

Can we use masked priming in an online setting?

The effect of prime exposure duration in online masked priming lexical decision

Bernhard Angele^{1,2}, Ana Baciero^{2,3}, Pablo Gómez⁴, & Manuel Perea^{2,5}

¹ Bournemouth University, Bournemouth, UK

² Universidad Antonio de Nebrija, Madrid, Spain

³ DePaul University, Chicago, USA

⁴ California State University San Bernardino, Palm Desert Campus, USA

⁵ Universitat de València, Valencia, Spain

Author Note

This research has been partly supported by Grants...

Correspondence concerning this article should be addressed to Bernhard Angele,
Department of Psychology, Faculty of Science and Technology, Talbot Campus, Fern Barrow,
Poole BH12 5BB, UK. E-mail: bangele@bournemouth.ac.uk

Abstract

Masked priming is one of the most important paradigms in the study of visual word recognition, but it is usually thought to require a laboratory setup with a known monitor and keyboard. To test if this technique can be used in an online setting, we conducted two online masked priming lexical decision task experiments using PsychoPy/PsychJS (Peirce et al., 2019). Importantly, we also tested the role of prime exposure duration effectively in an online experiment (33.3 vs. 50 ms in Experiment 1 and 16.7 vs. 33.3 ms in Experiment 2). We found that our online data are indeed very similar to the masked priming data reported by Gomez et al. (2013). Additionally, we found a clear effect of prime duration, with the priming effect (measured in terms of response time and accuracy) being stronger at 50 ms than 33.3 ms and no priming effect at 16.7 ms prime duration. From these results, we can conclude that modern online browser-based experimental psychophysics packages (e.g., PsychoPy) can present stimuli and collect responses on standard end user devices with enough precision. In sum, these findings provide us with confidence that masked priming can be used online, thus allowing us to reach populations that are difficult to test in a laboratory.

Keywords: Masked priming, Lexical decision task, Online experiments, PsychoPy, Prime duration

Word count: XXXXX

Can we use masked priming in an online setting?

The effect of prime exposure duration in online masked priming lexical decision

Masked priming (Forster & Davis, 1984) is one of the most important techniques to study the effects of orthography, phonology, morphology, and meaning in visual word recognition (see Forster, 1998; and Grainger, 2008, for reviews). Priming refers to the influence of a prime stimulus (e.g., *nurse*, *horse*) on a subsequently presented stimulus that the participant has to respond (e.g., “is *DOCTOR* a word?”). It is measured as the difference in a dependent variable (e.g., response time [RT]) between two conditions (e.g., unrelated: *horse-DOCTOR*; related: *nurse-DOCTOR*). In masked priming, the prime stimulus is presented very briefly (for less than 60 ms) and is itself preceded by a pattern mask (e.g., #####) for a much longer duration (typically 500 ms). The rationale of the procedure is to make participants unaware of the identity of the masked prime (Forster, 1998; Forster & Davis, 1984), thus minimizing the role of participants’ strategies. Indeed, masked priming experiments do not show the strategic effects that occur with visible, unmasked primes (e.g., Grossi, 2006; Perea & Rosa, 2002).

The masked priming paradigm has been used in a large number of studies over the last decades. For instance, a search of the expression “masked priming” in Google Scholar in May 2021 produced more than 10,000 hits. Nearly all masked priming experiments have been run in a laboratory setting, often using the DMDX software developed by Forster and Forster (2003). The issue we examine in the present paper is whether masked priming experiments can be safely conducted in an online setting. Even before the exceptional situation due to the COVID pandemic in 2020-21, in which many labs around the world were closed (or with minimal activity) for many months, online data collection has shown its many advantages: 1) easy access to a much more diverse population than that accessible at the typical university research laboratory; 2) independence from laboratory space constraints, and, often, lower costs as participants only need to be compensated for their time on the experiment; 3) no

time spent commuting, waiting for the experiment to start, etc. Indeed, researchers in decision making and economics have been using online paradigms for several decades now (e.g., Birnbaum & Birnbaum, 2000; Paolacci et al., 2010).

However, cognitive psychologists have been much slower in taking up online paradigms (see Brysbaert et al., 2016; Cai et al., 2017; Eerland et al., 2013; Rodd et al., 2016, for some exceptions), often due to concerns about the validity of the results. Such concerns are not limited to cognitive studies (see Aust et al., 2013), but they are exacerbated by the reliance on precise presentation times in cognitive psychology. Furthermore, in the masked priming technique, it is critical for the onset of the mask, the prime, and the target to occur at the nominal times. For instance, presenting the masked prime for longer than intended (e.g., 83 ms instead of the nominal 50 ms) would counteract the effect of the mask, making the prime consciously visible to the participant and possibly altering the processes of interest.

There have been attempts to address these concerns. Witzel et al. (2013) developed a Web version of DMDX (webDMDX) showing promising results in a trial experiment. However, webDMDX is a self-contained Windows executable file that participants have to download and run rather than a “true” online programming script that could be run inside of a browser. A downside of this format is that participants often are (and should be) understandably skeptical about downloading and running executable files from the Internet. Additionally, many participants may not have access to a Windows PC, or may be discouraged from participating by the extra work it takes to deploy the experiment on their computer. As a consequence, the use of webDMDX in masked priming experiments has been rather limited so far (see Alluhaybi & Witzel, 2020; Dubey et al., 2018, for exceptions).

Fortunately, in recent years, there have been significant improvements in how content can be presented on the World Wide Web. Most notably, the HTML5 standard now makes it possible to use Javascript in order to draw stimuli interactively and monitor participant responses with remarkable flexibility inside the browser. Participants do not have to install

any software, and the HTML5 standard is supported by a wide variety of devices, including mobile phones and tablets (Reimers & Stewart, 2015). There is now a variety of software packages taking advantage of the new capabilities to present experimental stimuli and collect data, both commercial, such as Gorilla (Anwyl-Irvine, Massonni, et al., 2020) or Testable (Rezlescu et al., 2020), and open-source such as jsPsych (de Leeuw, 2015) or PsychoJS (the Javascript version of PsychoPy 3, Peirce et al., 2019). In addition, online setups allow researchers to target any individual with an internet connection as a participant, from very different countries and backgrounds. Indeed, various on-line platforms (e.g., Prolific, Amazon Mechanical Turk) offer the possibility to recruit participants for on-line experiments based on various specific characteristics set up by the experimenter not necessarily in the country's lab (e.g., native French speakers, not older than 30 years old, not currently in college).

Of course, despite the technological advances, many cognitive psychologists still have concerns about timing and measurement precision. While Javascript-based experiments run on the participants' devices and thereby avoid any lag due to connection issues (e.g., to avoid delays, all stimuli are usually downloaded before the start of the experiment), experimenters have little control over which devices the experiment is run on beyond the option of explicitly preventing the experiment to run on specific device types such as mobile devices. Moreover, experimenters have no control at all over what other applications are running on the device, screen size and resolution, viewing distance, properties of the keyboard/touchscreen, etc., as all of these are determined by the device or the participants' preferences. As Reimers and Stewart (2015) point out, there are two ways of testing whether timing and response issues are problematic: (1) comparing a Web-based experiment directly with an established lab-based version by measuring presentation timings (using a photodiode) and response timings on various device configurations and (2) attempting to replicate existing lab-based findings using a Web-based paradigm. If the results of the Web-based study are comparable to previous lab-based results, this suggests that whatever the deviations in stimulus and response timing are, they are not severe enough to affect the

overall findings in the paradigm in question.

The first approach has the advantage that differences in presentation timings can be objectively recorded and evaluated. A very thorough recent example of this approach is the “timing mega-study” by Bridges et al. (2020), who compared the timing in experiments run in lab-based setups with the timing in online packages run in different browsers. The very similar study by Anwyl-Irvine, Dalmaijer, et al. (2020) compares only online packages and browsers with regard to timing. Overall, Bridges et al. (2020) found that online packages were capable of presenting visual stimuli with “reasonable” precision, although the lab-based packages were slightly better in this regard. This first approach is important in order to establish that a certain level of precision and accuracy can be achieved at all. If this is not possible, there is no point in moving forward to the second approach and replicating specific paradigms. However, it is of course impossible to test every possible device and configuration that participants might use. On the other hand, some of the differences in precision and accuracy between setups that can be observed using a photodiode may be too small to have an influence on actual participant performance. Therefore, we consider replication of previous key lab-based effects a more important test of online paradigms than photodiode measurements. Based on the results by Bridges et al. (2020) and Anwyl-Irvine, Dalmaijer, et al. (2020), modern Javascript-based stimulus presentation systems are capable of sufficiently fast and precise stimulus presentation. To establish whether masked priming studies can be successfully run online, the next step is now to follow the second approach and implement the masked priming paradigm online and test whether results obtained via in-lab studies can be replicated, which is at the heart of the present study. Importantly, we will do so using PsychoPy/PsychoJS (Peirce et al., 2019) as it showed high precision and accuracy across the great majority of platforms (Anwyl-Irvine, Dalmaijer, et al., 2020; Bridges et al., 2020), in addition to being an open-source software.

Specifically, in this study we were interested in whether we could replicate, and extend,

a key phenomenon in laboratory masked priming lexical decision using an online setup: masked identity priming is commonly described as a savings effect. As first suggested by Forster (1998), for a masked identity prime, “the lexical entry is already in the process of being opened, and hence the evaluation of this entry begins sooner,” whereas for an unrelated prime, “the entry for the target word would be closed down (since it fails to match the prime), and no savings would occur” (p. 213). Thus, according to the savings account, a target word like *DOCTOR* would enjoy an encoding advantage when preceded by an identity prime such as *doctor* than when preceded by an unrelated prime such as *pencil* (i.e., a head-start). One implication of such benefit is that the RT distributions of the unrelated and identity pairs should reflect a shift rather than a change in shape. Furthermore, this shift should be approximately similar in magnitude to the prime-target stimulus-onset asynchrony (SOA). Empirical evidence supporting this view has been obtained in several papers not only with skilled adults but also with developing readers (e.g., Gomez et al., 2013; Gomez & Perea, 2020; Taikh & Lupker, 2020; Yang et al., 2021). Moreover, this pattern of results fits very well with the diffusion model (Ratcliff et al., 2004). This model proposes that, when making a two-choice decision, the resultant RT can be explained as the sum of non-decision parameters, which are the encoding time and response execution (T_{er}) and decision parameters, which refer to the process of accumulation of information until a decision criteria is reached. Importantly, in the decision process, the information gathered from the stimulus can vary in noise, depending on its quality, which modifies the rate at which information is accumulated (i.e., the *drift rate*). With regards to RTs from masked priming tasks, Gomez et al. (2013) found that the difference between identity and unrelated conditions could be accounted by a change in the T_{er} parameter, while there were no differences across conditions in the parameter that corresponds to the quality of evidence gathered (i.e., drift rate)—note that changes in drift rate would necessarily produce a skewer RT distribution in the slower, unrelated condition.

Critically, the above pattern is *specific* to masked priming. When primes are visible

(i.e., unmasked priming), identity priming effects are stronger in the upper quantiles of the RT distribution than in the lower quantiles (i.e., a change in shape rather than a shift in RT distributions; see Gomez et al., 2013). Fits from the diffusion model show that this result corresponds to changes in both the T_{er} parameter and the drift rate (see Gomez et al., 2013). Hence, when the prime is visible, it does influence the quality of the information accumulated of the target word. Clearly, this dissociation between masked and unmasked priming reflects qualitative differences in the way primes affect the processing of the target: purely encoding in masked priming (with an expected effect close to the prime duration) vs. both encoding + information quality in unmasked priming.

In the present paper, we took advantage of the above marker to examine whether online masked priming studies follow the same pattern as in-lab masked priming studies. Specifically, we manipulated prime exposure duration in identity vs. unrelated primes: 33.3 vs. 50 ms in Experiment 1, and 16.7 vs. 33.3 ms in Experiment 2—note that targets were presented immediately after the primes (i.e., prime exposure duration was equal to the prime-target SOA). The rationale of Experiment 1 is that if the actual exposure duration of the primes is the nominal exposure duration, then we would expect the typical shift between the identity and unrelated response time distributions, which according to the savings hypothesis (Forster, 1998) would be greater for 50 ms than for 33.3 ms exposure duration (i.e., the head-start would be greater for 50 ms identity primes than for 33.3 ms identity primes). This outcome would indicate that the on-line masked priming studies reproduce a characteristic signature of laboratory masked priming studies. Alternatively, if the online presentation conditions lead to a greater actual exposure duration on the participant’s device compared to that specified in our experiment (e.g., if prime durations were, on average, 20 ms longer than intended), then the 50 ms primes may no longer be adequately masked, but may rather be consciously perceived. If this is the case, the prime could affect not only the encoding, but also core decision processes (i.e., the drift rate), which would be reflected as a stronger priming effect in the higher quantiles of the distribution (i.e., the two RT

distributions would have a different shape). In this scenario, one should be very cautious when running online masked priming experiments—at least with the typical software and hardware currently available.

To further constrain the research questions, Experiment 2 was designed to be analogous to Experiment 1, except for the use of a very short prime exposure duration (i.e., 16.7 ms). Similar prime exposure durations have shown very weak masked priming lexical decision experiments in a laboratory setting: smaller than 5 ms for a prime duration of 14 ms (Ziegler et al., 2000) and smaller than 9 ms for a prime duration of 20 ms (Tzur & Frost, 2007)—in the Tzur and Frost (2007) experiment, this difference increased to 16.7 ms when using a very high level of contrast in the computer screen. Thus, if the size of the priming effect is roughly similar to the prime exposure duration, we would expect a much larger priming effect at the 33.3 ms prime exposure duration than at the 16.7 ms prime exposure duration. If we do observe a large effect at the 16.7 ms prime exposure duration (e.g., above 20-25 ms), this would suggest, again, that there is a qualitative difference between using the masked priming technique in the laboratory and in online experiments. Keep in mind that we are using a software that has very good control over the exposure duration (Anwyl-Irvine, Dalmaijer, et al., 2020; Bridges et al., 2020). Figure 1 displays the link between all these verbal hypotheses, the process model that corresponds to each of them, and their predictions in the RT distributions.

All in all, replicating the results observed in controlled laboratory masked priming studies would provide some grounds to the validity of online masked priming tasks, even in a scenario with no control over many variables (e.g., the devices in which the experiment is run, or the additional applications that are running in the background of said device), as has been done with other paradigms that also require a high control of the presentation timing and location of the stimuli (e.g., Parker et al., 2021). Furthermore, the present experiments go beyond an online replication: they allow us to test masked priming effects not only across

conditions (identity vs. unrelated) but also within conditions (the effect of identity primes, or unrelated primes, across two prime durations) (e.g., Jacobs et al., 1995). Thus, the within-subject manipulation of prime exposure duration allows us to obtain the whole picture of priming effects—also including the examination of potential inhibitory effects of unrelated primes.

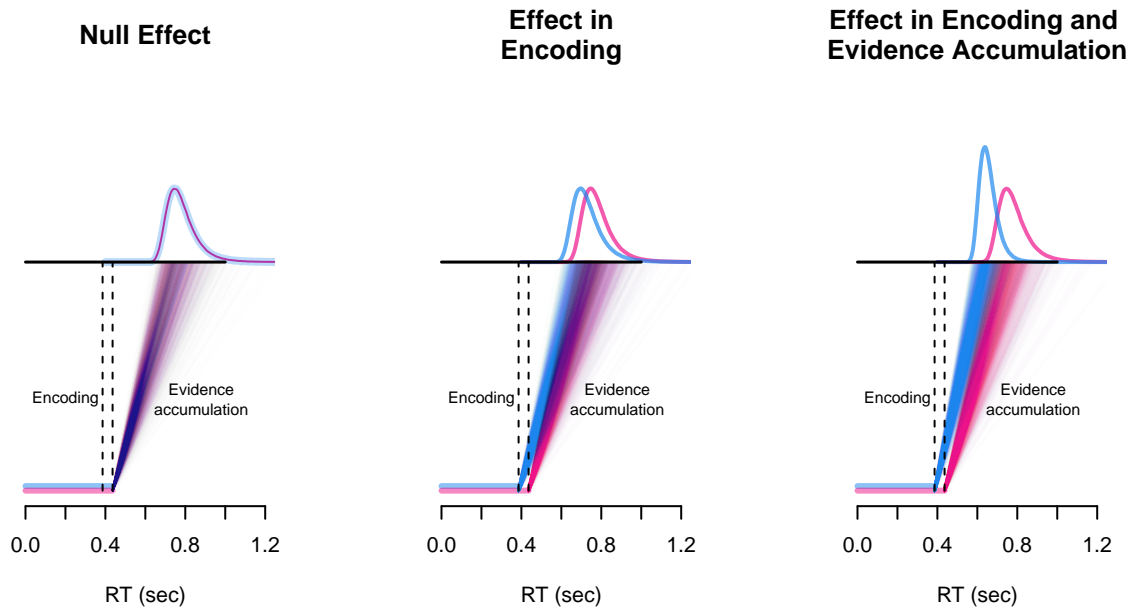


Figure 1. Mapping from hypotheses to data via evidence accumulation models. The bottom part of each graph represents sample paths, and the top part shows the cumulative density functions. From left to right: *Null Effect* - there are no differences between the conditions; *Effect in Encoding* - the difference between the conditions is on the encoding time, hence the RT distributions are shifted; and *Effect of Encoding and Evidence Accumulation* - the differences between the conditions is on the rate of evidence accumulation, thus increasing the effect size for longer RTs (right-tail of the distribution).

The study was pre-registered on the Open Science Framework (OSF) prior to data collection. The registration form, together with the materials, data files, and R scripts can be found at <https://osf.io/d2txs/>.

Experiment 1

In the first experiment, we tested whether we could observe reliable effects of masked priming at prime durations of 33.3 ms and 50 ms (roughly corresponding to two and three frames, respectively, at a refresh rate of 60 Hz).

We report here how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the two experiments.

Method

Participants. Participants were recruited through Prolific (www.prolific.co, 2021). The experiment was accessed by 101 participants. Out of these, 89 provided experimental data. Two of these participants did not complete the experiment. A further ten were excluded because of low accuracy (less than .8, which was the pre-registered criterion). In the end, we analyzed the data from 77 participants (36 female), aged from 18 to 71 (mean age: 31.14). All these participants indicated that English was their first language in the Prolific screening questions. Based on their IP addresses, 47 participants were based in the UK, 23 were based in the US, three participants were based in Canada, and two participants were based in Ireland. Two participants could not be localized in this way. All participants were naïve to the purpose of the experiment and received £1.25 for their participation (corresponding to £5/hour). Participants could use either a desktop/laptop computer or a mobile device. Because of a technical display issue with PsychoJS and the Safari browser, participants who tried to access the experiment using that browser, including all participants on iOS devices, were advised to change browser or device and restart the experiment.

Rationale for sample size and stopping rule. Brysbaert and Stevens (2018) recommended that masked priming experiments should have at least 1,600 observations per condition. In order to account for potentially smaller effect sizes in an online experiment, we set a target of 3,000 observations per condition (12,000 observations total), which

corresponds to a minimum of 50 participants given that there were 240 word stimuli in the experiment (see below). Our stopping rule was to keep collecting data until 3,000 valid observations were found. This goal was met and exceeded in our initial data collection with a budget of £200.

Materials. We selected 240 six-letter English words from the English Lexicon Project (Balota et al., 2007). The mean Zipf frequency based on the HAL corpus (Lund & Burgess, 1996) was 3.8 (range: 1.9–5.5). The mean OLD20 (Yarkoni et al., 2008) was 2.1 (range: 1.4–3). We also selected 240 matched, orthographically legal six-letter nonwords. For each target, we created an identical prime (e.g. *region* — *REGION* and *fainch* — *FAINCH*) and an unrelated prime consisting of another word from the list (e.g. *launch* — *REGION* and *miluer* — *FAINCH*). Appendix A contains a list of the items.

Procedure. Participants were able to sign up for the experiment on the Prolific website. On signing up, they were redirected to the participant agreement form on the Qualtrics online survey development environment (Qualtrics, 2020). After indicating their agreement to participate, participants were forwarded to Pavlovia (Pavlovia, 2020), where the actual lexical decision task was implemented in PsychoJS. In the experiment, all stimuli were presented in the center of the screen in black Courier New font on a white background. As we do not know the exact dimensions of each participant’s screen, all stimulus sizes and positions were defined in PsychoPy’s “height” units, with the bottom left of a 16:10 aspect ratio screen being represented as (-.8, -.5) and the top right being (.8, .5). The height for all text stimuli was 0.1 units. Each trial began with a six-character pattern mask (#####) set to be presented for 500 ms, followed first by the lowercase prime (e.g. *region*) set to be presented for either 33.3 or 50 ms, and then by the uppercase target (e.g. *REGION*). Participants were instructed to respond to the target stimulus as quickly as possible by pressing the “Z” key of their keyboard (if their device had one) if the target was not a valid English word or the “M” key if the target was a valid English word. Participants on a device without a keyboard were instructed to respond by touching one of two rectangular touch

areas labeled “Z = Non-word” (presented at -0.4, -0.3) and “M = Word” (presented at 0.4, -0.3). The touch areas each had a width of 0.4 and a height of 0.2 and were presented in white with a black outline. If participants did not respond within two seconds of the target onset, a “Too slow!” feedback message was shown for 500 ms and the trial ended. The experimental trials were preceded by 16 practice trials during which participants also received feedback on the accuracy of their responses. No feedback apart from the trial timeout feedback was given during the experimental trials. Every 120 trials, participants were asked to take a short break before continuing the experiment. After completing the experiment, participants were redirected to a debriefing form on Qualtrics and from there back to Prolific in order to receive their participation payment.

Data analysis. We analyzed the data by fitting Bayesian linear and generalized linear mixed models, using the *brms* package (Bürkner, 2017, 2018) in R (R Core Team, 2021)¹. We only analyzed trials where the target stimulus was a word. For the response time (RT) analysis, we excluded trials with RTs lower than 250 ms and incorrect responses (5.77 % of trials). For the accuracy analysis, we only excluded trials with RTs lower than 250 ms (0.28 % of trials). As the trials automatically ended after 2000 ms, there were no RTs longer than this. For both RTs and accuracy, we fitted a model with priming condition (unrelated vs. identical) and prime duration (33.3 ms vs. 50 ms) as well as their interaction as the fixed

¹ The full list of software we used for our analyses is as follows: R [Version 4.0.5; R Core Team (2021)] and the R-packages *bayestestR* [Version 0.9.0; Makowski et al. (2019)], *brms* [Version 2.15.0; Bürkner (2017); Bürkner (2018)], *dplyr* [Version 1.0.5; Wickham et al. (2021)], *forcats* [Version 0.5.1; Wickham (2021a)], *ggplot2* [Version 3.3.3; Wickham (2016)], *papaja* [Version 0.1.0.9997; Aust and Barth (2020)], *patchwork* [Version 1.1.1; Pedersen (2020)], *purrr* [Version 0.3.4; Henry and Wickham (2020)], *Rcpp* [Version 1.0.6; Eddelbuettel and François (2011); Eddelbuettel and Balamuta (2018)], *readr* [Version 1.4.0; Wickham and Hester (2020)], *readxl* [Version 1.3.1; Wickham and Bryan (2019)], *rworldmap* [Version 1.3.6; South (2011)], *see* [Version 0.6.2; Lüdtke et al. (2020)], *sp* [Version 1.4.5; Pebesma and Bivand (2005)], *stringr* [Version 1.4.0; Wickham (2019)], *tibble* [Version 3.1.0; Müller and Wickham (2021)], *tidyr* [Version 1.1.3; Wickham (2021b)], *tidyverse* [Version 1.3.0; Wickham et al. (2019)], and *xfun* [Version 0.22; Xie (2021)].

effects. For the discrete predictors, we used contrasts as follows: For priming condition, identical was coded as -0.5 and unrelated was coded as 0.5. For priming duration, 33.3 ms was coded as -0.5 and 50 ms was coded as 0.5. We used the maximal random effects structure possible, with random intercepts and slopes for condition, prime duration, and the interaction for participants and items. We used the ex-Gaussian distribution to model response times, with both the mean of the Gaussian component μ and the scale parameter of the exponential component β (equalling the inverse of the rate parameter λ) being allowed to vary between conditions. To model response accuracy, we used the Bernoulli distribution with a logit link. We used the default priors suggested by *brms* except for the coefficients for the fixed effects, for which we applied weakly informative priors of $\beta \sim N(0, 100)$ in order to rule out improbably large effect sizes. Each model was fitted using four chains with 5000 iterations each with 1000 warmup iterations (10,000 iterations with 2000 warmup iterations for the accuracy models). We consider an effect as credible if the 95% Credible Interval (CrI) estimated from the posterior distribution does not contain zero. In addition, to better visualize the distributional features of the latency data, we computed the delta plots for both priming and prime duration effects.

Results

Descriptive statistics for response times and accuracy for both words and nonwords in the experimental conditions are reported in Table 1 (although note that we only analyzed the word trials).

Table 1

Mean, Median, Standard Deviation (SD), range of correct RTs (in ms) and Accuracy (proportion of all responses) in Experiment 1 for each condition.

Stimulus Type	Prime Duration	Relatedness	Mean	Median	SD	Min	Max	Accuracy
Nonword	33.3 ms	Identity	701	665	191	263	1,885	0.91
Nonword	33.3 ms	Unrelated	705	665	195	256	1,949	0.92
Nonword	50 ms	Identity	701	658	192	256	1,938	0.91
Nonword	50 ms	Unrelated	702	658	193	251	1,952	0.93
Word	33.3 ms	Identity	631	599	169	254	1,942	0.94
Word	33.3 ms	Unrelated	654	619	171	254	1,887	0.93
Word	50 ms	Identity	609	575	162	265	1,866	0.95
Word	50 ms	Unrelated	650	620	159	294	1,801	0.93

Response times. Table 2 shows the mean, standard error, lower and upper bounds of the 95% CrI of the estimate of each fixed effect in the RT model, as well as the \hat{R} for each estimate, which indicate that the model was fitted successfully as they are all close to 1.

The RT model indicates that the mean of the normal distribution μ was higher in the unrelated condition than the identical ($b = 31.35$, 95% CrI [27.66, 35.01]), and higher in the 33.3 ms prime duration condition than in the 50 ms prime duration condition ($b = -11.38$, 95% CrI [-14.75, -8.02]). The interaction term indicates that the priming effect was stronger in the 50 ms condition than the 33.3 ms condition ($b = 19.31$, 95% CrI [12.14, 26.46]). The shape parameter of the exponential distribution β was affected very little by prime relatedness ($b = 0.03$, 95% CrI [-0.01, 0.07]). However, the 50 ms prime exposure duration ($b = -0.08$, 95% CrI [-0.12, -0.04]) seems to be associated with a slightly lower β , i.e., a slightly weaker right skew of the distribution, than the 33.3 ms condition. On the other hand, there

did not seem to be an interactive effect of prime relatedness and prime exposure time on the shape of the distribution ($b = 0.03$, 95% CrI [-0.05, 0.11]).

Table 2

Posterior Mean, Standard Error (SE), 95% CrI and \hat{R} for the fixed effects of the model fitted for correct word RTs in Experiment 1.

Parameter	mean	SE	lower bound	upper bound	\hat{R}
Intercept (μ)	633.620	6.504	620.936	646.430	1.009
Intercept (β)	4.669	0.031	4.607	4.729	1.003
Relatedness (μ)	31.353	1.878	27.659	35.006	1.001
Prime Duration (μ)	-11.382	1.704	-14.746	-8.018	1.001
Relatedness:Prime Duration (μ)	19.309	3.699	12.141	26.455	1.000
Relatedness (β)	0.032	0.020	-0.007	0.070	1.000
Prime Duration (β)	-0.081	0.022	-0.124	-0.038	1.000
Relatedness:Prime Duration (β)	0.029	0.041	-0.052	0.110	1.000

Note. β is the scale parameter (the inverse of the rate parameter λ) of the ex-Gaussian distribution.

These results can be visualized in the delta plots depicted in Figure 2. Delta plots are residual quantile plots that show the distributional differences between conditions (De Jong et al., 1994). As can be seen in Panel A, there is an identity priming effect (computed as the difference in response times between responses to the unrelated condition and responses to the identity condition) of a parallel magnitude across all quantiles for both the 33.3 ms and the 50 ms prime durations, and the effect size is greater for the 50 ms prime duration condition than for the 33.3 ms one. We also found a slight increase of priming effects for the longest responses (quantile .9) in the 33.3 ms prime duration condition. This apparent anomaly can be understood better by looking at Panel B of the same figure. In this panel, we show the size of the prime duration effect (computed as the difference in response times

between responses to the 50 ms condition and responses to the 33.3 ms condition) across RT quantiles. While the identity condition produced a shift in the distributions of response times (i.e., the difference between conditions is constant across quantiles), the unrelated condition yielded virtually the same response times in the 33.3 and 50 ms conditions, except for a small increase at the 50 ms prime duration for the very long responses (i.e., .9 quantile).

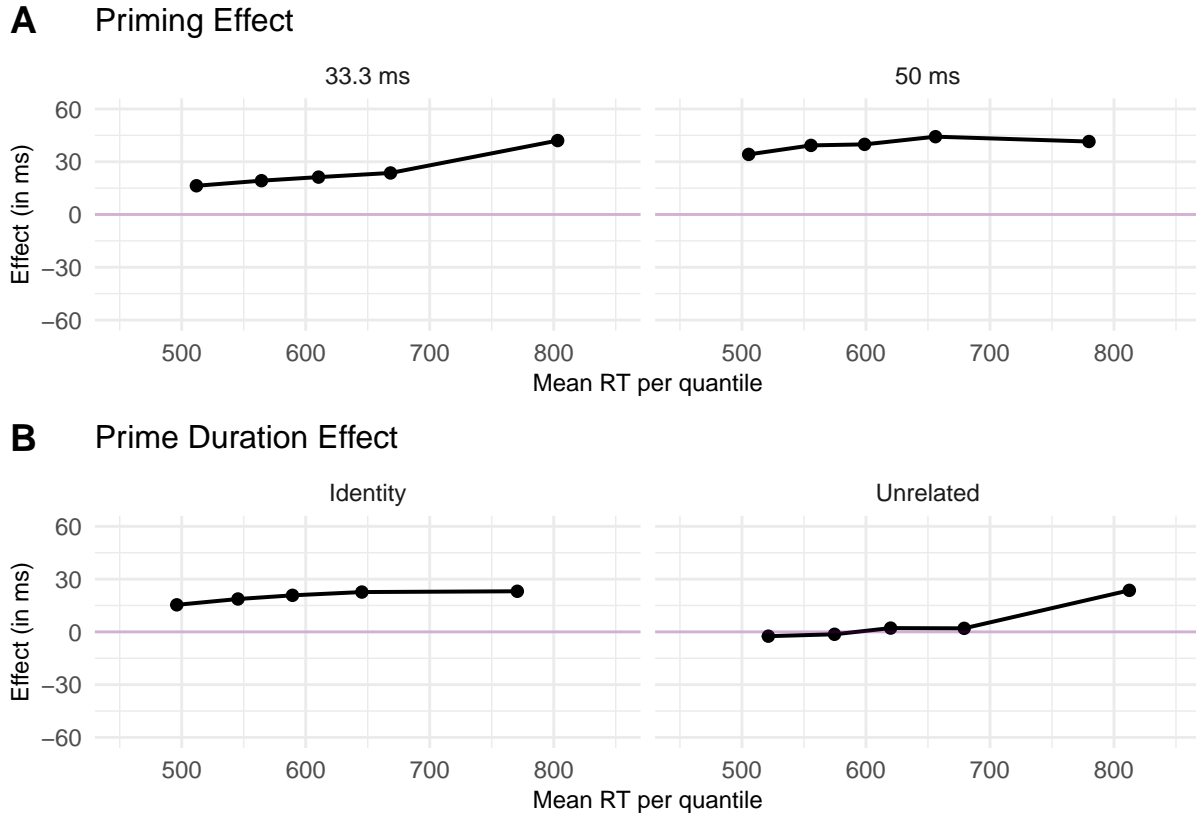


Figure 2. Delta plots depicting the magnitude of the effect over time in Experiment 1. Each dot represents the mean RT at the .1, .3, .5, .7 and .9 quantiles. *Panel A*) Difference of RTs between unrelated and related trials for the 33.3 ms prime duration (left) and the 50 ms prime duration (right). *Panel B*) Difference of RTs between 50 ms and 33.3 ms prime duration trials for the identity (right) and the unrelated (left) conditions.

Accuracy. Table 3 shows the mean, standard error, lower and upper bounds of the 95% CrI of the estimate of each fixed effect in the accuracy model, as well as the \hat{R} for each estimate, which indicate that the model was fitted successfully as they are all close to 1.

The accuracy model indicates that participants were less likely to produce a correct response in the unrelated condition than the identical condition ($b = -0.50$, 95% CrI [-0.71, -0.30]). The mean of the posterior distribution for prime duration suggests that accuracy was slightly lower in the 33.3 ms prime duration condition than in the 50 ms prime duration condition, but as the CrI included 0, this is not credible ($b = 0.20$, 95% CrI [-0.01, 0.42]). The interaction term indicates that the effect of priming condition on response accuracy (with the identical condition leading to higher accuracy) was stronger in the 50 ms condition than the 33.3 ms condition ($b = -0.53$, 95% CrI [-0.94, -0.14]).

Table 3

Posterior Mean, Standard Error (SE), 95% CrI and \hat{R} for the fixed effects of the model fitted for response accuracy on word trials in Experiment 1.

Parameter	mean	SE	lower bound	upper bound	\hat{R}
Intercept	3.451	0.122	3.217	3.695	1.000
Relatedness	-0.496	0.105	-0.714	-0.301	1.000
Prime Duration	0.195	0.109	-0.012	0.417	1.000
Relatedness:Prime Duration	-0.533	0.204	-0.943	-0.145	1.000

Discussion

The results from Experiment 1 reveal that we were able to replicate benchmark masked priming effects using an online experiment. The size of the effect is similar to that observed in previous studies [e.g., Gomez et al. (2013); PEREA; LUPKER...]. In addition, we also saw a clear difference between the 33.3 ms prime duration and the 50 ms prime duration, indicating that the experiment can reliably implement timing differences of up to one frame across a variety of participant devices. While the shape of the distribution changed slightly between the 33.3 ms and the 50 ms prime exposure durations, we did not observe an effect of the prime relatedness condition on the shape parameter β of the exponential distribution,

suggesting, according to the savings hypothesis by Forster (1998), that only encoding processes were affected by the relatedness manipulation. Moreover, as can be observed in Figure 2 the effect magnitude was close to the stimulus-onset asynchrony (see also Perea et al., 2018).

Of course, just because there was a difference between the conditions, this does not necessarily mean that the timings in the two prime duration conditions actually corresponded to the display durations set in the experiment script, just that they were different. Indeed, to better define the priming effect, one needs a baseline that serves as a reference point (i.e., a minimum intensity priming condition; see Jacobs et al., 1995). In order to further explore this question, we performed a second experiment in which we set the prime to be displayed for an even shorter duration. As described in the Introduction, a 16.7 ms prime exposure duration should yield a negligible priming effect (Tzur & Frost, 2007; Ziegler et al., 2000) so the pattern should be qualitatively different effects from the 33.3 and 50 ms durations used in Experiment 1. If it does not, this casts doubt on the timing accuracy in online experiments. In this experiment, we also include the 33.3 ms prime duration condition to not only have a better scheme to compare the two experiments, but also to be able to test the within-condition effect (Jacobs et al., 1995)—assuming the 16.7 ms prime duration serves as a baseline.

Experiment 2

In the second experiment, we tested whether we could observe reliable effects of masked priming at prime durations of 16.7 ms and 33.3 ms (roughly corresponding to one and two frames at a refresh rate of 60 Hz).

Method

Participants. As in Experiment 1, participants were recruited through Prolific (www.prolific.co, 2021). The experiment was accessed by 102 participants. Out of these, 87

provided experimental data. One of these participants did not complete the experiment. A further seven were excluded because of low accuracy (again, less than .8). The remaining 79 participants were aged from 18 to 69 (mean age: 31.14). Of the participants, 40 identified as male, and 39 identified as female. All these participants indicated that English was their first language in the Prolific screening questions. Based on their IP addresses, 56 participants were based in the UK, 14 were based in the US, two participants were based in Canada, two participants were based in South Africa, and one participant each was based in Hungary and Ireland. Three participants could not be localized in this way. As in Experiment 1, all participants were naïve to the purpose of the experiment, and received £1.25 for their participation (corresponding to £5/hour). Participants could use either a desktop/laptop computer or a mobile device. Because of a technical display issue with PsychoJS and the Safari browser, participants who tried to access the experiment using that browser, including all participants on iOS devices, were advised to change browser or device and restart the experiment.

Rationale for sample size and stopping rule. As in Experiment 1, our stopping rule was to keep collecting data until 3,000 valid observations were collected. This goal was met and exceeded in our initial data collection with a budget of £200.

Materials. The materials were identical to those used in Experiment 1.

Procedure. The procedure was identical to Experiment 1, the only difference being that the primes were set to be displayed for either 16.7 ms or 33.3 ms.

Data analysis. We analyzed the data in the same way as in Experiment 1, again only analyzing trials where the target stimulus was a word. For the response time (RT) analysis, we excluded trials with RTs lower than 250 ms and incorrect responses (4.86 % of trials). For the accuracy analysis, we only excluded trials with RTs lower than 250 ms (0.08 % of trials). For priming duration, 16.7 ms was coded as -0.5 and 33.3 ms was coded as 0.5. Otherwise, the model specifications were identical to those in Experiment 1.

Table 4

Mean, Median, Standard Deviation (SD), and range of correct RTs (in ms) and Accuracy (proportion of all responses) in Experiment 2 for all conditions.

Stimulus Type	Prime Duration	Relatedness	Mean	Median	SD	Min	Max	Accuracy
Nonword	16.7 ms	Identity	721	680	191	330	1,929	0.93
Nonword	16.7 ms	Unrelated	719	677	187	284	1,920	0.94
Nonword	33.3 ms	Identity	719	668	198	351	1,924	0.94
Nonword	33.3 ms	Unrelated	718	672	197	281	1,912	0.94
Word	16.7 ms	Identity	660	625	162	311	1,892	0.94
Word	16.7 ms	Unrelated	662	623	169	308	1,899	0.95
Word	33.3 ms	Identity	650	618	158	280	1,873	0.96
Word	33.3 ms	Unrelated	667	633	164	269	1,920	0.94

Results

Descriptive statistics for RTs and accuracy in all the experimental conditions are reported in Table 4.

Response times. As in Experiment 1, the RT model indicates that the mean of the normal distribution μ was higher in the unrelated condition than the identical ($b = 8.80$, 95% CrI [5.42, 12.29]). For the main effect of prime duration, the CrI contains 0, suggesting that, when averaging across the relatedness conditions, there is no strong difference between the 16.7 ms and the 33.3 ms prime duration ($b = -3.48$, 95% CrI [-7.09, 0.16]). However, the interaction term demonstrates that this is actually due to the fact that there was a strong priming effect in the 33.3 ms condition, but only a negligible effect in the 16.7 ms condition ($b = 15.35$, 95% CrI [8.64, 22.05]). The shape parameter of the exponential distribution β was affected very little by prime relatedness ($b = 0.03$, 95% CrI [-0.01, 0.08]), prime exposure

duration ($b = 0.01$, 95% CrI $[-0.03, 0.06]$), or their interaction ($b = -0.03$, 95% CrI $[-0.12, 0.05]$), suggesting that the shape of the RT distribution was not affected by the manipulations in Experiment 2. Table 5 shows the mean, standard error, lower and upper bounds of the 95% CrI of the estimate of each fixed effect in the RT model, as well as the \hat{R} for each estimate, which indicate that the model was fitted successfully as they are all close to 1.

Table 5

(*ref:exp2-blmm-rt-table-caption*)

Parameter	mean	SE	lower bound	upper bound	\hat{R}
Intercept (μ)	658.462	9.372	640.004	676.606	1.002
Intercept (β)	4.668	0.042	4.585	4.749	1.005
Relatedness (μ)	8.799	1.758	5.420	12.286	1.000
Prime Duration (μ)	-3.481	1.841	-7.095	0.161	1.000
Relatedness:Prime Duration (μ)	15.347	3.425	8.639	22.046	1.000
Relatedness (β)	0.031	0.023	-0.013	0.076	1.000
Prime Duration (β)	0.013	0.022	-0.030	0.055	1.000
Relatedness:Prime Duration (β)	-0.030	0.043	-0.116	0.055	1.000

Note. β is the scale parameter (the inverse of the rate parameter λ) of the ex-Gaussian distribution.

We also created the delta plots of data from Experiment 2 (see Figure 3). Panel A, shows there is no priming effect for the 16.7 ms condition, but a consistent effect across quantiles for the 33.3 ms condition (parallel to the one found in Experiment 1). Interestingly, when examining the delta plots for the prime duration effect, we can observe a slight facilitation for identity primes, together with a slight hindering for unrelated primes.

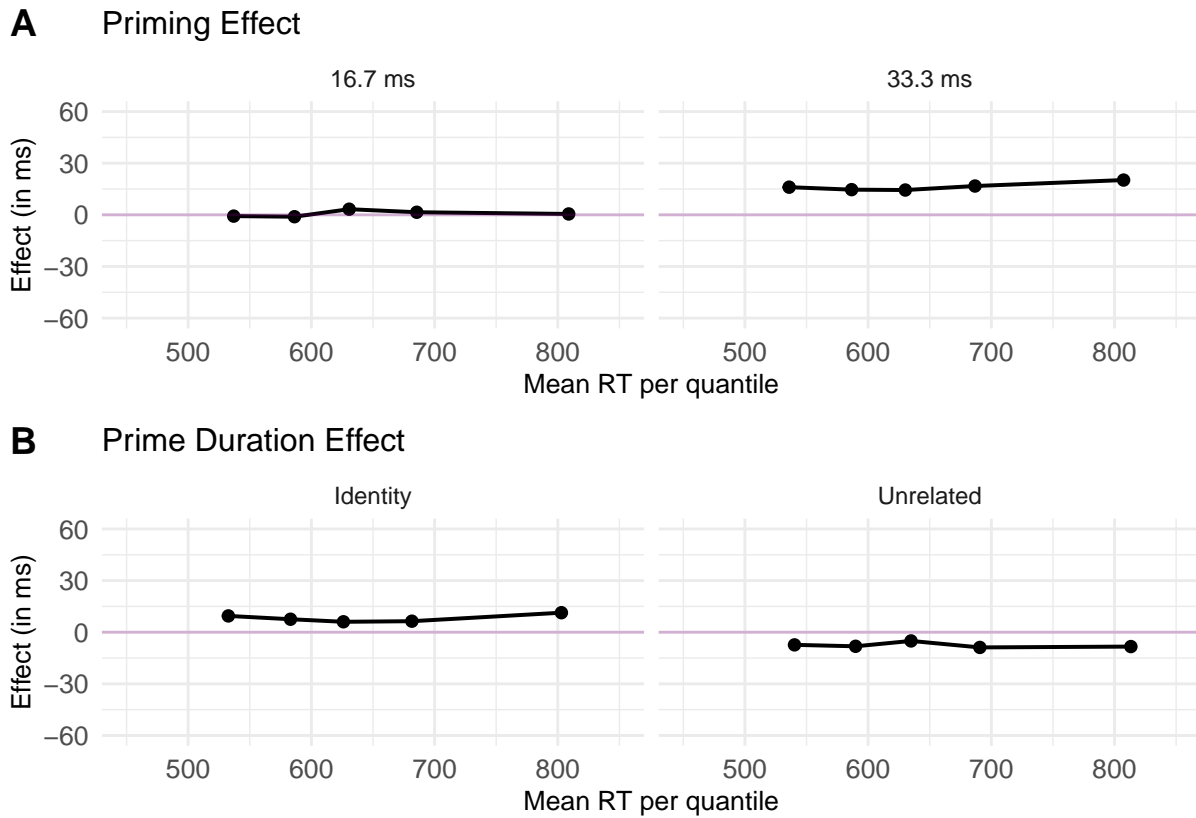


Figure 3. Delta plots depicting the magnitude of the effect over time in Experiment 2.

Accuracy. The accuracy model indicates that participants were less likely to produce a correct response in the unrelated condition than the identical condition ($b = -0.22$, 95% CrI [-0.43, 0.00]). The mean of the posterior distribution for prime duration suggests that accuracy was slightly lower in the 16.7 ms prime duration condition than in the 33.3 ms prime duration condition, but as the CrI included 0, this is not credible ($b = -0.05$, 95% CrI [-0.31, 0.18]). The interaction term indicates that the expected effect of priming condition on response accuracy (with the identical condition leading to higher accuracy) only present in the 33.3 ms condition, and reversed in the 16.7 ms condition ($b = -0.71$, 95% CrI [-1.16, -0.30]), although the effect in the 16.7 ms condition was very weak. Table 6 shows the mean, standard error, lower and upper bounds of the 95% CrI of the estimate of each fixed effect in the accuracy model, as well as the \hat{R} for each estimate, indicating that the model was fitted successfully as they are all close to 1.

Table 6

Posterior Mean, Standard Error (SE), 95% CrI and \hat{R} for fixed effects of the model fitted for response accuracy on word trials in Experiment 2.

Parameter	mean	SE	lower bound	upper bound	\hat{R}
Intercept	3.736	0.135	3.475	4.007	1.000
Relatedness	-0.218	0.109	-0.434	-0.004	1.000
Prime Duration	-0.054	0.126	-0.313	0.183	1.000
Relatedness:Prime Duration	-0.708	0.219	-1.165	-0.302	1.000

Discussion

In Experiment 2, we found the pattern we expected from previous research: In the mean μ of the Gaussian distribution, we observed a robust identity priming effect in response time and accuracy in the 33.3 ms prime duration, but a very weak effect in the 16.7 ms prime duration (Tzur & Frost, 2007; Ziegler et al., 2000). This outcome suggests that the timing in our online experiments was likely to be quite close to the timing set in the experiment script. In addition, we did not observe an effect of the prime relatedness on the shape parameter β of the exponential distribution. Thus, indicating there was no evidence for a difference in the shape of the distribution between the 16.7 and 33.3 ms prime duration. Moreover, the magnitude of the effect was close to the magnitude of the prime-target stimulus-onset asynchrony, as can be seen in the delta plots in Figure 3 (see Perea et al., 2018). Hence, we replicated again the commonly observed savings effect (Forster, 1998). Critically, because the 16.7 ms prime duration condition yielded virtually no priming effects, it serves a within-condition baseline that allows us to qualify the priming effect (Jacobs et al., 1995) in this case for trials that had a 33.3 ms prime duration. Specifically, our findings show a small inhibitory effect for unrelated primes, and a slight facilitatory effect for identity primes. **AS OBSERVED IN OTHER STUDIES...**

General Discussion

In this study, we set out to test whether we could replicate benchmark masked priming effects both qualitatively (i.e., shift in the RT distributions) and quantitatively (i.e., effect sizes) using an online, browser-based experiment software. **EXPLAIN A BIT WHAT WE DID**

Our results indicate that main masked priming effects obtained in the lab-based studies can also be obtained in online-based studies. We observed the effect sizes predicted by Forster’s (1998) savings hypothesis: Our data show a shift in the mean of the Gaussian distribution, but no change in the shape parameter β of the exponential distribution, suggesting that our priming manipulations affected — as intended — encoding processes, but not conscious decision-making processes. Furthermore, the size of the priming effect was not only directly influenced by the prime duration, suggesting the experimental software was able to control the display timing of the prime accurately, but also of a similar magnitude to the prime duration (within the range reported in previous studies, e.g., 35-47 ms for a 50 ms prime duration in Perea et al., 2018).

While accurate display timings are expected in a laboratory-based experiment, where the equipment is known and can be measured, they are much less certain in a situation where the experiment runs on a participant’s own device, which could be any of a wide variety of consumer devices including Windows PCs, Macs, tablets, and mobile phones sold in the last decade. The fact that we can observe results that very closely resemble lab results demonstrates the sophistication in modern browsers’ Javascript performance, including browsers on mobile devices, as well as the quality of the Javascript implementation of PsychoPy. Furthermore, our results not only replicate findings in previous masked priming laboratory studies, but also extend previous work showing the validity of on-line studies measuring response times (e.g., Brysbaert et al., 2016; Cai et al., 2017; Eerland et al., 2013; Rodd et al., 2016) to the masked priming technique. Thus, the present study opens the door

to a wider use of online experiments in cognitive research, especially in reaction-time sensitive fields like word recognition. Not only does this enable researchers to continue collecting data in times of social distancing, but it also makes it possible to collect data from a larger population than previously possible. For instance, people from different countries and/or cultures, from different age groups, bilinguals/ multilinguals, even from those who do not have computers at home, but they do have smartphones. Using a Javascript-based experiment software, anyone with a smartphone can be an experiment participant. Additionally, deploying experiments online also means that data can be collected very quickly and efficiently, allowing research to progress more rapidly.

In conclusion, our results give us confidence that high-quality behavioral data using the masked priming paradigm can be collected online using Javascript-based experiment platforms. We hope that future research takes advantage of these new methods in order to make research faster, more inclusive, and more efficient.

References

- Alluhaybi, I., & Witzel, J. (2020). Letter connectedness and arabic visual word recognition. *Quarterly Journal of Experimental Psychology*, 73(10), 1660–1674. <https://doi.org/10.1177/1747021820926155>
- Anwyl-Irvine, A., Dalmaijer, E. S., Hodges, N., & Evershed, J. K. (2020). Realistic precision and accuracy of online experiment platforms, web browsers, and devices. *Behavior Research Methods*. <https://doi.org/10.3758/s13428-020-01501-5>
- Anwyl-Irvine, A., Massonni, J., Flitton, A., Kirkham, N., & Evershed, J. K. (2020). orilla in our midst: An online behavioral experiment builder. *Behavior Research Methods*, 52(1), 388–407. <https://doi.org/10.3758/s13428-019-01237-x>
- Aust, F., & Barth, M. (2020). *papaja: Create APA manuscripts with R Markdown*. <https://github.com/crsh/papaja>
- Aust, F., Diedenhofen, B., Ullrich, S., & Musch, J. (2013). Seriousness checks are useful to improve data validity in online research. *Behavior Research Methods*, 45(2), 527–535. <https://doi.org/10.3758/s13428-012-0265-2>
- Balota, D. A., Yap, M. J., Hutchison, K. A., Cortese, M. J., Kessler, B., Loftis, B., Neely, J. H., Nelson, D. L., Simpson, G. B., & Treiman, R. (2007). The English Lexicon Project. *Behavior Research Methods*, 39(3), 445–459. <https://doi.org/10.3758/BF03193014>
- Birnbaum, M. H., & Birnbaum, M. O. (2000). *Psychological Experiments on the Internet*. Elsevier. <http://books.google.com?id=sw4NHyThFFkC>
- Bridges, D., Pitiot, A., MacAskill, M. R., & Peirce, J. W. (2020). The timing mega-study: comparing a range of experiment generators, both lab-based and

- online. *PeerJ*, 8, e9414. <https://doi.org/10.7717/peerj.9414>
- Brysbaert, M., & Stevens, M. (2018). Power Analysis and Effect Size in Mixed Effects Models: A Tutorial. *Journal of Cognition*, 1(1), 9. <https://doi.org/10.5334/joc.10>
- Brysbaert, M., Stevens, M., Mander, P., & Keuleers, E. (2016). The impact of word prevalence on lexical decision times: Evidence from the dutch lexicon project 2. *Journal of Experimental Psychology: Human Perception and Performance*, 42(3), 441.
- Bürkner, P.-C. (2017). brms: An R package for Bayesian multilevel models using Stan. *Journal of Statistical Software*, 80(1), 1–28. <https://doi.org/10.18637/jss.v080.i01>
- Bürkner, P.-C. (2018). Advanced Bayesian multilevel modeling with the R package brms. *The R Journal*, 10(1), 395–411. <https://doi.org/10.32614/RJ-2018-017>
- Cai, Z. G., Gilbert, R. A., Davis, M. H., Gaskell, M. G., Farrar, L., Adler, S., & Rodd, J. M. (2017). *Accent modulates access to word meaning: Evidence for a speaker-model account of spoken word recognition*. <https://doi.org/10.31234/osf.io/5x3tb>
- De Jong, R., Liang, C.-C., & Lauber, E. (1994). Conditional and unconditional automaticity: A dual-process model of effects of spatial stimulus-response correspondence. *Journal of Experimental Psychology: Human Perception and Performance*, 20(4), 731.
- de Leeuw, J. R. (2015). jsPsych: A JavaScript library for creating behavioral experiments in a Web browser. *Behavior Research Methods*, 47(1), 1–12. <https://doi.org/10.3758/s13428-014-0458-y>
- Dubey, N., Witzel, N., & Witzel, J. (2018). Script differences and masked translation

- priming: Evidence from hindi-english bilinguals. *Quarterly Journal of Experimental Psychology*, 71(11), 2421–2438.
<https://doi.org/10.1177/1747021817743241>
- Eddelbuettel, D., & Balamuta, J. J. (2018). Extending extitR with extitC++: A Brief Introduction to extitRcpp. *The American Statistician*, 72(1), 28–36.
<https://doi.org/10.1080/00031305.2017.1375990>
- Eddelbuettel, D., & François, R. (2011). Rcpp: Seamless R and C++ integration. *Journal of Statistical Software*, 40(8), 1–18. <https://doi.org/10.18637/jss.v040.i08>
- Eerland, A., Engelen, J. A. A., & Zwaan, R. A. (2013). The influence of direct and indirect speech on mental representations. *PLoS ONE*, 8(6), e65480.
<https://doi.org/10.1371/journal.pone.0065480>
- Forster, K. (1998). The pros and cons of masked priming. *Journal of Psycholinguistic Research*, 27(2), 203–233.
- Forster, K., & Davis, C. (1984). Repetition priming and frequency attenuation in lexical access. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 10(4), 680–698. <https://doi.org/10.1037/0278-7393.10.4.680>
- Forster, K., & Forster, J. (2003). DMDX: A Windows display program with millisecond accuracy. *Behavior Research Methods, Instruments, & Computers*, 35(1), 116–124.
- Gomez, P., & Perea, M. (2020). Masked identity priming reflects an encoding advantage in developing readers. *Journal of Experimental Child Psychology*, 199, 104911. <https://doi.org/10.1016/j.jecp.2020.104911>
- Gomez, P., Perea, M., & Ratcliff, R. (2013). A diffusion model account of masked

versus unmasked priming: Are they qualitatively different? *Journal of Experimental Psychology: Human Perception and Performance*, 39(6), 1731–1740.
<https://doi.org/10.1037/a0032333>

Grainger, J. (2008). Cracking the orthographic code: An introduction. *Language and Cognitive Processes*, 23(1), 1–35. <https://doi.org/10.1080/01690960701578013>

Grossi, G. (2006). Relatedness proportion effects on masked associative priming: An ERP study. *Psychophysiology*, 43(1), 21–30.
<https://doi.org/10.1111/j.1469-8986.2006.00383.x>

Henry, L., & Wickham, H. (2020). *Purrr: Functional programming tools*.
<https://CRAN.R-project.org/package=purrr>

Jacobs, A. M., Grainger, J., & Ferrand, L. (1995). The incremental priming technique: A method for determining within-condition priming effects. *Perception & Psychophysics*, 57(8), 1101–1110. <https://doi.org/10.3758/bf03208367>

Lund, K., & Burgess, C. (1996). Producing high-dimensional semantic spaces from lexical co-occurrence. *Behavior Research Methods, Instruments, & Computers*, 28(2), 203–208. <https://doi.org/10.3758/BF03204766>

Lüdecke, D., Ben-Shachar, M. S., Waggoner, P., & Makowski, D. (2020). See: Visualisation toolbox for 'easystats' and extra geoms, themes and color palettes for 'ggplot2'. *CRAN*. <https://doi.org/10.5281/zenodo.3952153>

Makowski, D., Ben-Shachar, M. S., & Lüdecke, D. (2019). bayestestR: Describing effects and their uncertainty, existence and significance within the bayesian framework. *Journal of Open Source Software*, 4(40), 1541.
<https://doi.org/10.21105/joss.01541>

- Müller, K., & Wickham, H. (2021). *Tibble: Simple data frames*.
<https://CRAN.R-project.org/package=tibble>
- Paolacci, G., Chandler, J., & Ipeirotis, P. G. (2010). *Running Experiments on Amazon Mechanical Turk* (SSRN Scholarly Paper ID 1626226). Social Science Research Network. <https://papers.ssrn.com/abstract=1626226>
- Parker, A., Egan, C., Grant, J. H., Harte, S., Hudson, B. T., & Woodhead, Z. V. J. (2021). The role of orthographic neighbourhood effects in lateralized lexical decision: A replication study and meta-analysis. *PeerJ*, 9, e11266.
<https://doi.org/10.7717/peerj.11266>
- Pavlovica. (2020). *Pavlovica*. <https://pavlovica.org/>
- Pebesma, E. J., & Bivand, R. S. (2005). Classes and methods for spatial data in R. *R News*, 5(2), 9–13. <https://CRAN.R-project.org/doc/Rnews/>
- Pedersen, T. L. (2020). *Patchwork: The composer of plots*.
<https://CRAN.R-project.org/package=patchwork>
- Peirce, J., Gray, J. R., Simpson, S., MacAskill, M., Höchenberger, R., Sogo, H., Kastman, E., & Lindeløv, J. K. (2019). PsychoPy2: Experiments in behavior made easy. *Behavior Research Methods*, 51(1), 195–203.
<https://doi.org/10.3758/s13428-018-01193-y>
- Perea, M., Marcet, A., Lozano, M., & Gomez, P. (2018). Is masked priming modulated by memory load? A test of the automaticity of masked identity priming in lexical decision. *Memory & Cognition*, 46(7), 1127–1135.
<https://doi.org/10.3758/s13421-018-0825-5>
- Perea, M., & Rosa, E. (2002). Does the proportion of associatively related pairs

modulate the associative priming effect at very brief stimulus-onset asynchronies?

Acta Psychologica, 110(1), 103–124.

[https://doi.org/10.1016/s0001-6918\(01\)00074-9](https://doi.org/10.1016/s0001-6918(01)00074-9)

Prolific. (2021). *Prolific / online participant recruitment for surveys and market research*. <https://www.prolific.co/>

Qualtrics. (2020). *Qualtrics XM // the leading experience management software*. <https://www.qualtrics.com/uk/>

R Core Team. (2021). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. <https://www.R-project.org/>

Ratcliff, R., Gomez, P., & McKoon, G. (2004). A diffusion model account of the lexical decision task. *Psychological Review*, 111(1), 159–182.
<https://doi.org/10.1037/0033-295X.111.1.159>

Reimers, S., & Stewart, N. (2015). Presentation and response timing accuracy in Adobe Flash and HTML5/JavaScript Web experiments. *Behavior Research Methods*, 47(2), 309–327. <https://doi.org/10.3758/s13428-014-0471-1>

Rezlescu, C., Danaila, I., Miron, A., & Amariei, C. (2020). *Chapter 13 - More time for science: Using Testable to create and share behavioral experiments faster, recruit better participants, and engage students in hands-on research* (B. L. Parkin, Ed.; Vol. 253, pp. 243–262). Elsevier. <https://doi.org/10.1016/bs.pbr.2020.06.005>

Rodd, J. M., Cai, Z. G., Betts, H. N., Hanby, B., Hutchinson, C., & Adler, A. (2016). The impact of recent and long-term experience on access to word meanings: Evidence from large-scale internet-based experiments. *Journal of Memory and Language*, 87, 16–37. <https://doi.org/10.1016/j.jml.2015.10.006>

- South, A. (2011). Rworldmap: A new r package for mapping global data. *The R Journal*, 3(1), 35–43.
http://journal.r-project.org/archive/2011-1/RJournal_2011-1_South.pdf
- Taikh, A., & Lupker, S. J. (2020). Do visible semantic primes preactivate lexical representations? *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 46(8), 1533–1569. <https://doi.org/10.1037/xlm0000825>
- Tzur, B., & Frost, R. (2007). SOA does not reveal the absolute time course of cognitive processing in fast priming experiments⁷³. *Journal of Memory and Language*, 56(3), 321–335. <https://doi.org/10.1016/j.jml.2006.11.007>
- Wickham, H. (2016). *ggplot2: Elegant graphics for data analysis*. Springer-Verlag New York. <https://ggplot2.tidyverse.org>
- Wickham, H. (2019). *Stringr: Simple, consistent wrappers for common string operations*. <https://CRAN.R-project.org/package=stringr>
- Wickham, H. (2021a). *Forcats: Tools for working with categorical variables (factors)*. <https://CRAN.R-project.org/package=forcats>
- Wickham, H. (2021b). *Tidyr: Tidy messy data*. <https://CRAN.R-project.org/package=tidyr>
- Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L. D., François, R., Grolemund, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T. L., Miller, E., Bache, S. M., Müller, K., Ooms, J., Robinson, D., Seidel, D. P., Spinu, V., . . . Yutani, H. (2019). Welcome to the tidyverse. *Journal of Open Source Software*, 4(43), 1686. <https://doi.org/10.21105/joss.01686>
- Wickham, H., & Bryan, J. (2019). *Readxl: Read excel files*.

<https://CRAN.R-project.org/package=readxl>

Wickham, H., François, R., Henry, L., & Müller, K. (2021). *Dplyr: A grammar of data manipulation*. <https://CRAN.R-project.org/package=dplyr>

Wickham, H., & Hester, J. (2020). *Readr: Read rectangular text data*. <https://CRAN.R-project.org/package=readr>

Witzel, J., Cornelius, S., Witzel, N., Forster, K. I., & Forster, J. C. (2013). Testing the viability of webDMDX for masked priming experiments. *The Mental Lexicon*, 8(3), 421–449. <https://doi.org/10.1075/ml.8.3.07wit>

Xie, Y. (2021). *Xfun: Miscellaneous functions to support packages maintained by 'yihui xie'*. <https://CRAN.R-project.org/package=xfun>

Yang, H., Jared, D., Perea, M., & Lupker, S. J. (2021). Is letter position coding when reading in L2 affected by the nature of position coding used when bilinguals read in their L1? *Memory & Cognition*. <https://doi.org/10.3758/s13421-020-01126-1>

Yarkoni, T., Balota, D., & Yap, M. (2008). Moving beyond Coltheart's N: A new measure of orthographic similarity. *Psychonomic Bulletin & Review*, 15(5), 971–979. <https://doi.org/10.3758/PBR.15.5.971>

Ziegler, J. C., Ferrand, L., Jacobs, A. M., Rey, A., & Grainger, J. (2000). Visual and Phonological Codes in Letter and Word Recognition: Evidence from Incremental Priming. *The Quarterly Journal of Experimental Psychology*, 53A(3), 671–692.