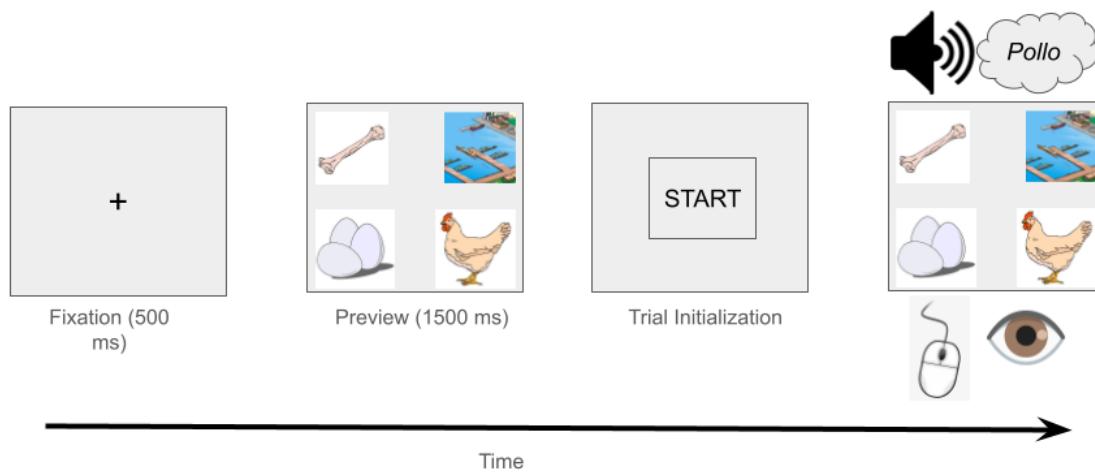
312 If the headphone screener was passed, participants were next introduced to the VWP task. This
313 began with instructional videos providing specific guidance on the ideal experiment setup for eye-tracking
314 and calibration procedures. You can view the videos here: <https://osf.io/mgkd2/>. Participants were then
315 required to enter full-screen mode before calibration. A 9-point calibration procedure was used. Calibration

316 occurred every 60 trials for a total of 3 calibrations. Participants had three attempts to successfully complete
 317 each calibration phase. If calibration was unsuccessful, participants were directed to an early exit screen,
 318 followed by the questionnaire.

319 In the main VWP task, each trial began with a 500 ms fixation cross at the center of the screen. This
 320 was followed by a preview screen displaying four images, each positioned in a corner of the screen. After
 321 1500 ms, a start button appeared in the center. Participants clicked the button to confirm they were focused
 322 on the center before the audio played. Once clicked, the audio was played, and the images remained visible.
 323 Participants were instructed to click the image that best matched the spoken target word, while their eye
 324 movements were recorded. Eye movements were only recorded on that screen. Figure 2 displays the VWP
 325 trial sequence.

Figure 2

VWP trial schematic



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

329

Preprocessing Data

330 After the data is collected you can begin preprocessing your data. Below we highlight the steps
 331 needed to preprocess your webcam eye-tracking data and get it ready for analysis. For some of this prepro-
 332 cessing we will use the newly created `webgazeR` package (v. 0.7.2).

333 For preprocessing visual world webcam eye data, we follow seven general steps (see Figure 3):

334 1. Reading in data

335 2. Data exclusion

336 3. Combining trial- and eye-level data

337 4. Assigning areas of interest (AOIs)

338 5. Time binning

339 1. Downsampling

340 2. Upsampling (optional)

341 6. Aggregating (optional)

342 7. Visualization

343 For each of these steps, we will display R code chunks demonstrating how to perform each step with

344 helper functions (if applicable) from the `webgazeR` (Geller, 2025) package in R.

345 Load Packages

346 Package Installation and Setup

347 Before proceeding, make sure to load the required packages by running the code below. If you

348 already have these packages installed and loaded, feel free to skip this step. The code in this tutorial will not

349 run correctly if any of the necessary packages are missing or not properly loaded.

350 **webgazeR Installation.** The `webgazeR` package is installed from the Github repository using the

351 `remotes` (Csárdi et al., 2024) package.

```
library(remotes) # install github repo

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

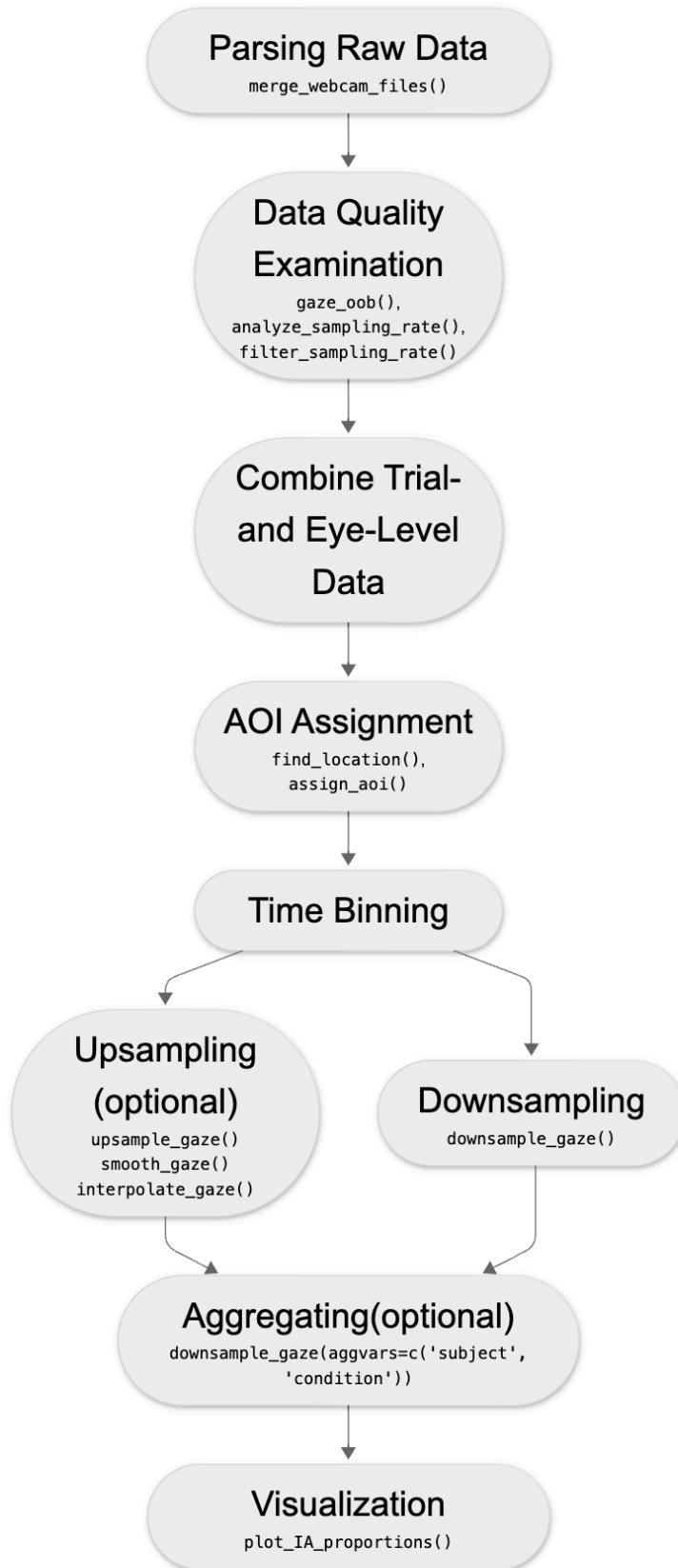
352 Once this is installed, `webgazeR` can be loaded along with additional useful packages. The following

353 code will load the required packages or install them if you do not have them on your system.

```
# List of required packages
required_packages <- c(
  "tidyverse",      # data wrangling
```

Figure 3

Preprocessing steps for webcam eye-tracking data using webgazeR functions



```

"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
)

```

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

356 **Reading in Data**

357 ***Behavioral, Trial-level, Data***

358 To process eye-tracking data you will need to make sure you have both the behavioral data and
 359 the eye-tracking data files. We have all the data needed in the repository by navigating to the L2 sub-
 360 folder from the main project directory (~/`data/L2`). For the behavioral data, Gorilla produces a `.csv` file
 361 that includes trial-level information (here contained in the object `L2_data`). The files needed are called
 362 `data_exp_196386-v5_task-scf6.csv`. and `data_exp_196386-v6_task-scf6.csv`. We have two
 363 files because we ran a modified version of the experiment.

364 The `.csv` files contain meta-data for each each trial, such as what picture were presented on each
 365 trial, which object was the target, reaction times, audio presentation times, what object was clicked on, etc.
 366 To load our data files into our R environment, we use the `here` (Müller, 2020) package to set a relative
 367 rather than an absolute path to our files. We read in the data files from the repository for both versions of
 368 the task and merge the files together. `L2_data` merges both `data_exp_196386-v5_task-scf6.csv` and
 369 `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

```

370 ***Eye-Tracking Data***

371 Gorilla currently saves each participant’s eye-tracking data on a per-trial basis. The `raw` subfolder in
 372 the project repository contains the eye-tracking files by participant for each trial individually (~`/data/L2/raw`).
 373 Contained in those files, we have information pertaining to each trial such as participant id, time since trial
 374 started, x and y coordinates of looks, convergence (the model’s confidence in finding a face (and accurately
 375 predicting eye movements), face confidence (represents the support vector machine (SVM) classifier score
 376 for the face model fit), and information pertaining to the the AOI screen coordinates (standardized and user-
 377 specific). The `vwp_files_L2` object below contains a list of all the files contained in the folder. Because
 378 `vwp_files_L2` contains trial data as well as calibration data, we remove the calibration trials and save the
 379 non-calibration to to `vwp_paths_filtered_L2`.

```
# Get the list of all files in the folder

# thank you to Reviewer 1 for suggesting this code
vwp_files_L2 <- list.files(here::here("data", "L2", "raw"), full.names = TRUE,
  ~ pattern = "\\.(csv|xlsx)$") %>%
# remove calibration trials
discard(~ grepl("calibration", .x))
```

380 When data is generated from Gorilla, each trial in your experiment is saved as a separate file. To ana-
 381 lyze the data, these individual files need to be combined into a single dataset. The `merge_webcam_files()`
 382 function from `webgazeR` is designed for this purpose. It reads all trial-level files from a specified folder—
 383 regardless of file format (.csv, .tsv, or .xlsx)—and merges them into one cohesive tibble or data frame.

384 Before using `merge_webcam_files()`, ensure your working directory is set to the location where
 385 the raw files are stored. The function automatically standardizes column names using `clean_names()`, binds
 386 the files together, and filters the data to retain only the relevant rows. Specifically, it keeps rows where the type
 387 column equals “prediction”, which are the rows that contain actual eye-tracking predictions. It also filters
 388 based on the `screen_index` argument: if you collected gaze data across multiple screens, you can specify one
 389 or several indices (e.g., `screen_index = c(1, 4, 5)`).

390 In addition to merging and filtering, `merge_webcam_files()` requires the user to explicitly map
 391 critical columns—subject, trial, time, and x/y gaze coordinates. This makes the function highly flexible
 392 and robust across different experimental platforms. For instance, the function automatically renames the
 393 `spreadsheet_row` column to trial, and converts subject and trial into factors for compatibility with downstream
 394 analyses.

395 Currently, the `kind` argument supports “gorilla” data, but future extensions will add support for other
 396 platforms like Labvanced (Kaduk et al., 2024), PsychoPy (Peirce et al., 2019), and PCIbex (Zehr & Schwarz,
 397 2018). By explicitly allowing platform specification and flexible column mapping, `merge_webcam_files()`
 398 ensures a consistent and streamlined pipeline for preparing webcam eye-tracking data for analysis.

399 As a general note, all steps should be followed in order due to the renaming of column names. If you
 400 encounter an error it might be because column names have not been changed.

```
setwd(here::here("data", "L2", "raw")) # set working directory to raw data folder

edat_L2 <- merge_webcam_files(vwp_files_L2, screen_index=4, col_map =
  ↵ list(subject = "participant_id", trial="spreadsheet_row",
  ↵ time="time_elapsed", x="x_pred_normalised", y="y_pred_normalised"),
  ↵ kind="gorilla")
```

401 To ensure high-quality data, we applied a set of behavioral and eye-tracking exclusion criteria prior
 402 to merging datasets. Participants were excluded if they met any of the following conditions: (1) failure
 403 to successfully calibrate throughout the experiment (fewer than 100 completed trials), (2) low behavioral
 404 accuracy (below 80%), (3) low sampling rate (below 5 Hz), or (4) a high proportion of gaze samples falling
 405 outside the display area (greater than 30%).

406 Successful calibration is critical for reliable eye-tracking measurements, as poor calibration directly
 407 compromises the spatial accuracy of gaze data (Blascheck et al., 2017). Requiring a sufficient number of
 408 completed trials is crucial for ensuring adequate statistical power and stable individual-level parameter esti-
 409 mates, particularly in tasks with high trial-to-trial variability (Brysbaert & Stevens, 2018). We choose 100
 410 trials as this meant participants passed at least two calibration attempts during the study. Behavioral accuracy
 411 ($\geq 80\%$) was used as an additional screening measure because low task performance may indicate a lack
 412 of attention, misunderstanding of the task, or random responding, all of which could undermine both the
 413 behavioral and eye-movement data quality (Bianco et al., 2021). Filtering based on sampling rate ensures
 414 that datasets with too few gaze samples (due to technical or environmental issues) are removed, as low sam-
 415 pling rates significantly degrade temporal precision and bias gaze metrics (Semmelmann & Weigelt, 2018).
 416 Finally, we excluded participants with excessive off-screen data ($>30\%$) because this indicates poor gaze
 417 tracking, likely caused by head movement, poor lighting, or loss of face detection. At this time, there is no
 418 set guide on what constitutes acceptable data loss for webcam-based studies. We felt 30% was a reasonable
 419 cut-off. At the trial-level, we also removed incorrect trials and trials where sampling rate was < 5 Hz.

420 What we will do first is create a cleaned up version of our behavioral, trial-level data L2_data by
 421 creating an object named eye_behav_L2 that selects useful columns from that file and renames stimuli to
 422 make them more intuitive. Because most of this will be user-specific, no function is called here. Below we
 423 describe the preprocessing done on the behavioral data file. The below code processes and transforms the
 424 L2_data dataset into a cleaned and structured format for further analysis. First, the code renames several
 425 columns for easier access using janitor::clean_names() (Firke, 2023) function. We then select only the
 426 columns we need and filter the dataset to include only rows where screen_name is “VWP” and zone_type
 427 is called “response_button_image”, representing the picture selected for that trial. Afterward, the function
 428 renames additional columns (tlpic to TL, trpic to TR, etc.). We also renamed participant_private_id
 429 to subject, spreadsheet_row to trial, and reaction_time to RT. This makes our columns consistent

⁴³⁰ with the edat_L2 above for merging later on. Lastly, reaction_time (RT) is converted to a numeric format
⁴³¹ for further numerical analysis.

⁴³² It is important to note here that what the behavioral spreadsheet denotes as trial is not in fact the trial
⁴³³ number used in the eye-tracking files. Thus it is imperative you use spreadsheet_row as trial number to
⁴³⁴ 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, screen_name)
  ~ %>%
  # Filter the rows where 'Zone.Type' equals "response_button_image"
  # participants clicked on preview screen so now need to filter based on screen.
  ~
  dplyr::filter(screen_name == "VWP", 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))
```

435 ***Audio onset***

436 Because we are playing audio on each trial and running this experiment from the browser, audio
 437 onset is never going to be consistent across participants. In Gorilla there is an option to collect advanced
 438 audio features (you must make sure you select this when designing the study) such as when the audio play
 439 was requested, played, and ended. We will want to incorporate this timing information into our analysis
 440 pipeline. Gorilla records the onset of the audio which varies by participant. We are extracting that in the
 441 `audio_rt_L2` object by filtering `zone_type` to `content_web_audio` and a response equal to “AUDIO
 442 PLAY EVENT FIRED”. This will tell us when the audio was triggered in the experiment. We are creating
 443 a column called (`RT_audio`) which we will use later on to correct for audio delays. Please note that
 444 on some trials the audio may not play. This is a function of the browser a participant is using and the
 445 experimenter has no control over this (see <https://support.gorilla.sc/support/troubleshooting-and-technical/technical-checklist#autoplayingsoundandvideo>). When running your experiment on a different platform,
 446 make sure you try and request this information, or at the very least acknowledge audio delay.
 447

```
audio_rt_L2 <- L2_data %>%
  janitor::clean_names() %>%
  select(participant_private_id, zone_type, spreadsheet_row, reaction_time,
  ~ response) %>%
  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",
    "Fired" = "response") %>%
  select(-zone_type) %>%
  mutate(RT_audio = as.numeric(RT_audio))
```

448 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"))
```

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

449 Trial Removal

450 As stated above, participants who did not successfully calibrate 3 times or less were rejected from the
 451 experiment. Deciding to remove trials is ultimately up to the researcher. In our case, we removed participants
 452 with less than 100 trials. Let's take a look at how many participants meet this criterion by probing the
 453 `trial_data_rt_L2` object. In Table 2 we can see several participants failed some of the calibration attempts
 454 and do not have an adequate number of trials. Again we make no strong recommendations here. If you decide
 455 to use a criterion such as this, we recommend pre-registering your choice.

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

456 Let's remove participants with less than 100 trials from the analysis using the below code.

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

457 ***Low Accuracy***

458 In our experiment, we want to make sure accuracy is high (> 80%). Again, we want participants that
 459 are fully attentive in the experiment. In the below code, we keep participants with accuracy equal to or above
 460 80% and only include correct trials and assign 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 %>%
  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
```

461 ***RTs***

462 There is much debate on how to handle reaction time (RT) data (see Miller, 2023). Because of this.
 463 we leave it up to the reader and researcher to decide what to do with RTs. In this tutorial we leave RTs
 464 untouched.

465 ***Sampling Rate***

466 While most commercial eye-trackers sample at a constant rate, data captured by webcams are widely
 467 inconsistent. Below is some code to calculate the sampling rate of each participant. Ideally, you should
 468 not have a sampling rate less than 5 Hz. It has been recommended you drop those values (Bramlett &
 469 Wiener, 2024) The below function `analyze_sample_rate()` calculates the sampling rate for each subject
 470 and each trial in our eye-tracking dataset (`edat_L2`). The `analyze_sample_rate()` function provides
 471 overall statistics, including the option to report mean or median (Bramlett & Wiener, 2024) sampling rate
 472 and standard deviation of sampling rates in your experiment. Sampling rate calculations followed standard
 473 procedures (e.g., Bramlett & Wiener, 2024; Prystauka et al., 2024). The function also generates a histogram
 474 of sampling rates by-subject. Looking at Figure 4, the sampling rate ranges from 5 to 35 Hz with a median

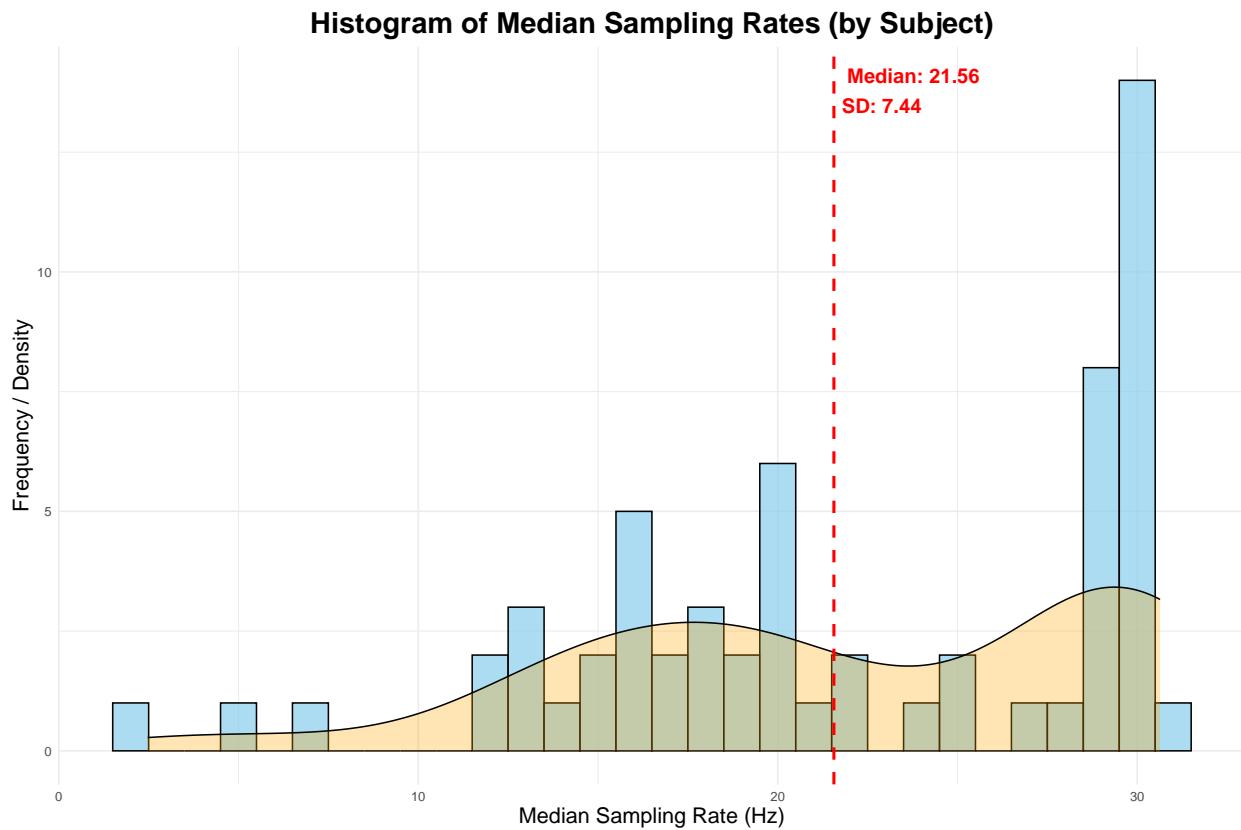
475 sampling rate of 21.56. This corresponds to previous webcam eye-tracking work (e.g., Bramlett & Wiener,
 476 2024; Prystauka et al., 2024)

```
samp_rate_L2 <- analyze_sampling_rate(edat_L2, summary_stat="Median")
```

477 Overall Median Sampling Rate (Hz): 21.56
 478 Overall SD of Sampling Rate (Hz): 7.44

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.



479 When using the above function, separate data frames are produced by-participants and by-trial. These
 480 can be added to the behavioral data frame using the below code.

```
trial_data_L2 <- merge(trial_data_acc_clean_L2, samp_rate_L2, by=c("subject",  

  ↵ "trial"))
```

481 Now we can use this information to filter out data with poor sampling rates. Users can use the
 482 `filter_sampling_rate()` function. The `filter_sampling_rate()` function is designed to process a

483 dataset containing participant-level and trial-level sampling rates. It allows the user to either filter out data
 484 that falls below a certain sampling rate threshold or simply label it as “bad”. The function gives flexibility
 485 by allowing the threshold to be applied at the participant-level, trial-level, or both. It also lets the user decide
 486 whether to remove the data or flag it as below the threshold without removing it. If `action = remove`, the
 487 function will output how many subjects and trials were removed using the threshold. We leave it up to the
 488 user to decide what to do with low sampling rates and make no specific recommendations. Here we use the
 489 `filter_sampling_rate()` function to remove trials and participants from the `trial_data_L2` object.

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

490 *Out-of-Bounds (Outside of Screen)*

491 It is essential to exclude gaze points that fall outside the screen, as these indicate unreliable estimates
 492 of gaze location. The `gaze_oob()` function quantifies how many data points fall outside these bounds, using
 493 the eye-tracking dataset (e.g., `edat_L2`) and the standardized screen dimensions—here set to (1, 1) because
 494 Gorilla recommends using standardized coordinates. If the `remove` argument is set to TRUE, the func-
 495 tion applies an outer-edge filtering method to eliminate these out-of-bounds points (see Bramlett & Wiener,
 496 2024). The outer-edge approach appears to be a less biased approach based on demonstrations from Bram-
 497 lett and Wiener (2024), where they showed minimal data loss compared to other approaches (e.g., inner-edge
 498 approach).

499 The function returns a summary table showing the total number and percentage of gaze points that
 500 fall outside the bounds, broken down by axis (X, Y), as well as the combined total (see Table 3). It also returns
 501 three additional tibbles: (1) missingness by-subject, (2) missingness by-trial, and (3) a cleaned dataset with
 502 all the data merged, and the problematic rows removed if specified. These outputs can be referenced in a
 503 final report or manuscript. As shown in Figure 5, no fixation points fall outside the standardized coordinate
 504 range.

```
oob_data_L2 <- gaze_oob(data=edat_L2, subject_col = "subject",
                           trial_col = "trial",
                           x_col = "x",
                           y_col = "y",
                           screen_size = c(1, 1), # standardized coordinates have
                           ↳ screen size 1,1
                           remove = TRUE)
```

Table 3

Out of bounds gaze statistics by-participant (for 6 participants)

subject	totaltrials	totalpoints	outsidecount	subjectmissing%	xoutsidecount	youtsidecount	xoutside%	youtside%
12102265	60.00	6,192.00	1,132.00	18.28	202.00	947.00	3.26	15.29
12102286	240.00	11,765.00	354.00	3.01	267.00	181.00	2.27	1.54
12102530	240.00	9,011.00	385.00	4.27	244.00	147.00	2.71	1.63
12110559	240.00	11,887.00	415.00	3.49	194.00	221.00	1.63	1.86
12110579	178.00	5,798.00	1,061.00	18.30	696.00	435.00	12.00	7.50
12110585	240.00	13,974.00	776.00	5.55	83.00	694.00	0.59	4.97

```
#| echo: false

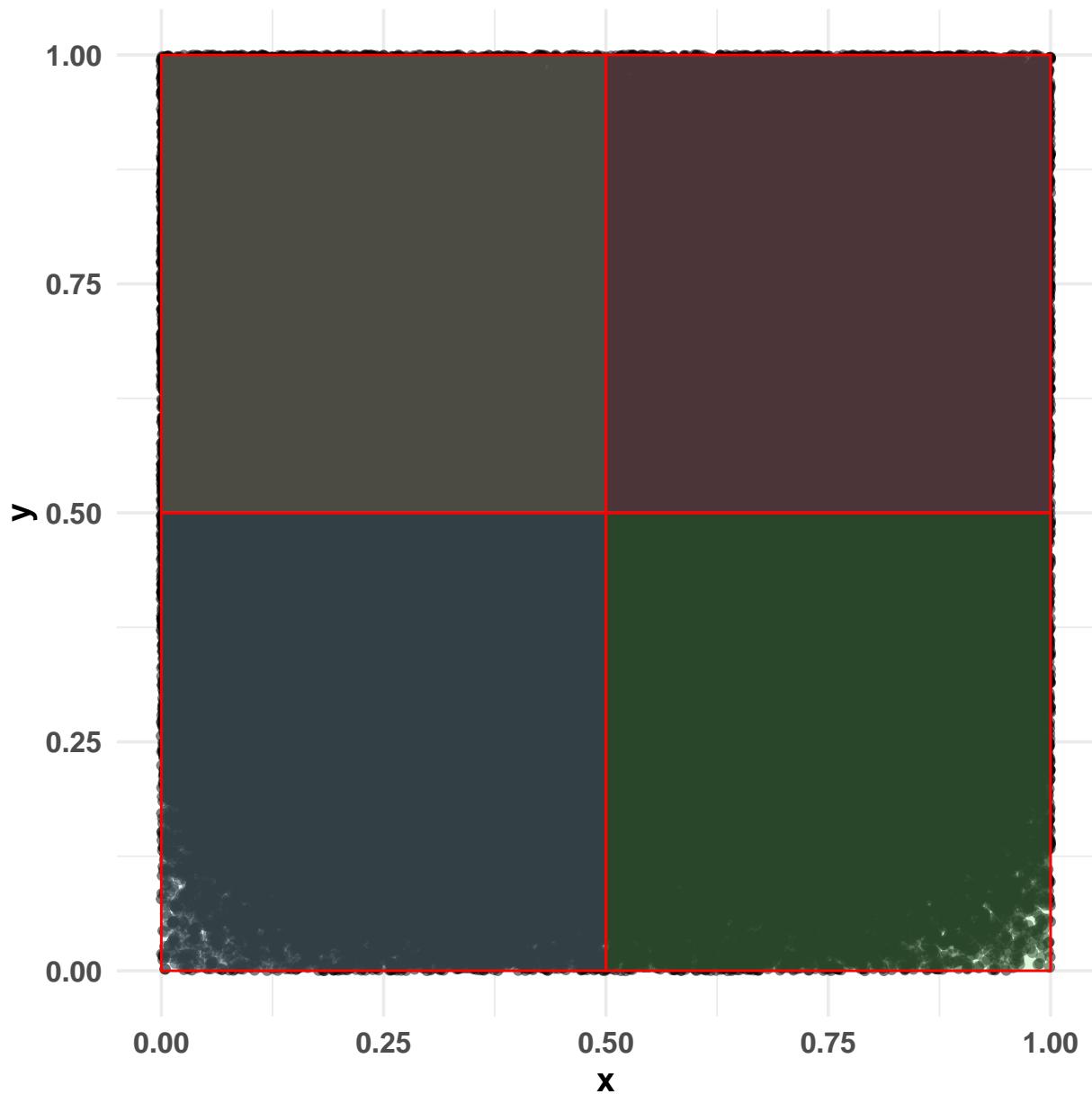
oob_data_L2$subject_results %>%
  mutate(across(where(is.numeric), ~round(.x, 2))) %>%
  rename_with(~ gsub("_", "\n", .x)) %>%           # Replace underscores with line
  ↪   breaks
  rename_with(~ gsub("percentage", "%", .x, ignore.case = TRUE)) %>%  # Replace
  ↪   'percent' with '%'
  head() %>%
    flextable() %>%
    fontsize(size = 12) %>%  # Reduce font size
    padding(padding = 1) %>%
    font(fontname = "Times New Roman", part = "all") %>%
    set_table_properties(layout="autofit") %>% # Reduce padding inside cells
    autofit() %>%
    theme_apa()
```

505 We can use the `data_clean` tibble returned by the `gaze_oob()` function to filter out trials and sub-
 506 jects with more than 30% missing data. The value of 30% is just a suggestion and should not be used as a
 507 rule of thumb for all studies nor are we endorsing this value.

```
# remove participants with more than 30% missing data and trials with more than
  ↪  30% missing data
filter_oob <- oob_data_L2$data_clean %>%
  filter(trial_missing_percentage <= 30 | subject_missing_percentage <= 30)
```

Figure 5

Looks to each quadrant of the screen



508 **Eye-tracking data**509 ***Convergence and Confidence***

510 To ensure data quality, we removed rows with poor convergence and low face confidence from our
 511 eye-tracking dataset. As described in Prystauka et al. (2024), the Gorilla eye-tracking output includes two
 512 key columns for this purpose: `convergence` and `face_conf` (similar variables may be available in other
 513 platforms as well). The `convergence` column contains values between 0 and 1, with lower values indicating
 514 better convergence—that is, greater model confidence in predicting gaze location and finding a face. Values
 515 below 0.5 typically reflect adequate convergence. The `face_conf` column reflects how confidently the al-
 516 gorithm detected a face in the frame, also ranging from 0 to 1. Here, values above 0.5 indicate a good model
 517 fit.

518 Accordingly, we filtered the `edat_L2` dataset to include only rows where `convergence < 0.5` and
 519 `face_conf > 0.5`, and saved the cleaned dataset as `edat_1_L2`.

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

520 ***Combining Eye and Trial-Level Data***

521 Next, we will combine the eye-tracking data and behavioral data. In this case, we'll use `merge` to
 522 add the behavioral data to the eye-tracking data. This ensures that all rows from the eye-tracking data are
 523 preserved, even if there isn't a matching entry in the behavioral data (missing values will be filled with NA).
 524 The resulting object is called `dat_L2`.

```
dat_L2 <- merge(edat_1_L2, filter_edat_L2)
```

525 **Areas of Interest**526 ***Zone Coordinates***

527 In the lab, we can control many aspects of the experiment that cannot be controlled online. Partic-
 528 ipants will be completing the experiment under a variety of conditions including, different computers, with
 529 very different screen dimensions. To control for this, Gorilla outputs standardized zone coordinates (labeled
 530 as `x_pred_normalised` and `y_pred_normalised` in the eye-tracking file) . As discussed in the Gorilla
 531 documentation, the Gorilla lays everything out in a 4:3 frame and makes that frame as big as possible. The
 532 normalized coordinates are then expressed relative to this frame; for example, the coordinate 0.5, 0.5 will
 533 always be the center of the screen, regardless of the size of the participant's screen. We used the normalized

Table 4

Quadrant coordinates in standardized space

loc	x_normalized	y_normalized	width_normalized	height_normalized	xmin	ymin	xmax	ymax
TL	0.00	0.50	0.50	0.50	0.00	0.50	0.50	1.00
TR	0.50	0.50	0.50	0.50	0.50	0.50	1.00	1.00
BL	0.00	0.00	0.50	0.50	0.00	0.00	0.50	0.50
BR	0.50	0.00	0.50	0.50	0.50	0.00	1.00	0.50

534 coordinates in our analysis (in general, you should always use normalized coordinates). However, there are
 535 a few different ways to specify the four coordinates of the screen, which are worth highlighting here.

536 **Quadrant Approach.** One way is to make the AOIs as big as possible, dividing the screen into four
 537 quadrants. This approach has been used in several studies [e.g., (Bramlett & Wiener, 2024; Prystauka et al.,
 538 2024). Table 4 lists coordinates for the quadrant approach and Figure 6 shows how each quadrant looks in
 539 standardized space.

540 **Matching Conditions with Screen Locations.** The goal of the below code is to assign condition
 541 codes (e.g., Target, Unrelated, Unrelated2, and Cohort) to each image in the dataset based on the screen
 542 location where the image is displayed (e.g., TL, TR, BL, BR).

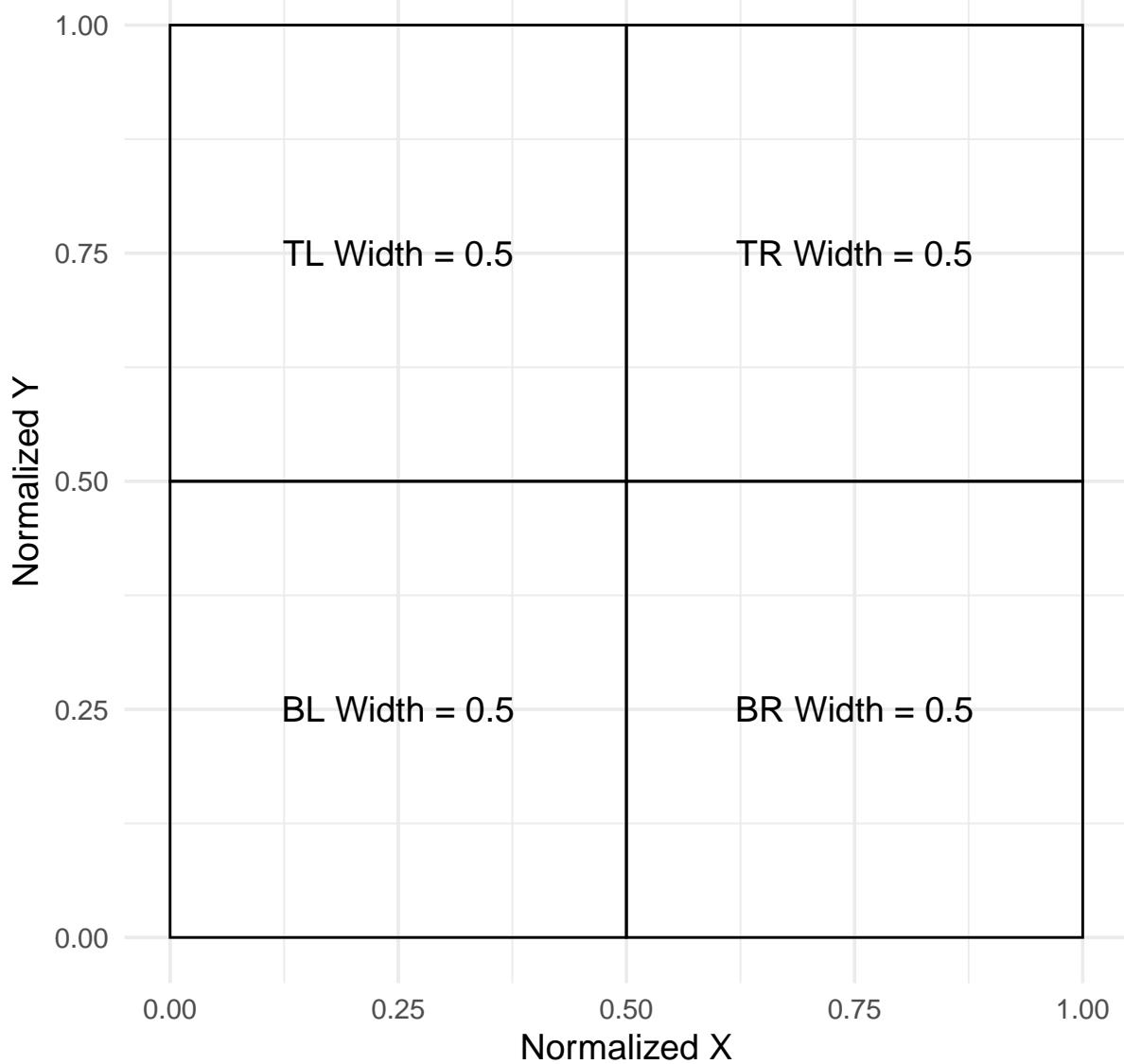
543 For each trial, the images are dynamically placed at different screen locations, and the code maps
 544 each image to its corresponding condition based on these locations.

```
# 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,
```

Figure 6

AOI coordinates in standardized space using the quadrant approach

Quadrants with Width Annotations



```

    TRUE ~ NA_character_
),
Unrelated2 = case_when(
  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_
)
)
)

```

545 In addition to tracking the condition of each image during randomized trials, a custom function,
 546 `find_location()`, determines the specific screen location of each image by comparing it against the list
 547 of possible locations. This function ensures that the appropriate location is identified or returns NA if no
 548 match exists. Specifically, `find_location()` first checks if the image is NA (missing). If the image is NA,
 549 the function returns NA, meaning that there's no location to find for this image. If the image is not NA, the
 550 function creates a vector called `loc_names` that lists the names of the possible locations. It then attempts to
 551 match the given image with the locations. If a match is found, it returns the name of the location (e.g., TL,
 552 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 = TL, TR = TR, BL = BL, BR = BR), Target),
    cohort_loc = find_location(c(TL = TL, TR = TR, BL = BL, BR = BR), Cohort),
    unrelated_loc = find_location(c(TL = TL, TR = TR, BL = BL, BR = BR),
      ~ Unrelated),
    unrelated2_loc = find_location(c(TL = TL, TR = TR, BL = BL, BR = BR),
      ~ Unrelated2)
  ) %>%

```

```
ungroup()
```

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

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

558 In `AOI_L2` we label looks to Targets, Unrelated, and Cohort items with 1 (looked) and 0 (no look)
 559 using the `case_when` function from the `tidyverse` (Wickham, 2017)

```
AOI_L2 <- AOI_L2 %>%
  mutate(
    target = case_when(loc1 == targ_loc ~ 1, TRUE ~ 0),
    unrelated = case_when(loc1 == unrelated_loc ~ 1, TRUE ~ 0),
    unrelated2 = case_when(loc1 == unrelated2_loc ~ 1, TRUE ~ 0),
    cohort = case_when(loc1 == cohort_loc ~ 1, TRUE ~ 0)
  )
```

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

```
dat_long_aoi_me_L2 <- AOI_L2 %>%
  select(subject, trial, condition, target, cohort, unrelated, unrelated2, time,
        ~ x, y, RT_audio) %>%
```

```

pivot_longer(
  cols = c(target, unrelated, unrelated2, cohort),
  names_to = "condition1",
  values_to = "Looks"
)

```

565 We further clean up the object by first cleaning up the condition codes. They have a numeral app-
 566 pended to them and that should be removed. We then adjust the timing in the `gaze_sub_L2_comp` object by
 567 aligning time to the actual audio onset. To achieve this, we subtract `RT_audio` from time for each trial. In
 568 addition, we subtract 300 ms from this to account for the 100 ms of silence at the beginning of each audio
 569 clip and 200 ms to account for the oculomotor delay when planning an eye movement (Viviani, 1990). Ad-
 570 ditionally, we set our interest period between 0 ms (audio onset) and 2000 ms. This was chosen based on the
 571 time course figures in Sarrett et al. (2022) . It is important that you choose your interest area carefully and
 572 preferably you preregister it. The interest period you choose can bias your findings (Peelle & Van Engen,
 573 2021). We also filter out gaze coordinates that fall outside the standardized window, ensuring only valid data
 574 points are retained. The resulting object `gaze_sub_long_L2` provides the corrected time column spanning
 575 from -200 ms to 2000 ms relative 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)

```

576 Samples to Bins

577 *Downsampling*

578 Downsampling into larger time bins is a common practice in gaze data analysis, as it helps create
 579 a more manageable dataset and reduces noise. When using research grade eye-trackers, downsampling is
 580 an optional step in the preprocessing pipeline. However, with consumer-based webcam eye-tracking it is

Table 5

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

condition	condition1	time_bin	Fix
TCUU-ENGSP	cohort	-200.00	0.26
TCUU-ENGSP	cohort	-100.00	0.26
TCUU-ENGSP	cohort	0.00	0.25
TCUU-ENGSP	cohort	100.00	0.25
TCUU-ENGSP	cohort	200.00	0.23
TCUU-ENGSP	cohort	300.00	0.23

581 recommended you downsample your data so participants have consistent bin sizes (e.g., (Slim et al., 2024;
 582 Slim & Hartsuiker, 2023)). In `webgazeR` we included the `downsample_gaze()` function to assist with this
 583 process. We apply this function to the `gaze_sub_L2_long` object, and set the `bin.length` argument to 100,
 584 which groups the data into 100-millisecond intervals. This adjustment means that each bin now represents a
 585 100 ms passage of time. We specify time as the variable to base these bins on, allowing us to focus on broader
 586 patterns over time rather than individual millisecond fluctuations. There is no agreed upon downsampling
 587 value, but with webcam data larger bins are preferred (see Slim & Hartsuiker, 2023).

588 In addition, the `downsample_gaze()` allows you to aggregate across other variables, such as
 589 `condition`, `condition1`, and use the newly created `time_bins` variable, which represents the time in-
 590 tervals over which we aggregate data. The resulting downsampled dataset, output as Table 5, provides a
 591 simplified and more 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"))
```

592 To simplify the analysis, we combine the two unrelated conditions and average them (this is for the
 593 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")))

```

594 The above will not include the subject variable. If you want to keep participant-level data we need
 595 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"))

```

596 *Upsampling*

597 Users may wish to upsample their data rather than downsample it. This is standard in some prepro-
 598 cessing pipelines in pupillometry (Kret & Sjak-Shie, 2018) and has recently been applied to webcam-based
 599 eye-tracking data (Madsen et al., 2021). Like downsampling, upsampling standardizes the time intervals
 600 between samples; however, it also increases the sampling rate, which can produce smoother, less noisy data.
 601 This is useful if you want to align webcam eye-tracking with other measures (e.g., EEG).

602 Our `webgazeR` package provides several functions to assist with this process. The
 603 `upsample_gaze()` function allows users to upsample their gaze data to a higher sampling rate (e.g., 250
 604 Hz or even 1000 Hz). After upsampling, users can apply the `smooth_gaze()` function to reduce noise
 605 (`webgazeR` uses a n-point moving average) followed by the `interpolate_gaze()` function to fill in miss-
 606 ing values using linear interpolation. Below we show you how to use the function, but do not apply to the
 607 data.

```

AOI_upsample <- AOI %>%
  group_by(subject, trial) %>%
  upsample_gaze(
    gaze_cols = c("x", "y"),
    upsample_pupil = FALSE,
    target_hz = 250)

```

```

AOI_smooth=smooth_gaze(AOI_upsample, n = 5, x_col = "x", y_col = "y",
                         trial_col = "trial", subject_col = "subject")

```

```

aoi_interp <- interpolate_gaze(deduplicated_data,x_col = "x_pred_normalised",
                                ← y_col = "y_pred_normalised",
                                trial_col = "trial", subject_col = "subject",
                                ← time_col="time" )

```

608 Aggregation

609 Aggregation is an optional step. If you do not plan to analyze proportion data, and instead want time
 610 binned data with binary outcomes preserved please set the `aggvars` argument to “none.” This will return a
 611 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")

```

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

```

# make only one unrelated condition
gaze_sub_id <- gaze_sub_id %>%
  mutate(condition1 = case_when(
    condition1 %in% c("unrelated", "unrelated2") ~ "unrelated",
    TRUE ~ condition1
  )) %>%
  group_by(subject, trial, time_bin, condition, condition1) %>%
  summarise(Looks = as.integer(any(Looks == 1)), .groups = "drop")

```

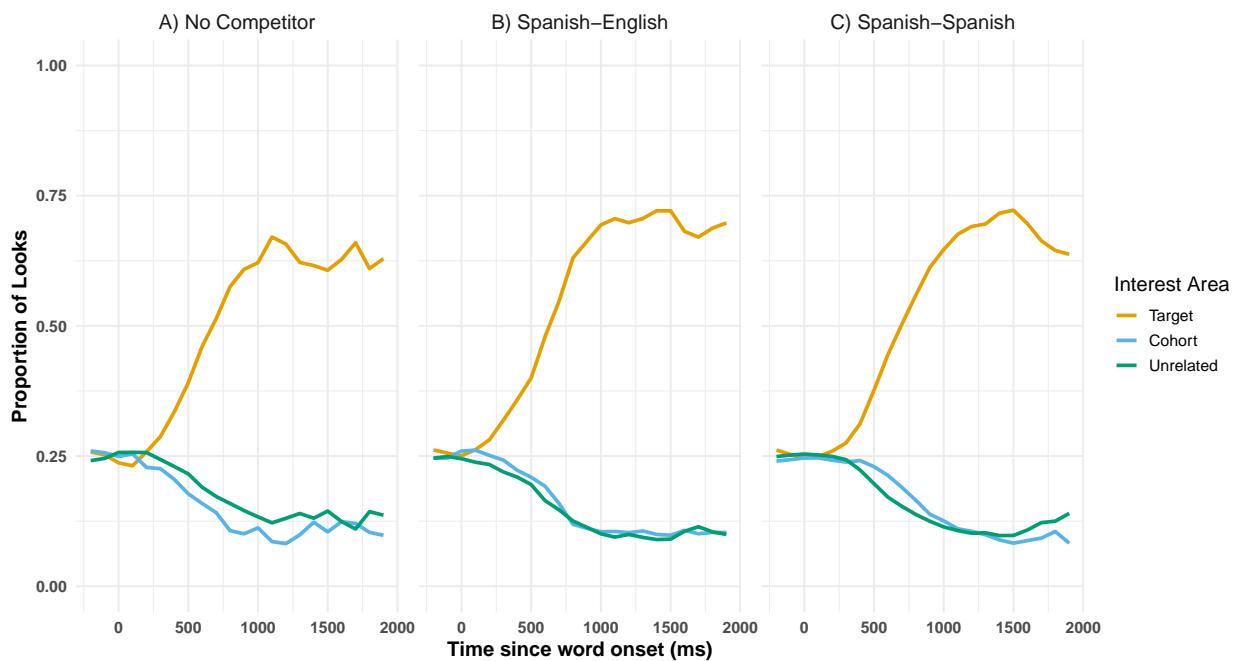
613 Visualizing Time Course Data

614 To simplify plotting your time-course data, we have created the `plot_IA_proportions()` function.
 615 This function takes several arguments. The `ia_column` argument specifies the column containing
 616 your AOI labels. The `time_column` argument requires the name of your time bin column, and the
 617 `proportion_column` argument specifies the column containing fixation or look proportions. Additional
 618 arguments allow you to specify custom names for each IA in the `ia_mapping` argument, enabling you to
 619 label them as desired. In order to use this function, you must use the `downsample_gaze()` function.

620 Below, we have plotted the time-course data for each condition in Figure 7. By default, the graphs
 621 utilize a color-blind-friendly palette from the `ggokabeito` package (Barrett, 2021). However, you can set
 622 the argument `use_color = FALSE` to generate a non-colored version of the figure, where different line types
 623 and shapes differentiate conditions. Additionally, since these are `ggplot` objects, you can further customize
 624 them as needed to suit your analysis or presentation preferences.

Figure 7

Comparison of L2 competition effect in the No Competitor (a), Spanish–English (b), the Spanish–Spanish (c) conditions



625 Gorilla Provided Coordinates

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

630 We will use the function `extract_aois()` to get the standardized coordinates for each quadrant on
 631 screen. You can use the `zone_names` argument to get the zones you want to use. In our example, we want the
 632 TL, BR, BL TR coordinates. We input the object from above `vwp_paths_filtered_L2` that contains all our
 633 eye-tracking files and extract the coordinates we want. These are labeled in Table 6. In Figure 8 we can see
 634 that the AOIs are a bit smaller than then when using the quadrant approach. We can take these coordinates
 635 and use them in our analysis. Looking at Figure 9, we see the data is a bit noisier than the quadrant approach,
 636 but the curves are reasonable.

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

Table 6

Gorilla provided standardized 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

```
#| echo: false

aois_L2 %>%
  flextable() %>%
  fontsize(size = 12) %>% # Reduce font size
  padding(padding = 0) %>%
  font(fontname = "Times New Roman", part = "all") %>%
  set_table_properties(layout="autofit") %>% # Reduce padding inside cells
  autofit() %>%
  theme_apa()
```

```
assign_L2_gor <- webgazeR:::assign_aoi(dat_colnames_L2,X="x", Y="y",aoi_loc =
  ↳ aois_L2)
```

637 Modeling Data

638 Once the data have been preprocessed, the next step is analysis. A variety of analytic approaches are
 639 available for VWP data, including growth curve analysis (GCA), cluster permutation analysis (CPA), gen-
 640 eralized additive mixed models (GAMMs), logistic multilevel models, and divergent point analysis (DPA).
 641 Fortunately, there is a wealth of excellent resources and tutorials demonstrating how to apply these methods
 642 to both lab-based (Coretta & Casillas, 2024; see Ito & Knoeferle, 2023; Mirman & CRC Press., n.d.; Seedorff
 643 et al., 2018; Stone et al., 2021) and online (see Bramlett & Wiener, 2024) visual world eye-tracking data.

644 This paper's goal, however, is to not evaluate different analytic approaches and tell readers what they
 645 should use. All methods have their strengths and weaknesses (see Ito & Knoeferle, 2023). Nevertheless,
 646 statistical modeling should be guided by the questions researchers have and thus serious thought needs to be
 647 given to the proper analysis. In the VWP, there are two general questions one might be interested in: (1) Are

Figure 8

Gorilla provided standardized coordinates for the four quadrants on the screen

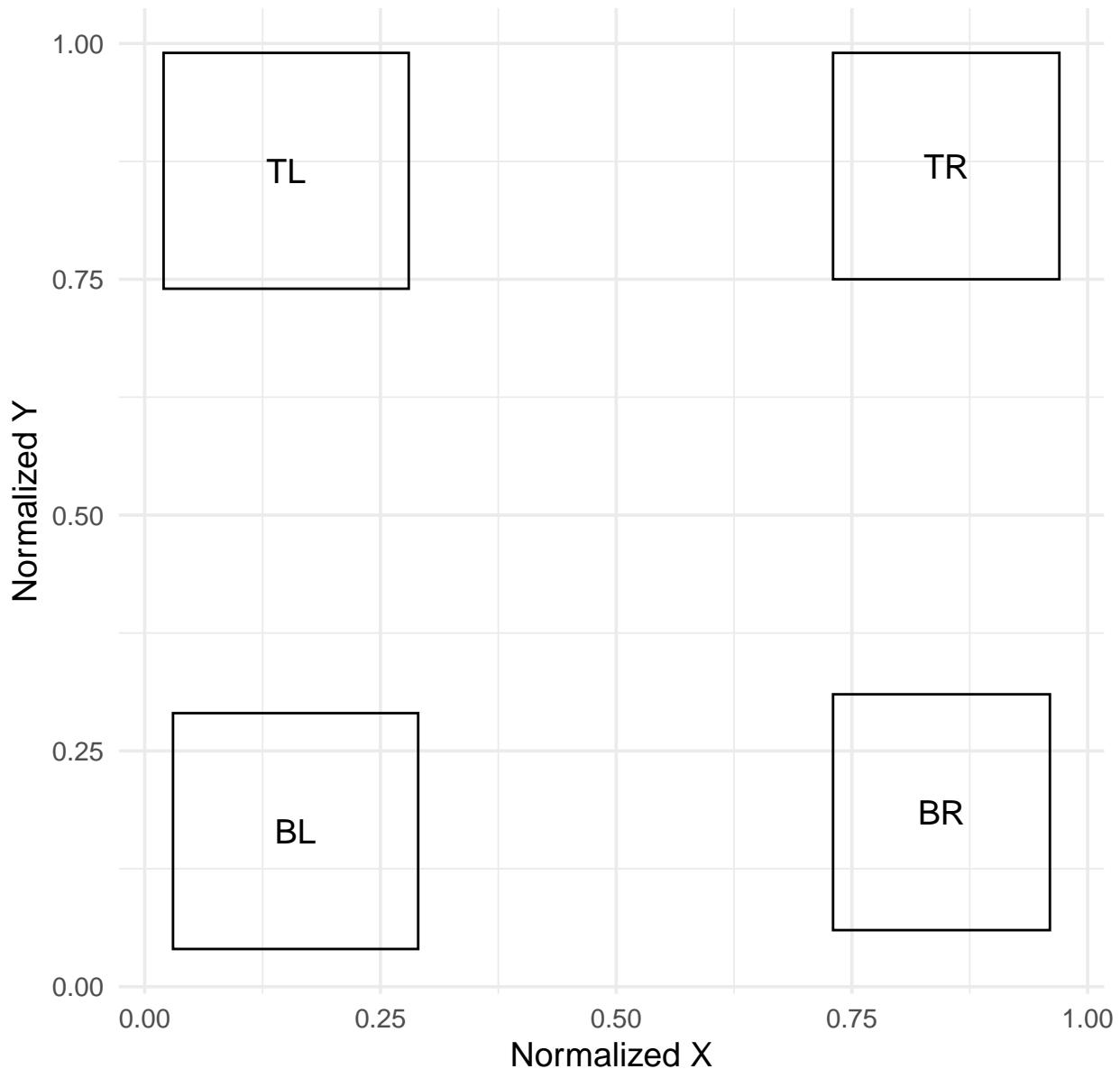
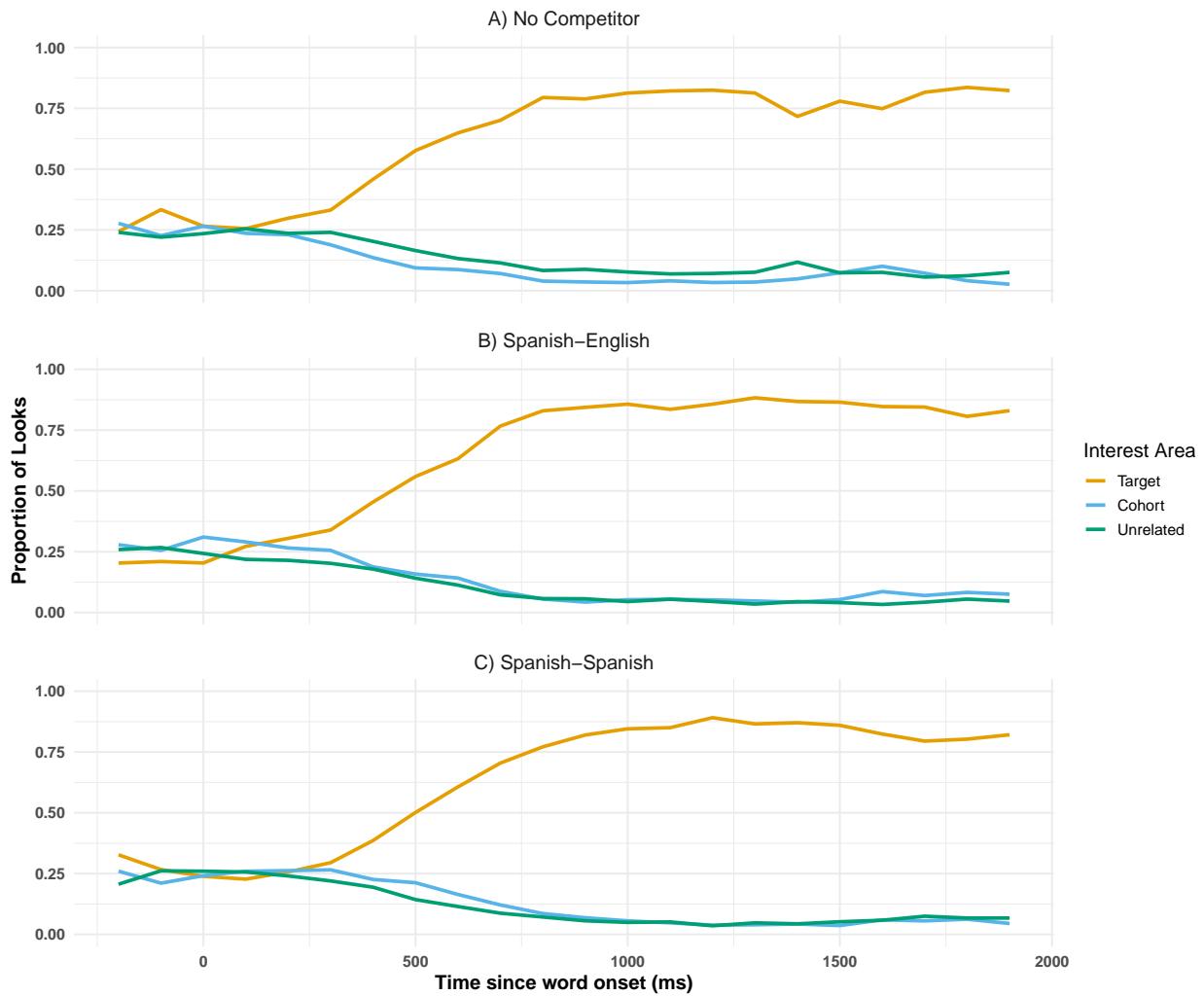


Figure 9

Comparison of competition effects with Gorilla standardized coordinates



648 there any overall difference in fixations between conditions and (2) Are there any time course differences in
649 fixations between conditions (and/or groups).

650 With our data, one question we might want to answer is if there are any fixation differences between
651 the cohort and unrelated conditions across the time course. One statistical approach we chose to highlight
652 to answer this question is a cluster permutation analysis (CPA). The CPA is suitable for testing differences
653 between two conditions or groups over an interest period while controlling for multiple comparisons and
654 autocorrelation. Given the time latency issues common in webcam-basted studies, Slim et al. (2024) recom-
655 mended using an approach like CPA.

656 CPA

657 CPA is a technique that has become increasingly popular, particularly in the field of cognitive neu-
658 ropsychology, for analyzing MEG and EEG data (Maris & Oostenveld, 2007). While its adoption in VWP
659 studies has been relatively slow, it is now beginning to appear more frequently (see Huang & Snedeker, 2020;
660 Ito & Knoeferle, 2023). Notably, its use is growing in online eye-tracking studies (see Slim et al., 2024; Slim
661 & Hartsuiker, 2023; Vos et al., 2022).

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

665 The clustering procedure involves three main steps:

- 666 1. Cluster Formation: With our data, a multilevel logistic model is conducted for every data point (con-
667 dition by time). Please note that any statistical test can be run here. Adjacent data points that surpass
668 the mass univariate significance threshold (e.g., $p < .05$) are combined into clusters. The cluster-
669 level statistic, typically the sum of the t-values (or F-values) within the cluster, is computed labeled
670 as SumStatistic is output below). By clustering adjacent significant data points, this step accounts for
671 autocorrelation by considering temporal dependencies rather than treating each data point as indepen-
672 dent.
- 673 2. Null Distribution Creation: Next, the same analysis is run as in step 1. However, the analysis is based
674 on randomly permuting or shuffling the conditions within subjects. This principle of exchangeability is
675 important here, as it suggests that the condition labels can be exchanged without altering the underlying
676 data structure. This randomization is repeated n times (e.g., 1000 shuffles), and for each permutation,
677 the cluster-level statistic is computed. This step addresses the issue of multiple comparisons by con-
678 structing a distribution of cluster-level statistics under the null hypothesis, providing a baseline against
679 which observed cluster statistics can be compared. By doing so, the method controls the family-wise
680 error rate and ensures that significant findings are not simply due to chance.
- 681 3. Significance Testing: The cluster-level statistics from the observed (real) comparison is compared to
682 the null distribution we created above. Clusters with statistics falling in the highest or lowest 2.5% of
683 the null distribution are considered significant (e.g., $p < 0.05$).

684 To perform CPA, we will load in the `permutes` (Voeten, 2023) and `permuco` (Frossard & Renaud,
685 2021) packages in R. Loading these packages allow us to use the `cluster.glmer()` function to run a cluster
686 permutation (10,000 is ideal) across multiple system cores to speed up the process. We run a CPA on the
687 `gaze_sub_id` object where each row in `Looks` denotes whether the AOI was fixated, with values of zero
688 (not fixated) or one (fixated).

689 Below you find sample code to perform multilevel CPA in R (please see the Github repository for
690 elaborated code needed to perform CPA).

Table 7

Clustermass statistics for the Spanish-Spanish condition

cluster	cluster_mass	p.cluster_mass	bin_start	bin_end	t	sign	time_start	time_end	
1	236.34		0	7	13	5.48	1	500	1,100

```
library(permutes) # cpa
library(permuco) # cpa

total_perms <- 1000

cpa.lme <- permutes::clusterperm.glmer(Looks~ condition1_code + (1|subject) +
  ~ (1|trial), data=gaze_sub_L2_cp1, series.var=~time_bin, nperm = total_perms)
```

In the analysis for the Spanish-Spanish condition, one significant cluster was observed between 500 and 1,100 ms, as indicated in the summary statistics from Table 7. The positive SumStatistic value associated with this cluster suggests that competition was greater during this time window. This result implies that cohorts in the Spanish-Spanish condition exhibited stronger effects or competition compared to unrelated items. In Figure 10 significant clusters are highlighted for both the Spanish-Spanish and Spanish-English conditions. Both conditions show one significant cluster. Overall, the analysis suggests that both the Spanish-Spanish and Spanish-English conditions demonstrate significant competitor effects.

Effect Size. It is important to address the issue of effect sizes in the context of CPA. Calculating effect sizes for CPA is not straightforward, as the technique is designed to evaluate temporal clusters rather than individual time points. (Slim et al., 2024; but also see Meyer et al., 2021) outline three possible approaches for estimating effect sizes in CPA: (1) computing the effect size within a predefined time window (often the same window used for identifying clusters), (2) calculating an average effect size across the entire cluster, and (3) reporting the maximum effect observed within the cluster. Each method has its trade-offs in terms of interpretability and comparability across studies, and the choice should be guided by theoretical considerations and the research question at hand.

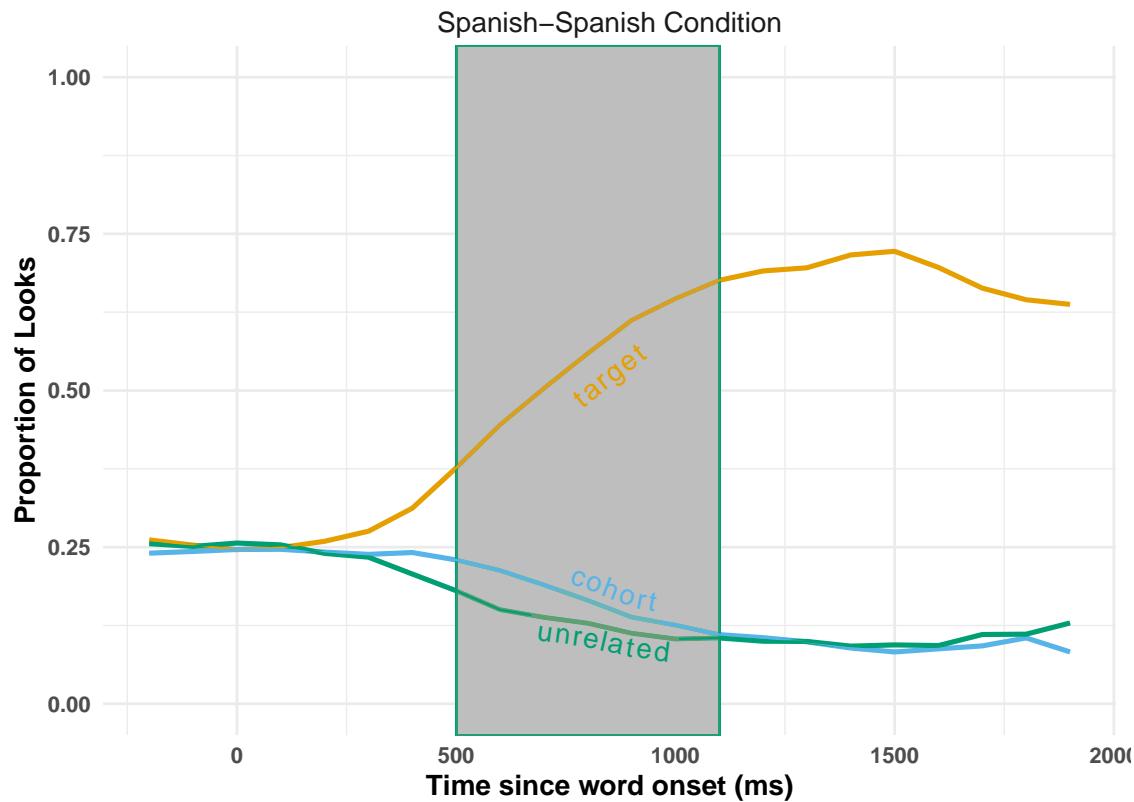
Discussion

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

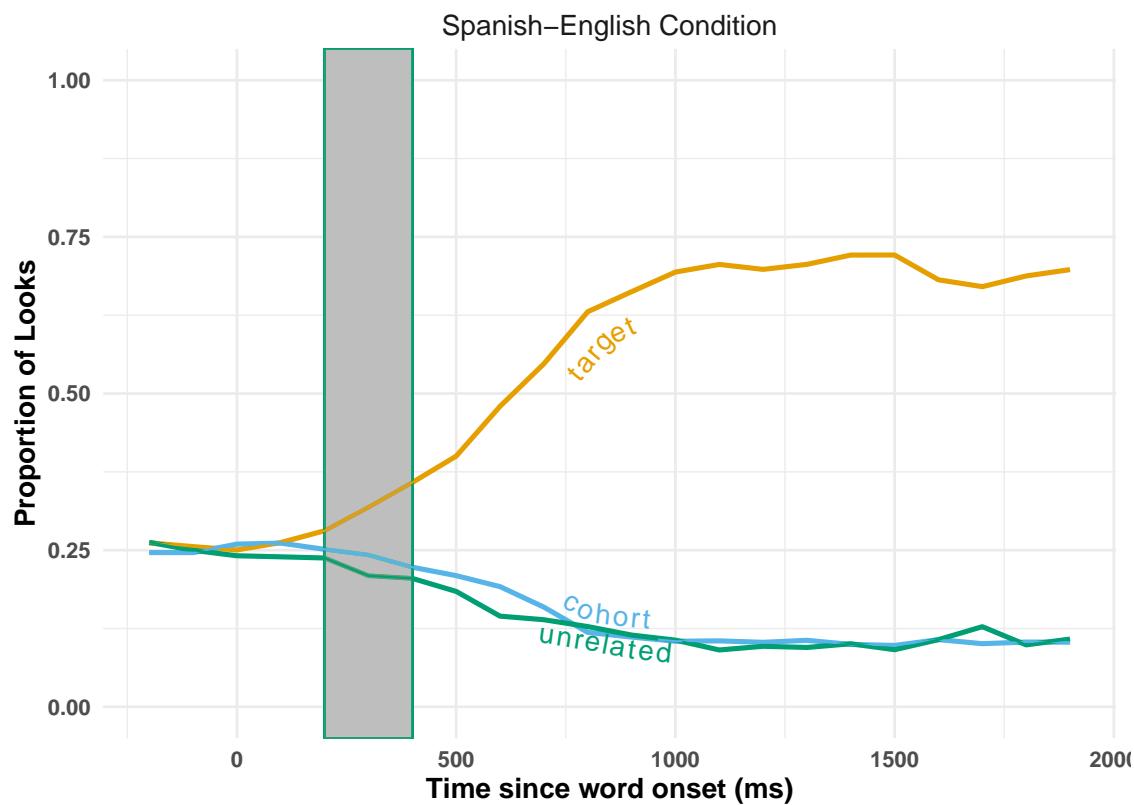
Figure 10

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.

A



B



712 In this tutorial, we covered the basic steps of running a visual world webcam-based eye-tracking
713 experiment. We highlighted these steps by using data from a cross-linguistic VWP looking at competitive
714 processes in L2 speakers of Spanish. Specifically, we attempted to replicate the experiment by Sarrett et al.
715 (2022) where they observed within- and between L2/L1 competition using carefully crafted materials.

716 **Replication of Sarrett et al. (2022)**

717 While the main purpose of this tutorial was to highlight the steps needed to analyze webcam eye-
718 tracking data, replicating Sarrett et al. (2022) allowed us to not only assess whether within and between
719 L2/L1 competition can be found in a spoken word recognition VWP experiment online, but also provide
720 insight in how to run VWP studies online and the issues associated with it.

721 Our conceptual replication yielded highly encouraging results, revealing robust competition effects
722 both within-language (Spanish-Spanish) and across-language (Spanish-English) conditions—closely mir-
723 roring those reported by Sarrett et al. (2022). However, several key analytic, methodological, and sample
724 differences between our study and theirs warrant discussion.

725 A major analytic difference lies in how the time course of competition was examined. While Sarrett
726 et al. (2022) employed a non-linear curve-fitting approach (see McMurray et al., 2010), we used cluster-
727 based permutation analysis (CPA). This methodological distinction limits direct comparisons regarding the
728 temporal dynamics of competition. Nonetheless, the overall time course patterns align surprisingly well: our
729 CPA identified a significant cluster starting at 500 ms, while Sarrett et al. (2022) observed effects beginning
730 around 400 ms—suggesting a modest delay of approximately 100 ms in our online data. This delay is still
731 markedly smaller than in previous webcam-based studies (e.g., Semmelmann & Weigelt, 2018; Slim et al.,
732 2024), reflecting progress in online eye-tracking. That said, it's important to note that CPA is not ideally
733 suited for making precise temporal inferences about onset or offset of effects (Fields & Kuperberg, 2019; Ito
734 & Knoeferle, 2023).

735 Design differences between the studies also play a critical role. In Sarrett et al. (2022), participants
736 previewed the images in each quadrant for 1000 ms, followed by the appearance of a central red dot they
737 clicked to trigger audio playback. After selecting the target, a 250 ms inter-trial interval (ITI) preceded the
738 next trial.

739 In contrast, our sequence began with a 500 ms fixation cross (serving as the ITI), followed by a longer
740 1500 ms preview. The images then disappeared, and participants clicked a centrally placed start button to
741 initiate audio playback, at which point the images reappeared. Upon target selection, the next trial began
742 immediately. We also imposed a 5-second timeout for non-responses. Additionally, our study included 250
743 trials—fewer than the 450 in the original study²—but still more than most webcam-based research. Despite
744 the reduced trial count, we observed parallel competition effects in both language conditions, underscoring
745 the robustness of the findings.

²The curve-fitting approach used by Sarrett et al. (2022) may have required a larger number of trials to obtain reliable fits. Their study included over 400 trials, while our design was more constrained.

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?

746 Several motivations guided these design adaptations. Online testing introduces greater variability in
 747 participants' setups (e.g., device type, connection quality), so we opted for a longer preview period to enhance
 748 the likelihood of observing competition effects. Prior work suggests this can boost competition signals in
 749 the VWP (Apfelbaum et al., 2021). The start-button mechanism ensured trials began from a centralized
 750 gaze position, helping minimize quadrant-based bias. Finally, the timeout feature helped mitigate issues of
 751 inattention common in unsupervised online environments.

752 Participant recruitment also differed. Sarrett et al. (2022) recruited students from a Spanish language
 753 course and assessed proficiency using the LexTALE-Spanish test (Izura et al., 2014). Our participants were
 754 recruited through Prolific with more limited screening, allowing us only to filter by native language and
 755 reported experience with another language. This constraint likely contributed to differences in language
 756 profiles between samples. Whereas Sarrett et al. (2022) included L2 learners with verified proficiency, our
 757 sample encompassed a broader and more variable group of L2 speakers, with limited verification of language
 758 skills (see Table 1 for details). This broader variability may help explain the absence of a sustained cohort
 759 competition effect in our study.

760 In sum, while there are notable differences in methods and samples, the convergence of competi-
 761 tion effects across both studies—within and across languages—supports the robustness of these phenomena
 762 across diverse research contexts. Still, we view these results as a promising step rather than definitive evi-
 763 dence. A more systematic investigation is needed to fully establish the generalizability of these effects.

Table 9

Responses to eye-tracking questions for participants who successfully calibrated (good) vs. participants who had trouble calibrating (bad)

Question	Response	Good	Bad
1.Do you have a history of vision problems (e.g., corrected vision, eye disease, or drooping eyelids)?	No	65.71	64.29
1.Do you have a history of vision problems (e.g., corrected vision, eye disease, or drooping eyelids)?	Yes	34.29	35.71
2.Are you on any medications currently that can impair your judgement?	No	100.00	98.21
2.Are you on any medications currently that can impair your judgement?	Yes	0.00	1.79
4.Does your room currently have natural light?	No	40.00	26.79
4.Does your room currently have natural light?	Yes	60.00	73.21
5.Are you using the built in camera?	No	14.29	8.93
5.Are you using the built in camera?	Yes	85.71	91.07
9.Was the environment you took the experiment in distraction free?	No	11.43	3.57
9.Was the environment you took the experiment in distraction free?	Yes	88.57	96.43

764 **Limitations**

765 ***Recruitment of L2 Speakers***

766 In this study, we used the Prolific platform to recruit L2 Spanish speakers. We specified criteria
767 requiring participants to be native English speakers who were also proficient in Spanish, reside in the United
768 States, and be between the ages of 18 and 36. These criteria yielded a potential recruitment pool of approx-
769 imately 1,000 participants. While this number is larger than what is typically available for in-lab studies, it
770 is still relatively limited given the overall size of the platform. Notably, English native speakers who are L2
771 learners of Spanish in the U.S. are not usually considered a particularly niche population, which highlights
772 the extent of the recruitment difficulty. Participant pools are likely to be even more limited when targeting
773 speakers of less commonly studied languages or with specific language backgrounds (e.g. heritage speakers).
774 Moreover, Prolific currently supports only an English user interface, which makes it harder to recruit non-
775 English speakers (Niedermann et al., 2024; Patterson & Nicklin, 2023). For second language research in
776 particular, researchers should be aware of these and other constraints (such as the limited filtering options to
777 control for proficiency) and consider incorporating language background questionnaires and/or proficiency
778 tasks directly into the study design. Ultimately, 181 participants signed up for the study, and recruitment
779 proved to be more challenging than expected. Researchers considering similar studies should be aware of
780 these limitations when targeting niche populations, even on large online platforms. Despite these challenges,
781 the final sample was sufficient for our planned analyses and opened up the possibility to target populations
782 you would be unable to capture otherwise.

783 ***Generalizability to Other Platforms***

784 We demonstrated how to analyze webcam eye-tracking data collected via the Gorilla platform using
785 WebGazer.js. Although we did not validate this pipeline on other platforms that support WebGazer.js—
786 such as PCIbex (Zehr & Schwarz, 2018), jsPsych (Leeuw, 2015), or PsychoPy (Peirce et al., 2019)—we
787 believe the pipeline is generalizable to these and to platforms that use other gaze estimation logarithms,
788 such as Labvanced (Kaduk et al., 2024). To support broader compatibility, the functions in the webgazeR
789 package are designed to work with a variety of file types—including .csv, .tsv, and .xlsx—and work with any
790 dataset that includes five essential columns: subject, trial, x, y, and time. We also provide a helper function,
791 `make_webgazer()`, to assist in renaming columns so your dataset can be adapted to the expected format.

792 We encourage researchers to test this pipeline in their own studies and report any issues or suggestions
793 on our GitHub repository. We are committed to improving webgazeR and welcome feedback that will make
794 the package more flexible, user-friendly, and adaptable to a wider range of experimental platforms.

795 ***Power***

796 While we successfully demonstrated competition effects similar to Sarrett’s study, we did not conduct
797 an a priori power analysis nor was it our intention. With webcam eye-tracking, it has been recommended
798 running twice the number of participants from the original sample, or powering the study to detect an effect

799 size half as large as the original (Slim & Hartsuiker, 2023; Van der Cruyssen et al., 2024). We did attempt
800 to increase our sample size 2x, but were unable to recruit enough participants through Prolific. However,
801 our sample size is similar to the lab based study. Regardless, researchers should be aware of this and plan
802 accordingly.

803 We strongly urge researchers to perform power analyses and justify their sample sizes (Lakens, 2022).
804 While tools like G*Power (Faul et al., 2007) are available for this purpose, we recommend power simulations
805 using Monte Carlo or resampling methods on pilot or sample data (see Prystauka et al., 2024; Slim & Hart-
806 suiker, 2023). Several excellent R packages, such as `mixedpower` (Kumle et al., 2021) and `SIMR` (Green &
807 MacLeod, 2016) make such simulations straightforward and accessible.

808 **Recommendations and Ways Forward**

809 While our findings support the promise of webcam eye-tracking for language research, several chal-
810 lenges remain that researchers should consider. One of the most significant issues is data loss due to poor
811 calibration. In our study, we excluded approximately 75% of participants due to calibration failure. These
812 attrition rates are in line with some previous reports (e.g., Slim & Hartsuiker, 2023), though others have
813 found substantially lower rates (Bramlett & Wiener, 2025; Prystauka et al., 2024). With this valuation, it is
814 important to understand the factors that lead to better quality data.

815 To address this, we included a post-task questionnaire assessing participants' setups and their experi-
816 ences with the experiment. These questions, included in Table 8, provide insights that informed the following
817 recommendations, which we also base on our experimental design and personal experience.

818 In our experimental design, participants were branched based on whether they successfully com-
819 pleted the experiment or failed calibration at any point. Table 9 highlights the comparisons between good
820 and poor calibrators. For the sake of brevity, we will discuss some recommendations based on questionnaire
821 responses and personal experience that will hopefully improve research using webcam eye-tracking.

822 **Prioritize External Webcams**

823 Our data suggest that participants using external webcams were significantly more likely to complete
824 the calibration successfully than those using built-in laptop cameras. External webcams typically offer higher
825 resolution and frame rates—both critical for accurate gaze estimation (Slim & Hartsuiker, 2023). Researchers
826 should, whenever possible, encourage participants to use external webcams and may consider administering
827 a brief pre-experiment questionnaire to screen for webcam type and exclude low-quality setups.

828 **Optimize Environmental Conditions**

829 Poor calibration was often reported in environments with natural light. Ambient lighting introduces
830 variability that can degrade tracking performance. We recommend that researchers instruct participants to
831 complete studies in rooms with consistent artificial lighting and minimal glare or shadows.

In addition to lighting, head movement and distance from the screen are critical for achieving reliable eye-tracking. Excessive movement or leaning in and out of the camera's view can disrupt the face mesh tracking used by WebGazer.js. Participants should be advised to remain still and maintain a consistent, moderate distance from the screen—approximately 50–70 cm, depending on their camera setup. We asked individuals to provide an approximate distance from their screens (arms length) but it is not clear how accurate this is. Providing clear guidance (e.g., via an instructional video) may help mitigate these issues and improve overall tracking fidelity.

A different platform, Labvanced (Kaduk et al., 2024) offers additional eye-tracking functionality including a virtual chinrest to ensure head movement is restricted to an acceptable range and warns users if they deviate from this range. Together this might make for a better eye-tracking experience with less data thrown out. This should be investigated further.

843 *Conduct a Priori Power Analysis*

To ensure adequate statistical power, researchers should conduct a priori power analyses either via GUI like GPower or perform Monte Carlo simulations/resampling on pilot data. This step is particularly important for online studies, where sample variability can be higher than in controlled lab environments. To this point, you will have to over-enroll your study due to the high attrition rate to reach your target goal, so please plan accordingly.

849 *Collect Detailed Post-Experiment Feedback*

Gathering detailed feedback about participants' setups—such as webcam type, browser, lighting conditions, and perceived ease of use—can provide valuable information about what contributes to successful calibration. These insights can inform more effective participant instructions and refined inclusion criteria for future studies.

By implementing these strategies, researchers can improve the quality and consistency of data collected through webcam-based eye-tracking. These recommendations aim to maximize the utility and reproducibility of remote eye-tracking research, particularly in language processing contexts.

857 *Conclusions*

This work highlights the steps required to process webcam eye-tracking data, demonstrating the potential of webcam-based eye-tracking for robust psycholinguistic experimentation. By providing a standardized pipeline for processing eye-tracking data, we aim to give researchers a clear and practical path for collecting and analyzing visual world webcam eye-tracking data. An interactive demo of the preprocessing pipeline—using data from a monolingual VWP—is available at the webgazeR website (https://jgeller112.github.io/webgazeR/vignettes/webgazeR_vignette.html), where users can explore the code and workflow firsthand.

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

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