The dynamics of buffered and triggered selection from RSVP streams

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Abstract

From an incoming stream of visual information, only a limited number of stimuli can be selected for extensive processing. Much of the literature assumes that selection of cued items in RSVP streams is a result of attentional sampling being triggered by the cue. We provide evidence for another process - selection from a buffer of stimulus representations. This can yield selection of stimuli presented before the cue, despite the common theoretical claim that such stimuli should be unavailable. Our novel statistical method provides quantitative evidence that stimuli presented before the cue are sometimes selected. This phenomenon occurred when two RSVP streams were presented simultaneously and one was cued at a random time. When the number of streams was increased, evidence for pre-cue reports diminished and selection was delayed. These results indicated that stimuli in RSVP evoke representations that persist long enough to be selected, provided attention is fast enough. The speed and variability of temporal selection of items is affected by endogenous attention and possibly by competition among stimulus representations. In conditions with fewer streams, faster selection and buffering may occur thanks to participants applying endogenous attention before the cue is presented, speeding the response to the cue and leading to more reports of the item before the cue.

Keywords: Attentional selection, temporal dynamics, rapid serial visual presentation, visual buffer

Public Significance

The visual system has limited processing capacity. It receives a stream of information, but can selectively process only some of this. Here we investigate the timing

properties of selection - referred to as “attention” - with sequences of objects, one of which participants must report. Attention in the sorts of experiments reported here is typically thought of as a process that is triggered by some stimulus, such as the sudden appearance of an object, often referred to as a “cue”. However, some experiments suggest that even before the cue, some items in these tasks are selected and processed. We investigate the presence of these pre-cue selections, and argue that they are due to changes in the speed of selection when participants can voluntarily dedicate attention to the cue’s possible locations. Under these conditions, selection is swift and may select information from a stimulus that was presented earlier because information about that stimulus persists in the visual system.

The visual world is dynamic and full of stimuli. The information provided by an observer's retinas changes rapidly due to the observer's movements and the movement of objects in the scene, so that old visual information is masked by subsequent stimulation at the same visual location. However, the brain cannot fully process all the stimuli in a busy visual scene and must selectively allocate attentional resources to behaviorally relevant stimuli. Masking - interference between spatial and temporally proximate visual stimuli - is typically assumed to limit the availability of sensory information (Enns & Di Lollo, 2000; Kahneman, 1968; Keyser & Perrett, 2002), so masking and the time course of attentional allocation provide constraints on the ability to select a stimulus that may be presented only briefly at a particular visual location, but is important to identify. In this article we investigate attentional selection's temporal qualities under conditions of masking - using rapid serial visual presentation (RSVP) with multiple concurrent streams of letters, one of which is cued for participants to report. Because masking limits the availability of visual information, attentional selection is sometimes assumed to occur via sampling from the incoming stream of visual information. However, we describe a phenomenon that is hard to reconcile with this assumption - participants may accurately report items presented before the time of a cue with a frequency that cannot be explained by guessing or target misidentification. These reports occur when there are only a few possible streams that can be cued, but not when there are many.

In an RSVP experiment, participants view a sequence of stimuli presented at a single spatial location and must report one item's identity based on some target feature. The time to complete an attention shift can be inferred from the temporal position of the stimulus reported by a participant (Reeves & Sperling, 1986). For example, a stream of individual letters may be presented with a random letter cued by a change in color or an enclosing circle. The time at which selection occurred may be inferred from the identity of the reported item, provided the stream contains no repeated stimuli. Over many trials, this method

produces a distribution of selection errors that facilitates inferences about the timing of attentional selection under particular conditions (i.e Chun, 1997; Reeves & Sperling, 1986; Weichselgartner & Sperling, 1987). However, these inferences assume that any given response was not a lucky guess - an assumption that may not be true. We will return to this point later.

It is sometimes assumed that RSVP stimuli at a particular time cannot be accurately reported unless attention has already shifted to the stream. This assumption stems from the theory that the quick succession of stimuli at a single spatial location causes sensory information to be masked so it is only available briefly (Grossberg & Stone, 1986; Reeves & Sperling, 1986; Shih & Sperling, 2002). In other words, under this assumption, attention is triggered by the cue and subsequently samples from the stream in order to select an item. Without attentional selection, stimulus representations are short-lived and not available for report, but with attentional selection, a selected stimulus' representation can be sustained such that it may be reported.

In some circumstances, a cue in an RSVP task appears to elicit reports of stimuli that appeared before a cue, which seems inconsistent with the theoretical assumption that a time-consuming shift of attention is necessary for sampling from the stream because unselected stimuli have limited availability due to masking.

Goodbourn and Holcombe (2015) presented participants with two simultaneous RSVP streams of letters and asked them to report the letter that appeared with a white ring around it. To account for the effect of guessing, they mixture-modelled the distribution of reports. Their results suggested that the non-guess reports included items from before the cue. This pattern of results also occurred in the data of Holcombe, Nguyen and Goodbourn (2017). Several studies that do not account for guesses with mixture modelling also observed reports of items before a cue and suggested that these were not guesses (Botella,

1992; Botella et al., 2001; Botella & Eriksen, 1991; Gathercole & Broadbent, 1984; McLean et al., 1983). These reports suggest that even without attentional selection, stimulus representations may persist beyond the presentation of a subsequent stimulus at the same location. In other words, they indicate that stimuli may be buffered prior to attentional selection in response to the cue.

Storage of irrelevant stimuli, also known as incidental memory, is not surprising in certain circumstances. Apart from the few papers mentioned above, however, the literature on selection of a cued item from a stream of rapidly presented stimuli has not considered a role for memory of items presented before the cue. Such responses, if they can be demonstrated empirically, are inconsistent with assumptions about attentional sampling. Reports of stimuli that were presented prior to an RSVP cue suggest that masking does not limit the availability of sensory information in the way the above models assume. Very few models of RSVP have attempted to explain or model reports of stimuli from before the cue, and none appear to have distinguished between circumstances in which such items are retained, at least briefly, for possible report and possible circumstances where this might not occur.

To explain the reports of stimuli from before a cue that they observed, Goodbourn and Holcombe (2015) proposed the involvement of a buffer containing visual representations of letters that rapidly decayed, but were not entirely overwritten by the next letters. Unlike an attention shift that samples the stream, which in RSVP is not assumed to operate on information stored in memory, the action of this buffer is not triggered by the cue. Instead, it is in operation before the cue appears, storing stimuli. The buffer may simply be letter representations in the brain becoming active and this activation persisting for a short time following the letter's presentation. On this account, a buffered item can be selected for tokenisation, consolidation into working memory, and response.

As the cue, Goodbourn & Holcombe (2015) presented a white ring around one of the letters in an RSVP stream. In addition to suggesting that reports of items before the cue were evidence that the activation of letters prior to the cue can persist (buffering), they also theorized that binding of the cue with an active letter representation is imprecise and sometimes results in temporal errors such as report of a still-active pre-cue letter. These pre-cue reports are the critical evidence for a buffering process. Such responses are unlikely under an attention shift, as that should be somewhat time-consuming, and thus they constitute critical evidence for buffering.

The buffer putatively responsible for reports of letters before the cue may be a brief store of visual information. Both iconic memory (Averbach & Coriell, 1961; Sperling, 1960) and the more recently-developed construct of fragile memory (Pinto et al., 2013; Sligte et al., 2008) could explain this. However, these memory stores are thought to be overwritten by subsequent stimuli presented in the same location, which implies they will not outlast the appearance of the next letter in an RSVP stream.

Contributions to theory

Evidence for buffering, in the form of responses from before the time of a selection cue, is thus at odds with the assumption that attention samples from the stream of incoming visual information, where attention is triggered by the cue and makes a selection after the cue's onset. We identify several models used to explain performance in RSVP tasks below. For some of these models, evidence about buffering serves to falsify assumptions about masking. Other models contain mechanisms that may allow for buffering if the models were modified. Evidence for buffering provides empirical constraints on assumptions about when buffered information would be available in these models.

One influential theory used a task of reporting multiple successive items from a stream after a cue (Reeves and Sperling, 1986). According to this theory and some later theories (Grossberg & Stone, 1986; Shih & Sperling, 2002), the representation of one stimulus is overwritten by the appearance of another stimulus in the stream, consistent with the theory of iconic memory. Attention is necessary for stimulus information to enter visual short term memory. This occurs when an attentional cue is detected, and, after being triggered, attention samples whatever stimulus representation is active in the stream of visual information with a variable latency. Thus, evidence for reports of pre-cue items that are not guesses challenges these models' assumption that attention must sample from the RSVP stream in order to sustain a stimulus representation.

Other theories share the assumption that attention must sample from a stream of incoming stimulus representations, but do not assume that stimulus information is completely overwritten by subsequent stimuli (Chun & Potter, 1995; Olivers & Meeter, 2008; Wyble et al., 2009). These theories posit stimulus representations that may persist during the processing of the next stimulus in RSVP. However, because these models are often designed to explain tasks in which pre-cue items are not viable candidates for report (i.e. numeral distractors and letter targets), they often do not simulate experiments in which attention selects pre-cue items. However, when applied to experiments in which distractors are candidates for report (i.e. all stimuli are words, as in Botella et al.'s, 2001, experiments), at least one of these models (Wyble et al., 2009) can simulate pre-cue reports, suggesting that similar modifications to the other models may lead to a similar result (Chennu et al., 2011). Stimulus representations' activation in these models falls over several hundred milliseconds. Investigating the conditions under which pre-cue stimuli are reported provides an empirical constraint on the way in which pre-cue stimulus information can be accessed in these models.

Work by Botella and colleagues directly addresses the possibility of reports of pre-cue stimuli. Botella, Suero & Barriopedro (2001) set out to explain the presence of pre- and post-cue responses in RSVP response distributions. In this model, following the ideas of Treisman & Gelade (1980), attention on some trials successfully focuses on the target, and in those cases there is no error. They suggest that in some trials attention fails to focus and responses are made by selecting one of several buffered representations of unbound features of the items in the RSVP stream - a process named “sophisticated guessing”. The model’s decay rate for non-target feature representations falls from its peak to zero over a period of roughly 200-250 ms (Botella et al, 2001; Figure 6), which accommodates the occasional reports of pre-cue items.

Vul and Rich’s (2010) theory of how participants perform in cued RSVP tasks also implies that some information about stimuli is buffered. Vul and Rich proposed that visual feature binding, including binding a cue to the simultaneous letter in an RSVP stream, involves uncertainty about which features occurred at the same time as the cue. Binding, on this theory, occurs via selection from a representation of the probability distribution of which features were presented when. This theory implies a buffer, because if feature representations did not persist beyond stimulus presentation there would be no distribution to sample from.

Here we develop a procedure that tests whether pre-cue reports in RSVP are more frequent than expected under guessing. This is the first time that a statistical test has been applied to determine whether such reports can be explained by guessing.

Having developed a statistic to establish the presence of pre-cue letter reports that are not guesses, we go on to investigate the processing that results in them. One factor that we describe here for the first time, which may explain pre-cue reports, is that not knowing which of many simultaneous streams will be cued has effects that include reducing the

number of pre-cue reports. We will suggest that this results from delayed selection due to dilution of attention among the streams.

Critical Evidence for the buffer: Accounting for guessing

Reports of items from before the time of a cue are key evidence for buffering. At least some of these reports, however, reflect random guesses or misidentifications of the target. We will refer to these as *identification failures*. These failures, when aggregated across trials, result in a nearly-uniform distribution spanning all times relative to the cue (Goodbourn & Holcombe, 2015). The remaining reports are those in which participants report a letter from a time related to the time of the cue as a result of processing that letter (rather than it being a guess or a misidentification of another letter). We refer to these as *efficacious* reports.

To investigate temporal selection, like other researchers we use rapid presentation rates to avoid ceiling levels of performance. With a presentation rate of 12 items per second, identification failures were estimated as comprising 25% of responses by Goodbourn & Holcombe (2015). Some of these identification failure responses will by chance be letters presented shortly before the cue. For example, when a participant makes a complete guess, occasionally that guess by chance will happen to be the letter presented just before the cue. In order to investigate buffering, we must account for trials in which identification failures led to a pre-cue report, because only efficacious pre-cue reports constitute evidence for buffering. The Goodbourn & Holcombe (2015) paradigm we use was designed to allow us to use mixture modelling to estimate of the proportion of trials that were identification failures and the proportion that were efficacious

Mixture Modelling and Model Comparison

Following Goodbourn and Holcombe (2015), we mixture model our participants' serial position error (SPE) distributions. The SPE refers to the temporal position of the

reported stimulus, in item units, relative to the target on a particular trial. Mixture modelling treats a distribution of SPEs as the result of two processes: *efficacious* responses (responses informed by the cue) and identification failures (Zhang & Luck, 2008).

We fit two such models to each participant's data. We fit the models using maximum likelihood estimation with an R package we developed (<https://doi.org/10.5281/zenodo.3545085>) and compare their fits in order to assess the relative evidence for buffering and attentional selection.

The shape of the efficacious distribution should differ depending on whether items are selected with an attention shift or from a buffer, as in Goodbourn and Holcombe's (2015) theory. An attention shift should produce a positively skewed distribution with no responses of items from before the cue (Figure 3). This is because the onset of the cue triggers the shift, imposing a lower bound on selection times so that variance in selection times will be distributed in the right tail of the distribution. The SPE distributions that have been interpreted as evidence for buffering, on the other hand, appear symmetric and have been modeled with symmetric distributions (Goodbourn & Holcombe, 2015; Holcombe et al., 2017).

Figure 3. Example mixtures for the Gaussian and gamma models. Both models combine a distribution of identification failures (the light grey area) with a distribution of efficacious selections (the dark grey area). The dashed line represents the density of the mixture resulting from combining these distributions. The mixture is fit to participants' SPE distributions. The distribution of efficacious selections differs between the models. In the left model, the efficacious distribution is a gamma distribution, which we use to model attention shifts. The right model represents buffering by using a Gaussian distribution as the efficacious distribution.

To investigate the presence of these processes, we fit models with different shapes for the efficacious distribution (Figure 3). We model attentional selection using a gamma distribution¹, which has positive skew and does not produce responses from before the cue. For the buffering model, the assumed efficacious distribution is a Gaussian, as in Goodbourn and Holcombe (2015). Combining these efficacious distributions with the distribution of identification failures produced two mixture models, a buffering model where the efficacious

¹We also attempted to model this component with a log-normal and a Gaussian truncated to provide skew. The log-normal performed poorly in a parameter recovery test, and the Gamma was preferred to the truncated Gaussian because the latter required an arbitrary choice of truncation point.

distribution is a Gaussian distribution, and an attention shift model where the efficacious distribution is a gamma distribution.

We fit both these models using maximum likelihood estimation. For each kind of model, this yields three parameter estimates: *Efficacy*, the proportion of reports that are related to the time of the cue, *Latency*, the mean time of the efficacious distribution relative to the cue, and *Precision*, the standard deviation of the efficacious distribution. Latency and precision are thus estimates of the temporal properties of successful selection, whereas efficacy estimates the proportion of trials for which participants detected the onset of the cue and identified a letter from around that time.

The Binomial Test

Previous studies provided no direct evidence for efficacious pre-cue selections. They relied on the indirect evidence of a best-fitting Gaussian mixture model having latency and precision estimates such that the Gaussian included some responses that were before the cue (Goodbourn & Holcombe, 2015). We developed a more direct test, which we call the binomial test, for efficacious reports of stimuli before the cue.

The test asks the question “Are responses at a particular SPE likely to include any efficacious responses?”. It answers by calculating a p-value corresponding to the number of responses found at the SPE of interest, assuming the null hypothesis that all the responses are identification failures. If the p-value is less than 0.05 for a particular SPE, we reject the null hypothesis of identification failures and infer that some of the tested participant’s responses at that SPE are efficacious. The details of the test are given in Appendix A and B. When applied to the number of responses at the SPE of -1, rejection of the null hypothesis constitutes evidence of buffering.

The present experiments

To investigate when buffered information is selected, we presented participants with various numbers of simultaneous RSVP streams, from two (the number used by Goodbourn and Holcombe, 2015) to 18. In each condition, we then assess the evidence for efficacious pre-cue reports of letters using the binomial procedure. We also compare the fits of the Gaussian to the gamma distributions in mixture modelling to assess the evidence for attention shifts.

Initially, we thought of the manipulation of the number of simultaneous streams as an investigation of the capacity of buffering, because limited capacity restricts processing for many visual tasks (i.e. Hawkins et al., 2016; Luck & Vogel, 1997; Treisman & Gelade, 1980; Wolfe, 1998). This is explicit in the pre-registration for our first experiment (<https://osf.io/7hkgd>), where we assumed that increasing the number of streams would result in a change from selection from the buffer to attentional selection from the stream. However, we came to realise that the use of buffering could reflect the speed of attentional engagement as well. If a stimulus representation has not yet decayed during the presentation of the next item, then efficacious pre-cue responses may occur when attentional engagement is fast enough to select the representation of an item presented in the very recent past. The size of the area that attention is dedicated to - in this case, a function of the number of RSVP streams - affects the speed of a reaction to a target. The larger the area, the slower the reaction time (Castiello & Umiltà, 1990, 1992). Thus pre-cue responses occurring when there are few RSVP streams may reflect the faster engagement of attention under those conditions.

The presence of efficacious pre-cue responses is critical evidence for the buffer. If we do not observe such responses using the binomial procedure, we conclude that there is no evidence that buffered items are used to perform the RSVP task. If, as the number of streams increases, we observe fewer efficacious responses from before the time of the cue,

delays in the latency of selection and potentially more skew in the efficacious distributions, this is evidence that selection of buffered information depends on the number of simultaneous streams.

Data and materials for all the experiments and analyses reported in this paper can be found on Github (https://github.com/cludowici/RSVP_Dynamics/).

Experiment 1

Method

Participants. Ten University of Sydney first-year undergraduates (9 female) ranging in age from 18 - 23 years ($M = 18.9$ years, $SD = 1.6$) participated for credit for a psychology course. This experiment was pre-registered, including a data collection stopping rule of the Bayes factor for the effect of number of streams on latency exceeding 10:1 in favour of either the null or alternative hypothesis (<https://osf.io/7hkqd>). We did not create the custom prior referred to in the pre-registration because there were no existing effect size estimates.

Apparatus. The experiment was controlled by a Macbook Pro running Psychopy 1.85. Stimuli were presented on a Mitsubishi Diamond Pro 2070SB CRT screen with a resolution of 1024 x 768 pixels and a refresh rate of 60 Hz. Participants rested their head on a headrest 56.5 cm away from the screen. To enable exclusion of trials in which participants broke fixation, movement of the right eye was tracked with an SR Research Eyelink 1000.

Stimuli. The stimuli were white Sloan letters (Pelli, Robson, & Wilkins, 1988) that vertically subtended 0.9° . The cue was a 0.98° radius white ring with a line width of 0.07° . The fixation point was a white dot with a radius of 0.14° . On each trial, RSVP streams were presented simultaneously at two or eight positions. Each stream consisted of all letters of the alphabet except C and W, presented in a random order. The letters of each stream

appeared at a rate of 15 items per second. Each letter was presented for three monitor frames (50 ms) with a blank period of one monitor frame (16.67 ms) in between items.

The cue appeared around a target letter in one of the streams, chosen randomly on each trial. The cue was presented for the same three monitor frames as the target letter. The target letter was at a random serial position in the stream between the seventh and the tenth items, inclusive. Streams were equally spaced about an imaginary circle with a radius of 3.0° , centered on fixation.

In the eight-stream condition, the equal positioning of stimuli about the circle resulted in a centre-to-centre spacing of 2.3° of visual angle. In the two-stream condition, the streams were presented on opposite sides of fixation with a separation of 6° of visual angle. With that constraint, across all experimental trials the two streams occupied all eight positions occupied by the eight-streams stimuli. The two streams appeared in every position the same number of trials across the experiment.

Figure 5. A schematic display of an eight-streams display, showing the cue.

At the end of each trial, a response array appeared that contained all 24 letters. Participants indicated the target by selecting a letter with the mouse. They were told to click with the right mouse button if they were “sure” and the left mouse button if they were “unsure” of their response.

Procedure. Participants completed 320 trials. Half were the two-stream condition and half were the eight-stream condition, randomly intermixed. On-screen instructions informed participants that on each trial they must keep their eyes fixed on the central point while “several rapid, randomly-ordered sequences of letters” appeared at two or eight locations on the screen. The instructions also informed participants that one letter would appear “with a white ring around it” and that their task was to report this letter by clicking on it in the response array.

Analysis. The first twenty trials were treated as practice and excluded from the analysis. Mixture models were fit to the remaining 300 trials with a custom R package (<https://doi.org/10.5281/zenodo.3545085>). To compare parameters between the two and eight streams condition, we computed Bayesian t-tests with JSZ priors (Rouder et al., 2009) using the BayesFactor package (Morey & Rouder, 2018) in R (R Core Team, 2019).

To assess how much the data of each participant, and in each condition, favored the Gaussian or skewed gamma distribution, we estimated the Bayes factor – the probability of the data according to one model divided by the probability according to the other model. This Bayes factor, with an uninformative prior over the model parameters, can be estimated using the Bayesian information criterion for each model (Raftery, 1999; Wagenmakers, 2007). We calculate the BIC for each model and the Bayes factor estimated from the BICs to assess which model is a better fit to each participant's data. This mixture model comparison gives us a ratio for the evidence of one model relative to the other. Bayes factors with a ratio greater than three in favour of a particular model are taken as evidence for that model.

Results

Fixation data were retrieved from the Eyelink 1000 using the fixation report from Eyelink Data Viewer (Version 1.11.900). Trials on which the participant made a fixation more than 1° of visual angle from the centre of the fixation point were excluded from further analysis. A mean of 17 (SD = 10) trials per participant were rejected in the two-streams condition. A similar mean of 15 (SD = 7.4) trials were rejected in the eight-streams condition. The distributions of SPEs for the two conditions are shown in Figure 6.

Figure 6. Serial position error (SPE) histograms for all conditions, summed over participants. The dashed vertical line at 0 in each plot represents the time of the cued item.

Sure/unsure responses. The statistics reported below indicate that when participants made a “sure” rather than an “unsure” response, they were more likely to have reported the target or a letter close in time to the target. There was, however, substantial variance in the number of “sure” responses, and some participants responded “sure” only rarely. The number of “sure” responses ranged from 1 to 61 with eight streams and 1 to 64 with two streams, corresponding to 0.007 to 0.46 and 0.007 to 0.45 of the trials in which participants maintained fixation in each condition, respectively. We fit a set of mixed effects logistic regressions predicting the odds of responding “unsure” with condition and the absolute value of SPE as predictors (see Appendix C). The absolute value of SPE was chosen as an independent variable to assess whether participants have insight into the extent to which their response differs from the target. These data were best explained by a model with two predictors, the absolute value of the SPE on each trial and the condition. The odds of responding “Unsure” increased by 25% for every serial position increase in distance

from the target item ($b = .23$, $z = 8.008$, $p = 1.17 \times 10^{-15}$). A similar result of confidence decreasing with the absolute value of SPE was reported by Botella (1992). The odds of an unsure response in the eight-streams condition were 64% of the odds in the two-streams condition ($b = -.45$, $z = 4.57$, $p = 4.8 \times 10^{-6}$). That is, participants were *less* likely to make an “unsure” response with eight streams than with two.

The number of “sure” responses were too few to reliably estimate the parameters of the mixture model for the different confidence responses, so “sure” and “unsure” responses are collapsed together for the mixture model and binomial analyses.

Model Comparison. The data strongly favored the Gaussian symmetric model with two streams, and only with eight streams did they favor the skewed gamma model (Figure 7). The Bayes factors indicated strong evidence for the Gaussian model for nine out of ten participants in the two-streams condition – Bayes factors ranged from 378 to 1.05×10^{15} in favour of the Gaussian model. One participant’s data did not favour either model (1.02).

Evidence for skew (the gamma model) was seen only in the eight streams condition, where data from three participants was fit best by the gamma model (BFs: .05, .26 and .17). The remaining seven participants had model fits that did not markedly favor either model (BFs ranging from .38 to 2.95).

Figure 7. Serial position error (SPE) histograms and model fits for three randomly-selected participants (rows) in the different conditions (columns) in Experiment 2. The density of the best fitting efficacious distributions are shown as the lines on each plot, scaled to near the height of the histograms. For two of these participants, the data did not allow us to discriminate between the Gaussian and gamma models, and the density curves from both efficacious distributions are plotted. For one of these participants, the skewed gamma distribution fit significantly better than the symmetric Gaussian distribution in the eight stream condition.

Parameter Estimates. Because for the majority (seven of ten) of the participants, the data for the eight streams condition did not strongly favor either model, we follow Goodbourn and Holcombe (2015) and interpret the parameters of the Gaussian mixture model for both conditions. Fortunately the pattern of the parameter values (described below) is the same when the parameters of the skewed (Gamma) model are used instead. The exception to this is the gamma mixture’s efficacy estimates, which are higher for the eight stream condition than for the two streams condition. This is likely to be because with few streams, participants

made efficacious selections of items from before the cue, which are not captured by the gamma distribution (it has no mass before zero).

Efficacy. Efficacy is the proportion of responses that are efficacious. The mean estimated efficacy for the two-streams condition is 0.74 (SD = 0.13), and the mean for the eight-streams condition is a very similar 0.76 (SD = 0.11), yielding tentative evidence for no difference, according to the Bayesian paired t-test ($BF_{10} = 0.38$, $d = 0.15$, 95% CI [-0.33, .65]).

Figure 8. Efficacy estimates for the two and eight streams conditions. The dark diamonds and error bars indicate the mean $\pm$ SE for each condition. The lighter circles and lines represent each participant's estimate.

Latency. The latency of the best-fitting efficacious distribution is longer in the eight streams ($M = 72.5$ ms, $SD = 16.6$) than in the two streams condition ($M = 40.0$ ms, $SD = 18$) according to a Bayesian paired t-test ($BF_{10} = 241$, $d = 1.87$, 95% CI [0.86, 2.89]).

Figure 9. Latency estimates, the mean time of the efficacious distribution, for the two and eight streams conditions. The dark diamonds and error bars indicate the mean $\pm$ SE for each condition. The lighter circles and lines represent each participant's estimate.

Precision. Precision was smaller (the efficacious distribution was narrower) for the eight streams conditions ($M = 41.3$, $SD = 10.5$) than for the two streams condition ($M = 61.2$ ms, $SD = 13.3$), Bayesian paired t-test $BF_{10} = 45.9$ ($d = 1.64$, 95% CI [0.56 2.72]).

Figure 10. Precision (the standard deviation of the efficacious distribution) for the two and eight streams conditions. The dark diamonds and error bars indicate the mean $\pm$ SE for each condition. The lighter circles and lines represent each participant's estimate.

Binomial Test. The binomial analysis indicates that in the two streams condition, eight of the ten participants had more SPEs of -1 than expected from our liberal estimate of the rate of identification failures. p -values for these participants ranged from 1.9×10^{-11} to 0.03. In contrast, in the eight streams condition, the null hypothesis that the SPEs of -1 are explainable by identification failures was not rejected for any of the participants.

Discussion

In the two streams condition, participants made efficacious reports of letters from before the cue, despite the fact that these letters had been replaced by a new letter when the cue appeared and triggered attentional sampling from the stream could not have selected them. We did not observe this kind of response in the eight streams condition. In addition, in the eight stream condition, the temporal distribution of efficacious reports occurs

later, is narrower, and is less likely to include reports of items from before the time of the cue.

Participants were more confident in their responses when there were eight streams than when there were two. This finding is similar to observations that participants tend to be more confident in their responses for difficult perceptual tasks relative to easier tasks (Baranski & Petrusic, 1994). Increasing the set size in a visual search task - a manipulation similar to our increase in the number of streams - results in more confident responses (Baldassi et al., 2006). This effect is typically thought to reflect decision processes or a lack of insight into task difficulty (Suantak et al., 1996).

A finding we were surprised by is that participants appear just as effective (equal efficacy) at selecting an item around the time of the cue in the eight stream condition as in the two stream condition, while the evidence for buffering in the eight stream condition is much weaker. This observation is surprising if we assume that pre- and post-cue responses are produced by buffering and sampling processes, respectively. When eight streams were presented, the selection process might change from often accessing information from a buffer to only sampling from the stream via an attention shift. But our finding of no change in efficacy is inconsistent with this theory, because buffering and sampling should have different efficacies. The lack of an effect for efficacy indicates that participants select letters from the stream in the same manner with two streams as well as eight, rather than buffering with two streams and sampling with eight.

If the additional attentional load of monitoring eight streams does not impair the effectiveness of selecting a letter from the stream, what might explain the lack of evidence for buffering with eight streams? Perhaps the loss of buffered responses results from changes in the speed of attention's engagement. When there are few streams, each stream receives more attentional resources prior to the cue and once the cue appears, attention is

faster to select an item in the cued stream. Efficacious pre-cue reports occur in these conditions, then, because attention is deployed fast enough to select a stimulus representation that has not yet decayed.

This theory can explain the lack of a change in efficacy, because in both the two- and eight-streams conditions attention is shifted to the cued location. The difference is that in the two-stream condition, attention samples more quickly from the stream. In Experiment 2, we further assessed the extent to which efficacy is resilient to an increasing number of streams by increasing the number of simultaneous RSVP streams to 18.

Experiment 2

Method

Participants. Thirteen participants took part in the experiment. Nine were undergraduates (six female) aged 18-21 years ($M = 19.9$ years, $SD = 1.4$) and four were graduate students (two female). The age of the graduate students was between 25 and 32. All were students at the University of Sydney. Eye movements for one participant were not recorded due to a computer error, so this participant was excluded from the analysis.

Stimuli. Participants viewed two, six, or 18 streams on each trial. The 18 streams condition comprised three concentric rings of six equally-spaced streams. The eccentricities of the rings were 3, 7 and 11.5 degrees. The ring with radius 7° was rotated clockwise by half the polar angular separation between the streams. The six streams condition consisted of six stimuli with equal eccentricity spaced around a circle. In the two streams condition, the streams were presented on opposite sides of fixation, at a polar angle randomly chosen from those occupied by the streams in the 18 streams condition. There were no differences in the eccentricities of the targets between the conditions. The cued stream was equally as likely to be at 3, 7, and 11.5 degrees of eccentricity in the two, six and eighteen streams conditions.

The role of eccentricity on the temporal dynamics of selection is explored in the supplementary material. Each stream consisted of the same 24 letters used in Experiment 1 with no repeats, presented in a random order.

Stimuli were eccentricity scaled with the parameters used by Strasburger (2005) for scaling numeral stimuli, resulting in letter heights of 0.9° , 1.62° and 2.43° for stimuli at 3, 7 and 11.5 degrees of eccentricity respectively. Cue diameter was scaled from 0.98° at 3° of eccentricity to 1.77° and 2.65° at 7° and 11° , respectively. The number of presentations of the cue at a particular location on the screen (and thus a particular eccentricity) was equal across conditions.

Stimuli were presented at a rate of approximately 12.5Hz – each stimulus was presented for 6 monitor frames (60 ms) with a blank period of 2 monitor frames (20 ms) between each item. The target letter was a random item in the stream between the 7th and the tenth items, inclusive.

Apparatus. Participants viewed stimuli in a dark room on a Mitsubishi Diamond Pro monitor from a distance of 42 cm, ensured by a headrest. The monitor refreshed at a rate of 100Hz. Movements of the right eye were measured with an SR Research Eyelink 1000.

Procedure. Thirteen undergraduate participants performed 270 trials, 90 for each number of streams (2, 6, and 18), randomly intermixed. One participant was dropped from the analysis because an error resulted in their session not being eyetracked.

Analysis. Mixture model fits and model comparisons were computed in the same manner as Experiment 1. Parameter estimates were compared using Bayesian within-subjects ANOVA implemented in the BayesFactor Package (Morey & Rouder, 2018) in R (R Core Team, 2019)

Figure 11. A schematic of a display from the 18 streams condition. Stimuli were arranged into three rings of six, equally-spaced streams each. Measurements in degrees represent the centre-to-centre spacing of objects in the same ring

Results

The mean number of trials discarded because of the presence of a fixation that fell more than 1° from the fixation point were 13.9 (SD = 11.4), 12.4 (SD = 10.0) and 15.3 (SD = 9.2) for the 2, 6 and 18 streams conditions, respectively. The distributions of SPEs for the three conditions are shown in Figure 12.

Figure 12. Serial position error (SPE) histograms for all conditions, summed over participants. The dashed vertical line at 0 in each plot represents the time of the cued item.

Model Comparisons. Participants' data in the two-streams condition all favoured the Gaussian mixture model over the skewed Gamma model with the exception of one participant (Table 3). The Gaussian model was also favoured in the six streams condition by the data of those participants whose data had Bayes factors that were not ambiguous. In the eighteen streams condition, evidence for the skewed gamma distribution emerged, with the data of five of the 12 participants. Example histograms and efficacious distributions are presented in Figure 13.

Figure 13. Serial position error (SPE) histograms and models fits for three randomly-selected participants (rows) from Experiment 2 for different numbers of streams (columns). The density of the best fitting efficacious distributions are shown with lines, scaled to near the height of the histograms. For participants whose data did not allow us to discriminate between the buffering and attention shift models, density curves from both efficacious distributions are plotted.

Table 3

The number of participants whose data favoured the symmetric (Gaussian) model versus the skewed gamma model.

<u>Condition</u>	<u>Gaussian</u>	<u>Gamma</u>	<u>Neither</u>
Two Streams	11	0	1
Six Streams	6	0	6
Eighteen Streams	2	5	5

Parameter Estimates. The parameter estimates are presented in Table 2.

Table 2

Means and standard deviations for the parameter estimates for each condition

Number of Streams	<u>Efficacy (SD)</u>	<u>Latency (SD)</u>	<u>Precision (SD)</u>
2	.73 (.11)	24.1 (31.9) ms	111.0 (50.0) ms
6	.74 (.09)	67.6 (30.9) ms	62.5 (17.5) ms
18	.74 (.08)	90.9 (27.1) ms	56.7 (9.74) ms

Efficacy. A Bayesian repeated measures ANOVA indicates no difference in efficacy across the three conditions ($BF_{10} = .19$, $\eta^2_G = 0.003$)

Figure 14. Efficacy estimates for the different conditions in Experiment 2. Efficacy was not affected by the number of streams.

Latency. Latency increased with the number of streams ($\eta^2_G = 0.46$). A Bayesian test of the ordering of the latency estimates in the same direction as Experiment 1 (2-streams < 6-streams < 18-streams) conducted in the manner described by <http://bayesfactor.blogspot.com/2015/01/multiple-comparisons-with-bayesfactor-2.html> found that this ordering was 7.8×10^6 times better able to explain the data than the null model and 5.98 times more likely than the model with no order restriction.

Figure 15. Latency estimates for the different conditions of Experiment 2. Latency increases with the number of streams.

Precision. The distributions narrowed (the precision estimates decreased) as the number of streams increased ($\eta^2_G = 0.40$). The data were most likely under a model with an order of precision estimates in the same direction as experiment 1a (2-streams > 6 streams > 18 streams). The data under this model were 1905 times more likely than under the null model and 4.1 times more likely than under a model with no order restriction.

Figure 16. Precision estimates for the different conditions in experiment 2. Precision narrows (the estimates decrease) as the number of streams increase.

Binomial Test. Ten of the 12 participants made significantly more SPE = -1 responses than predicted by our liberal estimate of identification failures in the two streams condition ($2.5 \times 10^{-11} \leq p \leq 0.02$), four in the six streams condition ($1.2 \times 10^{-5} \leq p \leq 0.01$) and none in the 18 streams condition (all $ps > 0.3$).

Discussion

The pattern of results is consistent with those of Experiment 1. With few streams, we found evidence for selections of pre-cue stimuli. With more streams, there was less evidence for pre-cue stimulus selection, indeed, there was essentially no evidence with 18 streams. The high efficacy of selection was not affected by the number of streams, despite selection becoming both delayed and less variable in time.

The lack of change in selection's efficacy across different numbers of streams argues against separate processes for selection from the buffer and attentional selection, because, as discussed earlier, it is unlikely that these processes have equal efficacy. This pattern of results, observed in the current experiment and Experiment 1, suggested to us that efficacious pre- and post-cue reports are the result of the same mechanism. One possible explanation is that participants are dedicating attention to the locations of the streams before the cue occurs in order to monitor for its appearance. Attending to many streams, relative to few, may have a number of detrimental effects here. Visual target detection slows when attention is spread over a larger area (Castiello & Umiltà, 1990; 1992), or when the number of potential target locations is increased (VanRullen et al., 2007). Attending to more locations also slows the speed of attentional selection in response to a cue. When the number of potential locations of a cue is increased, the latency of selection in response to the cue becomes longer (Carlson et al., 2006; Hogendoorn et al., 2010). This suggests that in our

task, more attentional resources are endogenously allocated to each stream prior to the onset of the cue when there are few streams relative to when there are many. If more of our participants' attentional capacity is dedicated to monitoring for the cue when there are few streams, selection in response to the cue may occur more quickly than when the resource is diluted among many streams.

Faster engagement of selection when there are few streams may enable selection of the representation of a pre-target stimulus if that stimulus' representation has not yet decayed despite the presentation of a second stimulus at the same time of the cue that should mask the first stimulus. But when more streams are presented, on this account, participants are less likely to make an efficacious response of a pre-cue letter, because their attentional resources are spread over a larger area, causing cue-triggered selection to be delayed.

Experiment 3

In the preceding discussion, we attributed the effects of increasing the number of streams to there being more streams in which the target might occur, causing participants to spread their attention over more streams prior to the presentation of the cue. But the effects may instead have occurred simply because there were more streams physically present on the screen. Santangelo et al. (2007) asked participants to detect the onset of a black dot and found that adding an irrelevant RSVP stream to the display slowed reaction times regardless of whether the participants had to attend to the stream or not. The presence of more streams might result in changes to the dynamics of selection through interference among stimulus representations, even if those streams were not potential locations for the cue and target.

One form of interference among simultaneously presented visual stimuli has been extensively studied: "crowding". Stimuli near each other can markedly impair identification

performance (Agaoglu & Chung, 2016; Bouma, 1970; Pelli & Tillman, 2008; Rosenholtz et al., 2019; Whitney & Levi, 2011). The size of the region in which crowding by a stimulus occurs scales approximately linearly with eccentricity. Stimuli with a centre-to-centre spacing of less than 0.4 to 0.5 of their eccentricity will be crowded (Pelli & Tillman, 2008). However, it is unlikely that crowding can explain our results because our stimuli were widely spaced enough to fall outside of the crowding zone. The centre-to-centre spacing in the eight-streams condition of Experiment 1 is 0.77 of the eccentricity. Even more widely spaced are the items in the 18-streams display of Experiment 2, those of the inner ring have a spacing of 3° , which is the same as their eccentricity.

Although crowding is unlikely to have occurred in our experiments, stimuli with larger spacings may sometimes yield interference effects (Kyllingsbæk et al., n.d.). To investigate whether this is the reason for the effect of number of streams in Experiments 1 and 2, we hold the level of potential interference between stimulus representations constant in Experiment 3 by always presenting the same number of streams on each trial. To manipulate attention, we varied the number of potential target locations and pre-cued those potential locations of the target. Any effect of the number of potential locations will then be attributable to dilution of attentional resources – less resources devoted to each stream.

Eight streams were presented on each trial, and participants were instructed to monitor two or eight streams for the cue. This mimics experiment 1 but controls for any interference effects as there are always eight streams. Thus any differences we observe in the latency and precision of these results are due to changes in attentional spreading rather than stimulus interference, which is fixed. A replication of the pattern of findings in experiment 1 would be evidence for the idea that these effects reflect participants spreading endogenous attention over many locations for the presence of the cue, rather than an effect of the amount of interference between stimuli.

Method

The method and analysis for this experiment were the same as that of Experiment 1, with the exception that eight streams were always displayed and a precue indicated the possible spatial positions of the cue on each trial. Participants viewed stimuli in a dark room on a Mitsubishi Diamond Pro monitor from a distance of 42 cm, ensured by a headrest. The monitor refreshed at a rate of 100Hz. Movements of the right eye were measured with an SR Research Eyelink 1000. Prior to the presentation of the RSVP streams on each trial, eight hash marks appeared on the screen for 250ms, occupying the same positions as the RSVP streams. Two or eight of these hash marks had white rings around them, representing the possible positions of the cue on that trial. The two-precue condition pre-cued the same locations as those occupied by the two streams in Experiment 1 (either side of fixation). A blank screen was presented for 500 ms after the precues. 13 undergraduate students from the University of Sydney participated and received course credit.

Results

A mean of 18 (SD = 13) trials were rejected based on eye movement away from fixation in the two-precue condition. A mean of 15 (SD = 12) trials were rejected in the eight-precue condition. Histograms for both conditions are shown in Figure 17.

Figure 17. Serial position error (SPE) histograms for all conditions, summed over participants. The dashed vertical line at 0 in each plot represents the time of the cued item.

Model Comparisons. Model fits largely favoured the Gaussian mixture model or did not distinguish between the models. See table 4 for the frequency of each fit in each condition.

Table 4

The results of the model comparisons. The number of participants whose data favoured each model.

Condition	<u>Gaussian</u>	<u>Gamma</u>	<u>Neither</u>
Two Precues	6	1	6
Eight Precues	6	2	5

Parameter Estimates.

Efficacy. The mean efficacy in the two-cues condition was 0.75 (SD = 0.07), and in the eight-precues condition was 0.71 (SD = 0.13; $BF_{10} = .65$, $d = 0.28$, 95% CI [-0.13, 0.70]).

A Bayesian paired t-test comparing efficacy estimates between conditions produced a Bayes factor close to 1, indicating that the test favored neither the null hypothesis of no difference nor the alternative hypothesis of a difference.

Figure 18. Efficacy estimates for Experiment 3

Latency. Latency was shorter for the two-precues condition ($M = 84.84$, $SD = 72.35$) than the eight-precues condition ($M = 108.12$, $SD = 69.37$; $BF_{10} = 21.9$, $d = 0.33$, 95% CI [0.15, 0.50]). One participant had very high latencies - around 280 ms - in both conditions and also large precision estimates of 180 ms and 162 ms in the two and eight-precue conditions, respectively. But removing this participant from the efficacy, latency and precision analyses did not change the pattern of results.

Figure 19. Latency estimates for Experiment 3

Precision. The null hypothesis of no difference in precision between the two conditions explained the data best, $BF_{10} = 0.35$. The two-precues condition had a mean of 90.3 ms (SD = 49.5). The eight-precues condition had a mean of 85.5 ms (SD = 39.3, $d = 0.08$, 95% CI [-0.16, 0.33]).

Figure 20. Precision estimates for Experiment 3

Binomial Test. Three participants in the two-precues condition had more SPEs of -1 than are easily explained by identification failures (p s < .001). One participant showed more SPEs of -1 than would be predicted by identification failures in the eight-precues condition (p = .01).

Comparison of effects between experiments (Exploratory Analysis). To compare the effect of pre-cueing and the effect of the number of streams, we combined the data from Experiments 1 and 3 and tested for differences between them in an exploratory analysis. We fit two linear mixed-effects models for each of the three mixture model parameters using the lme4 package in R (Bates et al., 2015). The models always contained random intercepts by participant and predicted each parameter with main effects of condition and experiment, or the main effects and an interaction between condition and experiment. This interaction term represents a test of the hypothesis that changing the number of pre-cued streams (Experiment 3) is different from changing the number of streams (Experiment 1). If that is the case for a given parameter estimate, then the best fitting model

for that estimate should contain an interaction term. To assess model fit, we calculated Bayes factors from each model's BIC using the approximation described by Wagenmakers (2007).

The Bayes factors produced by this analysis represent the ratio of evidence for the interactive model to the model without an interaction. This analysis indicated inconclusive evidence regarding a difference between experiments in the effects of condition on efficacy ($BF_{10} = .46$) and latency ($BF_{10} = 1.13$). For precision, there is some evidence for a difference between the experiments – more streams narrowed the efficacious distribution in Experiment 1 but not Experiment 3 ($BF_{10} = 3.77$).

The effect of spreading attention over many streams, as manipulated by precuing, does not completely explain the changes in temporal processing in experiment 1 because the effect of condition on precision differs between the experiments.

Discussion

By manipulating the number of task-relevant streams, while keeping the number presented constant, we replicated the findings of Experiment 1 in that a greater number of task-relevant streams yielded longer latencies and fewer efficacious reports of the item before the cue. Like Experiment 1, Experiment 3 produced strong evidence for an increase in latency as the number of relevant streams increased (Experiment 3), but without the confound of an additional number of streams presented. This suggests that the increase in latency found in Experiment 1 was due, at least in part, to changes in the number of locations that participants must dedicate their attention to. When participants spread their attention over many simultaneous streams, they are slower to orient their attention to the cued location than when there are fewer streams. Not all the changes in the temporal qualities of selection can be explained by participants spreading attention over the potential

locations of the cue, however. There was no apparent change in precision for different numbers of streams in Experiment 3, whereas in Experiment 1 precision was better for higher numbers of streams. The evidence for this difference between the experiments was only moderate, however, so more work is needed to confirm it.

The proportion of participants for which there was evidence of efficacious responses of pre-cue items was higher when there were only two pre-cued locations, suggesting that such responses reflect the application of endogenous attention over the possible locations of the cue. In other words, reports of letters from before the cue that are efficacious are more likely to occur when participants monitor a small number of locations for the cue.

General Discussion

The present experiments and analyses provide the strongest evidence to date that participants may make efficacious responses of pre-cue items in a cued RSVP task, confirming previous suggestions of such responses that have been used to support theories of buffering in RSVP (Botella et al., 2001; Goodbourn & Holcombe, 2015; Holcombe et al., 2017; Vul & Rich, 2010). Here we found that when selection was delayed by increases in the number of relevant RSVP streams, these responses seemed to no longer occur. Yet despite the absence of evidence for buffering when participants viewed many streams, the rate of efficacious selection of an item from the cued stream remained high.

The fact that efficacy did not change with the number of relevant streams indicates that selection may be parsimoniously explained by the same process across conditions. If a different process were involved when there were few streams, we would expect to observe a change in efficacy between conditions because different processes seem unlikely to have the same probability of success. Although it is certainly possible that a buffer-based process

has the same efficacy as a distinct selection process, parsimony favours an account in which a single process determines selection from the cued stream across all conditions.

We suggest that selection in all cases here is a result of cued attentional shifts, similar to theories in which attention samples items from the stream without any ability to sample them from a buffer (Grossberg & Stone, 1986; Reeves & Sperling, 1986; Shih and Sperling, 2002). However, our theory differs from these not only by positing a buffer, but also by suggesting that the interaction between endogenous and exogenous attention affects the latter's selection latency. Specifically, the time of selection is a function of the attentional resources endogenously allocated to the cued stream prior to the cue. Increases in selection latencies, and thus fewer pre-cue reports, occurred here when more relevant streams were present because less endogenous attention was allocated per relevant stream prior to the onset of the cue. When there are few streams in which the cue may appear, as in the two-precues condition of Experiment 3 or the conditions with few streams in Experiments 1 and 2, each stream receives a larger proportion of the available attentional resources. This speeds selection at the cued location relative to conditions with greater numbers of streams. That this pre-cue resource allocation is endogenous is supported by the finding in Experiment 3 that latency is manipulated by providing participants with information about the upcoming location of the cue. It is consistent with observations that attentional selection is slower when the number of possible cue locations is increased (Carlson et al., 2006; Hogendoorn et al., 2010).

Why are items presented before the cue sometimes selected? Much previous literature suggests that masking would terminate the representation of the SPE -1 stimulus, eliminating the possibility that attention selects that item. Information about RSVP stimuli, however, does persist in the visual system following masking by subsequent items in the stream (Marti & Dehaene, 2017). Smithson and Mollon (2006) found evidence that this

information can be available for report using a modification of the iconic memory paradigm (Sperling, 1960). Participants saw a 4 x 3 matrix of letters for 10 ms and were presented with a cue, indicating the row of letters to report, after the termination of the matrix. But before the cue was presented, a pattern mask was flashed for 20 ms. Participants could accurately report cued letters from the matrix when the cue was presented up to 700ms after the mask. The accuracy of this report was higher than was predicted by participants' attempts to report all items from the matrix after the mask. This is Sperling's (1960) partial report advantage, which indicates attentional selection from information in the visual system that persists when a stimulus is no longer presented. In this case, the persistence occurred despite masking. Similar results were reported by Smith et al. (2011). In our task, if attention is fast enough it may select an item before the cue as its representation can persist into the presentation of the cued stimulus.

Our theory explains the pattern of results found for latency, efficacy, and precision. As explained above, latency increases because with more streams, the endogenous application of attention must be spread over more locations, leading to a smaller attentional advantage for each stream and delaying selection. Diluting attentional resources changes selection latency, but not the probability of detecting the cue and identifying a letter. The latter process always proceeds via the same mechanism, and thus efficacy does not change across conditions in the three experiments.

The temporal distributions of the serial positions reported were narrower with larger numbers of streams in Experiments 1 and 2, but possibly not in Experiment 3 where the number of streams was constant but the number relevant to the task was varied. Perhaps there is competition among streams for cortical processing, whether they are relevant or not, and this causes stimulus representations to not persist as long as with fewer streams. The range of presentation times of stimuli that are simultaneously activated, and available for

selection, should then be narrower when more streams are presented. One caveat is that the previous evidence for long-range interference in the visual cortex is thin. The relevant neuroimaging studies that we are aware of all spaced stimuli closely enough that stimuli may have crowded each other, unlike our RSVP streams (Beck & Kastner, 2005, 2007; Kastner et al., 1998, 2001; Scalf & Beck, 2010). However, there is some neurophysiological evidence for long-range interference (Falkner et al., 2010; Schall et al., 2004; but see Holcombe, Chen & Howe, 2014, regarding interpretation of these) .

This explanation for the change in precision may seem inconsistent with the lack of any changes in efficacy in the present experiments. Narrowing the temporal range of stimuli available for attentional selection might be expected to result in a lower probability of an efficacious selection. However, selection is fast enough that even when it cannot select a long-lasting persistent representation, it still has ample time to select from the incoming stream of stimulus information before the stream ends. The longest latencies are found in the 18-streams condition of Experiment 2. In that condition, the shortest possible time between the target's onset and the end of the stream was 1120 ms (14 serial positions), and the mean latency was 90 ms. Evidently participants are able to select an item from the stream well before the stream ends, and thus their efficacy does not suffer even when persistence of item information is reduced. This may also explain why we were more likely to observe skew in the efficacious distribution with many streams relative to few. If representations decay faster when there are many streams, this will only affect the selection of representations of items that are no longer presented - the efficacious distribution's left tail. Attention can still select items presented after the cue, leading to skew in the distribution.

Relation to published theories of temporal selection

No published theory of attentional selection appears fully capable of explaining the results of the present experiments without modifications. Those theories that contain persisting stimulus representations do not include mechanisms by which the number of possible cue locations changes the speed of the attentional response to the cue and the number of simultaneous streams alters the persistence of stimulus representations (Botella et al., 2001; Chun & Potter, 1995; Olivers & Meeter, 2008; Vul & Rich, 2010; Wyble et al., 2009). However, our results suggest that these factors combine in order to change the frequency of efficacious reports of items from before the cue. Our results also disconfirm theories that assume that masking terminates item representations (e.g. Reeves & Sperling, 1986; Grossberg & Stone, 1986; Shih & Sperling, 2002).

As discussed, our results argue against Goodbourn and Holcombe's (2015) theory of separate processes for buffering and attentional sampling from an RSVP stream. The efficacy of our participants was invariant to the number of streams and the concomitant variation in the number of efficacious pre-cue reports, suggesting that a single process is responsible for the pre- and post-cue efficacious selections.

Several models assume that attentional sampling, triggered by the onset of a cue, is necessary in order to sustain a stimulus representation, which is otherwise overwritten by masking (Grossberg & Stone, 1986; Reeves & Sperling, 1986; Shih & Sperling, 2002). Our results demonstrate that this assumption is wrong. Stimulus representations persist long enough that a stimulus may be selected and reported even though it occurred before the cue. However, we believe that, even when the item reported occurred before the onset of the cue, these models are correct in assuming that selection is solely due to attention, rather than some other process (i.e. Goodbourn & Holcombe, 2015).

Are there any models of selection in RSVP that could be modified to explain our results? Reeves and Sperling (1986) modelled attentional shifts, but concluded that stimulus

representations could not overlap in time, as they found that modeling this did not improve model fits. Their task, however, may have produced slow shifts of attention that prevented reports of pre-cue stimuli. The task involved monitoring one RSVP stream for a target and then shifting attention to another stream in order to report the letters appearing there. This presumably involves an endogenous shift of attention, whereas our experiments used a peripheral cue which most likely induced an exogenous shift of attention. Endogenous attentional orienting is, on average, slower than exogenous orienting (Cheal & Lyon, 1991), so it may be that the speed of attentional selection was not fast enough to yield evidence of overlapping stimulus representations in their task. It remains to be seen whether Reeves and Sperling's (1986) model fits would be improved by assuming overlapping representations for a task with an exogenous cue.

Several theories use stimulus representations that persist briefly beyond the onset of another stimulus at the same location, but are not typically applied to tasks in which targets and distractors are viable options for report. These models might explain our results with modifications (Botella et al., 2001; Chun & Potter, 1995; Olivers & Meeter, 2008; Vul et al., 2008; Wyble et al., 2009). Our data provide constraints on the parameters of these theories. The effects of the number of streams and pre-cueing indicates that the speed of attentional selection and the decay rate of stimuli are affected by endogenous attention and competition between stimuli. The decay rate may be faster with many streams, leading to narrower distributions. Similarly, the application of endogenous attention alters the speed of selection. Modifying the theories to include an endogenous mechanism that affects the cue processing time and a decay parameter that varies with the number of stimuli on screen would change these theories so that they are consistent with the effects we have demonstrated.

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Appendix A

The Binomial Test

The binomial test provides an estimate of the probability of a particular number of pre-cue reports under the null hypothesis that these reports are identification failures. This provides a test for each serial position error. If the test yields a low probability for identification failures at a particular serial position, we conclude that efficacious reports contributed to the reports at that serial position.

In order to test if responses are identification failures, we use the windowed-uniform distribution of identification failures from our mixture modelling procedure as our null hypothesis. The SPE = -1 position corresponds to some proportion of this distribution and we use this as an estimate of the frequency of making an SPE=-1 response under the null hypothesis of all responses being identification failures. To calculate a probability of the frequency of reports at a particular SPE at least as extreme This allows calculation of a p-value that tells us the probability of observing a count of SPEs at -1 at least as extreme as the observed count if participants' responses are entirely comprised of identification failures. We will illustrate this before making the test more realistic by not assuming that all responses are identification failures.

To illustrate the binomial test, the distribution of selection errors of a participant from our first experiment is shown in Figure 3A. Identification failure responses have a nearly uniform distribution of SPEs. This distribution is the same as the identification failure distribution in our mixture model and it is windowed at extreme SPEs (Goodbourn & Holcombe, 2015). SPEs of -1 make up some proportion of this distribution (Figure 3B). To test whether there are more responses at -1 than expected from identification failures, we use the binomial distribution, where hits are SPEs of -1 and misses are all other SPEs

(Figure 3C). The proportion of the identification failure distribution at -1 is used as the probability of a hit in this distribution and the number of responses recorded by a participant as the number of observations. The p-value is the orange region of Figure 3C – the probability of a count of -1 SPEs at least as extreme as the observed count in the binomial distribution. As discussed below, we adjust the identification distribution to account for the fact that participants' SPE distributions are unlikely to be entirely due to identification failures. We interpret a p-value below .05 as good evidence against the null hypothesis that the $SPE = -1$ responses are entirely due to identification failures.

Figure 3. The process for testing whether the count at a particular SPE is greater than expected by identification failures. Panel **A** shows one participant's SPE histogram. The highlighted bar shows the five SPEs of -1 in this histogram. Panel **B** shows the distribution of SPEs associated with identification failures; the highlighted component is the proportion of the distribution corresponding to an SPE of -1. The points and lines of panel **C** show the binomial distribution associated with an SPE of -1 using the proportion of the identification failure distribution at -1 as the probability of success. The highlighted points in panel **C** show the proportion of the distribution with a count at least as extreme as that shown in panel **A**. The probability of a random draw in this highlighted region corresponds to the p-value for the highlighted component in panel **A**, according to the test.

Making the binomial test less conservative

The distribution of selections is extremely unlikely to be comprised entirely of identification failures because previous work has repeatedly found that selection error distributions depart from the identification failure distribution. They have a peak around the time of the target, indicating that in some trials participants successfully identify the target and suggesting that they sometimes identify a letter near the time of the target (Goodbourn & Holcombe, 2015; Holcombe et al., 2017; Vul, Nieuwenstein, & Kanwisher, 2008; Martini, 2013). Using their Gaussian mixture model, Goodbourn and Holcombe (2015) estimated that identification failures (which they referred to as “guessing”, although the concept also includes misidentifications) accounted for about a quarter of their participants’ responses.

Given that not all responses are identification failures, the assumption of the binomial test (as described so far) that all responses are identification failures is wrong, and this makes the test overly conservative. That is, by assuming that all responses are identification failures, the probability we assign to a particular count of $SPE = -1$ responses is too high because the identification failure rate assumed, 1, is higher than the actual value.

To make the test less conservative, a more realistic estimate of the proportion of responses that are identification failures is needed. However, we should avoid using an estimate expected to be lower than the actual value, because that would result in a liberal test (one for which the p-values are too low). To account for the fact that not all responses are identification failures we need some proxy for efficacy. This proxy for efficacy should be, if it is wrong, an underestimate to avoid yielding an identification failure rate that is too low, which would result in a liberal test.

We used the proportion of responses with SPEs of 0 as a conservative estimate of efficacy and its complement, $1 - p(SPE = 0)$, as a liberal estimate of the rate of identification failures. The identification failure rate liberal estimate is used to make the estimated proportion of SPEs of -1 expected from identification failures more realistic. This more

realistic estimate of the proportion of trials with an SPE of -1 for a particular participant is the product of the proportion of the identification failure distribution at -1 for that participant and the estimate of the failure rate. This adjusts the proportion of identification failures down from an unrealistic 100%. Doing so does not underestimate the expected proportion of identification failures, because efficacy estimated in this manner is conservative, as shown in Appendix B.

Our liberal estimate of the probability of a trial having $SPE = -1$, again then, is $p(SPE = -1 | Identification Failure) \times [1 - p(SPE = 0)]$. For each participant, we used the binomial distribution to calculate the probability of the observed number of $SPE = -1$ trials or a greater number. This is the p -value of our statistical test.

In summary, to assess evidence for buffering, we use a liberal estimate of the probability of a particular number of $SPE = -1$ trials that would occur if none of the efficacious trials resulted in an $SPE = -1$. As a liberal estimate, the probability is likely be higher than or the true value, so that the false positive rate should be lower than .05.

Binomial Analysis of published data

Vul et al. (2008) conducted an attentional blink experiment and implied that their data contained pre-cue efficacious responses, including for the first target. Taking their dataset, which was made available for the Goodbourn et al. (2016) re-analysis (<https://osf.io/fs93m/>), we applied the binomial test to quantitatively assess the evidence against the null hypothesis that the pre-cue responses were due to identification failures.

As an attentional blink experiment, Vul et al.'s (2008) task involved an RSVP stream of letters with a cue presented around two of them, separated by different numbers of items (lags). Figure 4 presents SPE distributions from participants for the first target (T1) for lags one to six from this experiment. Visual inspection suggests that the number of $SPE = -1$

responses exceeds that which could be explained by identification failures. We present the distributions for T1 only because items presented before the first target did not receive any cueing, whereas items from before the second target may have received cueing from the first target and are also subject to distortion from the attentional blink.

Figure 4. SPE histograms for T1 responses in Vul, Nieuwenstein and Kanwisher (2008), summed over participants. The dashed vertical line represents the target. Responses are approximately symmetric around the cue and the cluster around each distribution’s mode includes items from before the target, suggesting that some responses were drawn from a buffer.

For each lag between the first and second targets, we applied our binomial test to the data for the first target (T1). Using the $p < .05$ level, for nine or more of the eleven participants (depending upon the condition) we reject the null hypothesis that the $SPE = -1$ trials were generated entirely by identification failures (Table 1). p -values for the participants ranged from 3.9×10^{-18} to .047.

Table 1
Results of the binomial test applied to the data of the eleven participants in Vul

et al. (2008)

<u>Lag</u>	<u>Number of participants with $p < .05$</u>
1	11
2	9
3	10
4	9
5	9
6	9
7	10
8	11
9	9
10	11

Goodbourn and Holcombe (2015) also claimed that for their own experiments, some of the $SPE = -1$ trials were a result of efficacious trials rather than misidentifications. We applied the binomial test to the data for their two-stream, single-target condition, in which participants responded to a single cue in one of two streams. Nineteen of the 26 participants had more responses with an SPE of -1 than could be explained by identification failures. p -values for these participants ranged from 1.4×10^{-13} to .03.

These results provide quantitative evidence for efficacious pre-cue responses in RSVP tasks - an indication of buffering.

Appendix B

Our binomial test, we claim, uses a conservative measure of efficacy, which accounts for the likely fact that not all responses in our paradigm will be identification failures. To do this, we use the proportion of a participant's SPE distribution equal to zero as a measure of efficacy.

How can we be sure the proportion of responses at zero is a conservative estimate of efficacy? There are several conditions where this is not true. Firstly, it may be that all efficacious responses fall at zero. In this case the observed count of responses at this point over-estimates efficacy, because the observed count includes all efficacious responses plus some proportion of identification failures. Another undesirable situation is that in which all efficacious responses fall somewhere other than zero, in which case the count at zero contains only guesses, and our measure of efficacy actually represents the proportion of guesses at 0. These two scenarios represent extreme conditions under which we cannot use the count of responses with an SPE of 0 as a measure of efficacy. In other words, we want efficacious responses to be spread over multiple SPEs, one of which is zero.

Finally, the combination of efficacious responses and identification failures at zero may overestimate efficacy even if neither of the extreme conditions are met. In this situation the proportion of efficacious responses at zero and the proportion of identification failures at that SPE sum to greater than efficacy, in which case efficacy is overestimated and identification failures are underestimated by this measure.

To investigate whether or not these undesirable conditions are present in an RSVP experiment similar to our own, we used data from the two-stream single-target condition of Goodbourn and Holcombe (2015). The experiments described in the current paper involve multiple simultaneous RSVP streams, one of which is cued at one point in time. In Goodbourn and Holcombe's two-stream single-target condition, participants saw two RSVP streams, one of which was cued with a white ring indicated the target letter. The analyses reported in that paper for this condition analysed responses based on the spatial position of the cued stream in order to investigate potential spatial asymmetries in selection. However, there were no effects of spatial position on the efficacy, latency or precision of selection. We therefore collapsed the streams together and analysed the distribution of selections in the

cued stream, regardless of the spatial position of that stream on particular trials. This is the same analysis we use in the present experiments.

The proportion of efficacious responses and identification failures at zero can be estimated by fitting a mixture model to the SPE distributions, and thus whether the undesirable conditions are present. After fitting mixture models to the Goodbourn and Holcombe data, we looked at the proportions of the efficacious and identification failure components of the mixture corresponding to an SPE of 0. The proportion of the efficacious distribution at $SPE = 0$ for each participant was, on average, .44 ($SD = .1$, $min = .2$, $max = .7$). The proportion of non-guesses at 0 was .042 for each participant. The proportion at zero is the same for each participant because they each observed the same distribution of cue serial positions (Goodbourn and Holcombe, 2015). Summed, the proportions of estimated efficacious responses and estimated guesses at an SPE of zero did not exceed efficacy for any participant in this experiment, nor did the proportion of SPEs which were 0 did not exceed efficacy for any participant.

This analysis indicates that the majority of responses at zero are efficacious, but efficacious responses are spread over many SPEs. Summing the proportion of efficacious and identification failures at an SPE of zero does not overestimate efficacy for any of the participants in this analysis. The conditions necessary for using the proportion of SPEs of zero as a conservative measure of efficacy are met.

The complement of this conservative measure of efficacy, $1 - p(SPE = 0)$, is a liberal estimate of the rate identification failures. That is, while this allows us to account for the fact that not all responses are likely to be identification failures, it does not underestimate the rate of identification failures.

Appendix C

To investigate how confidence ratings changed as a function of SPE and condition, we fit five generalised linear mixed effects models, each of which predicted the odds of making an ‘unsure’ response. The predictors varied between models. These were: the absolute value of the SPE on each trial ($|SPE|$), the number of streams, and an interaction term. We fit five models using lme4 (Bates et al., 2015). The models all contained random intercepts by participant. The models were:

- 1) Intercept only
- 2) $|SPE|$
- 3) Number of Streams
- 4) Number of Streams & $|SPE|$
- 5) Number of Streams, $|SPE|$ and an interaction between these two variables

We interpreted the model with the lowest Bayesian Information Criterion (BIC) as the best fitting model. BIC values are presented in Table S1. The best fitting model contained $|SPE|$ and the number of streams as predictors. Fixed effects for the model are presented in table S2. Both variables had an effect on the odds of responding “unsure”. As $|SPE|$ increased, the odds of responding unsure increase by 0.25 ($B = 0.23$, $z = 8.008$, $p = 1.17 \times 10^{-15}$). Indicating that participants had some insight into whether or not their report was the target item. The odds of responding “unsure” decreased in the eight-streams condition by .36 ($B = -0.45$, $z = 4.57$, $p = 4.8 \times 10^{-6}$). Indicating that participants in this condition were, in general, more sure of their answers.

Table B1

Bayesian Information Criterion (BIC) values for the generalised mixed-effects models. The best fitting model is highlighted

<u>Model</u>	<u>BIC</u>
Intercept-only	2717.36
$ SPE $	2629.42
Number of Streams	2707.84

 SPE + Number of Streams	2616.39
SPE + Number of Streams + Interaction	2624.20

Table B2

Fixed Effects Estimates from the best fitting model

	<u>Estimate</u>	<u>Standard Error</u>	<u>z</u>	<u>p</u>
Intercept	1.58856	0.44099	3.602	0.000315
Number of Streams	-0.44869	0.09811	-4.573	4.80e-06
SPE	0.23420	0.02925	8.008	1.17e-15