


**The spatiotemporal link of temporal expectations: contextual temporal expectation is independent of spatial attention**

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1 **Abstract**

2 Temporal expectation is the ability to construct predictions regarding the timing of events,  
3 based on previously-experienced temporal regularities of different types. For example, cue-  
4 based expectations are constructed when a cue validly indicates when a target is expected to  
5 occur. However, in the absence of such cues, expectations can be constructed based on  
6 contextual temporal information, including the event's hazard-rate function – its moment-by-  
7 moment conditional probability that changes over time; and prior experiences, which provide  
8 probabilistic information regarding the event's predicted timing (sequential effects).

9 It was previously suggested that cue-based temporal expectation is exerted via  
10 synchronization of spatially-specific neural activity at a target's predictable time, within  
11 receptive fields corresponding to the target's expected location. Here, we tested if the same  
12 theoretical model holds for contextual temporal effects. Participants (n = 40) performed a  
13 speeded spatial-cueing detection task, with two-thirds valid spatial cues. The target's hazard-  
14 rate function was modulated by varying the foreperiod – the interval between the spatial cue  
15 and the target - among trials, and was manipulated between groups by changing the interval  
16 distribution. Reaction times were analyzed using both frequentist and Bayesian generalized  
17 linear mixed models, accounting for hazard and sequential effects. Results showed that the  
18 effects of contextual temporal structures on reaction times were independent of spatial  
19 attention. This suggests that the spatiotemporal mechanisms, thought to account for cue-based  
20 expectation, cannot explain other sources of temporal expectations. We conclude that  
21 expectations based on contextual structures have different characteristics than cue-based  
22 temporal expectation, suggesting reliance on distinct neural mechanisms.

23

24 *Keywords:* Temporal attention; Hazard-rate function; Sequential effect; FP-RT slope;

25 Reaction time

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**Significance statement**

28 Temporal expectation is the ability to predict an event onset based on temporal regularities. A  
29 neurophysiological model suggested that temporal expectation relies on the synchronization of  
30 spatially-specific neurons whose receptive fields represent the attended location. This model  
31 predicts that temporal expectation would be evident solely within the locus of spatial attention.  
32 Existing evidence supported this model for expectation based on associations between a  
33 temporal cue and a target, but here we show that it cannot account for another source of  
34 temporal expectation – expectation that is based on contextual information, i.e. hazard-rate and  
35 recent priors. These findings reveal the existence of different predictive mechanisms for cued  
36 and contextual temporal predictions, with the former depending on spatial attention and the  
37 latter non-spatially-specific.

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**Introduction**

40 Temporal expectation is the ability to construct predictions regarding the timing of  
41 events, based on temporal regularities. Multiple forms of such regularities can drive temporal  
42 expectation, including contextual information, when information regarding distributions of  
43 events and statistical inferences from recent experiences are used to predict the timings of  
44 future events; rhythms and other repetitive sequences, when events occur in predictable streams  
45 (e.g., Heideman et al., 2016; Breska and Deouell, 2017; Dankner et al., 2017; Breska and Ivry,  
46 2018); and cued-associations, when events are preceded by informative temporal cues (e.g.,  
47 Coull and Nobre, 1998; Miniussi et al., 1999). Studies show that expectations of all these

48 sources are associated with enhanced perceptual performances (e.g., Niemi and Näätänen,  
49 1981; Nobre et al., 2007; Nobre and van Ede, 2018).

50 Despite abundant evidence on behavioral effects of temporal expectation, relatively  
51 little is known regarding their neurophysiological correlates. One theoretical framework  
52 suggested that temporal expectation is the result of synchronization within neural populations  
53 at the time of the expected target. It was suggested that these neuronal populations are spatially  
54 specific – their receptive fields correspond to the expected target location (Rohenkohl et al.,  
55 2014; Nobre and van Ede, 2018). According to this view, temporal and spatial expectations are  
56 tightly linked, as temporal expectation is bound to be evident only within the locus of spatial  
57 attention: in order to gain from knowing *when* a target will occur, one has to know *where* it  
58 would occur. However, evidence for this spatiotemporal framework is limited to studies that  
59 manipulated cue-based temporal expectation (Doherty et al., 2005; Rohenkohl et al., 2014;  
60 Seibold et al., 2020). It remains unknown whether the same spatiotemporal mechanism  
61 accounts for temporal expectation based on other sources of regularities. Here, we examine  
62 whether this spatiotemporal framework could also explain expectations based on contextual  
63 information, i.e., induced by conditional probabilities or sequential effects.

64 *Conditional probability* is the likelihood of an event to occur, given that it has yet to  
65 occur. This probability changes continuously as time progresses and can be described as a  
66 function of time, termed the *hazard-rate* function. When the timings of events are uniformly  
67 distributed, the hazard-rate function is monotonically increasing, but other distributions would  
68 lead to different hazard-rate functions (Luce, 1986). The effect of the hazard-rate function was  
69 demonstrated by showing that higher conditional probability for target occurrence is associated  
70 with enhanced performance. In a common design, a warning signal (WS) alerts participants to  
71 an upcoming target, which follows after a varying time-interval (*foreperiod*). It is consistently

72 found that performance for targets appearing following long foreperiods is enhanced relative  
73 to targets appearing following shorter ones (Näätänen, 1970; Niemi and Näätänen, 1981).

74 Another source of information used to alleviate temporal uncertainty are prior  
75 experiences. The perceptual system constantly makes predictions and utilizes priors to make  
76 these predictions (Clark, 2013). These temporal predictions about the event's most probable  
77 onset time are reflected in the *sequential effect* – the cost and benefit in performance stemming  
78 from the relation between the foreperiods of sequential trials (Bertelson, 1961; Niemi and  
79 Näätänen, 1981). When a target appears following a foreperiod that is shorter than that of the  
80 previous trial, performance is reduced, relative to trials that were preceded by an identical  
81 foreperiod. This pattern is asymmetrical, as performance remains unchanged when a target  
82 appears following a foreperiod that is longer than the previous trial (Bertelson, 1961; Possamai  
83 et al., 1973).

84 Here, we manipulated spatial attention and temporal expectation simultaneously. In  
85 each trial, participants were presented with a spatial cue that was either congruent, incongruent,  
86 or neutral in respect to the location of the target that appeared after a varying interval  
87 (foreperiod). The distribution of the foreperiod intervals was varied between participants to  
88 create two different hazard-rate functions. We hypothesized that, unlike cue-based expectation,  
89 both hazard-rate and sequential effects are independent of spatial attention, indicating that the  
90 spatiotemporal framework suggested to account for temporal expectation does not account for  
91 these processes.

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## Materials and Methods

### 94 *Participants*

95 A total of 40 participants were included in this study, 20 in the ‘Uniform distribution’ group  
96 (12 females, 2 left-handed, Mean age  $25.35 \pm 3.5$  standard deviations [SD]) and 20 in the

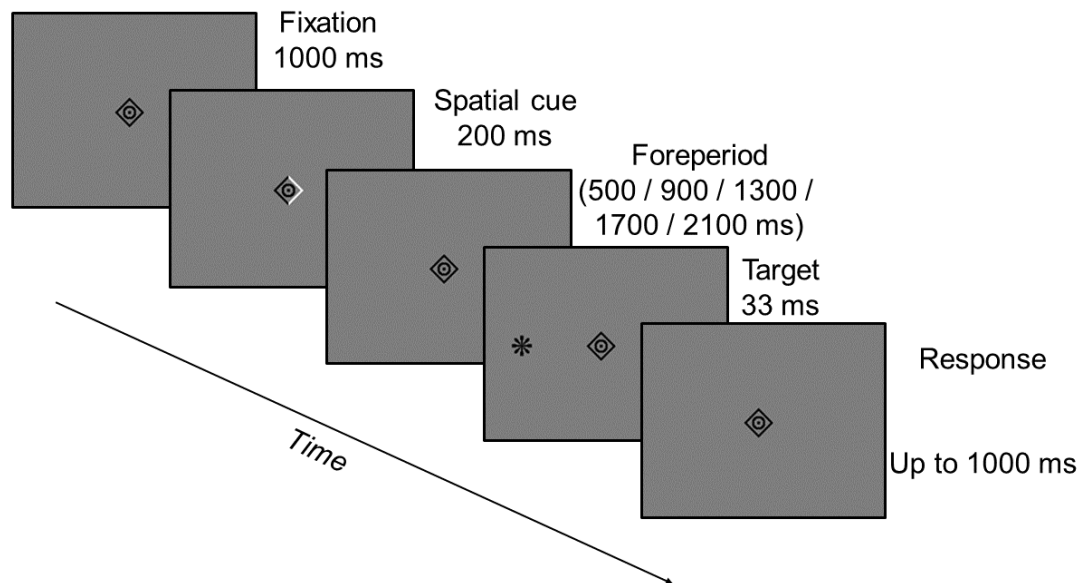
97 ‘Inverse U-shape distribution’ group (13 females, one left-handed, Mean age  $24.55 \pm 4.0$  SD).  
98 Participants received payment or course credit for their participation. All participants were  
99 healthy, reported normal or corrected-to-normal vision, and no history of neurological  
100 disorders. The experimental protocols were approved by the ethical committees of Tel-Aviv  
101 University and the School of Psychological Sciences. Prior to participation, participants signed  
102 informed consent forms.

### 103 *Stimuli*

104 The fixation object consisted of a dot ( $0.075^\circ$  radius) within a ring ( $0.15^\circ$  radius), embedded  
105 within a diamond shape ( $0.4 \times 0.4^\circ$ ). The edges of the diamond changed color from black to  
106 white, cueing attention to the left (two left edges became white) or right (two right edges  
107 became white) side of fixation object, or remaining neutral in respect to target location (all four  
108 edges became white) (see **Fig. 1**). The target was a black asterisk ( $0.4 \times 0.4^\circ$ ) presented at  $4^\circ$   
109 eccentricity to the right or left of fixation object. A 1000 Hz pure tone was sounded for 60 ms  
110 as negative feedback following errors. Fixation object and target were presented on a mid-gray  
111 background.

### 112 *Experimental design*

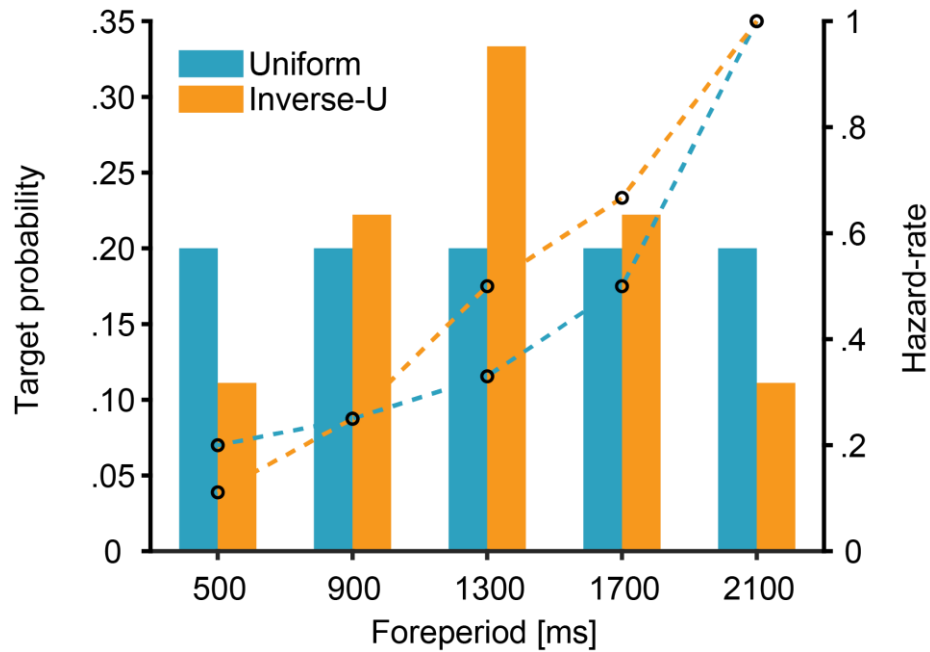
113 Participants were seated in a dimly lit room, with a computer monitor placed 100 cm in front  
114 of them (24" LCD ASUS VG248QE,  $1,920 \times 1,080$  pixels resolution, 120 Hz refresh rate, mid-  
115 gray luminance was measured to be  $110 \text{ cd/m}^2$ ). During the experiment, participants rested  
116 their heads on a chinrest. MATLAB R2015a (Mathworks, USA) was used to code and control  
117 the experiment, with stimuli displayed using Psychophysics Toolbox v3 (Brainard, 1997). Gaze  
118 position was monitored binocularly using EyeLink 1000 Plus infrared video-oculographic  
119 desktop mounted system (SR Research Ltd., Oakville, ON, Canada) throughout the  
120 experiment, at a sampling rate of 1000 Hz. This system has  $<0.01^\circ$  spatial resolution and an



**Figure 1.** *Trial progression.* Fixation period lasted until stable fixation was confirmed with online eye tracking procedure. Spatial cue was invalid in respect to target location in 25% of trials (as depicted), valid in 50% of trials and uninformative trials in 25% of trials. In two groups, foreperiods were sampled from either a uniform or an inverse-U distribution. Stable fixation was enforced during the foreperiod using online gaze-contingency. Participants were asked to make a single-button speeded response within 1000 ms of target onset. An error tone was played when participants responded before target onset, or failed to respond within the time limit. Stimuli size and eccentricity increased for display purposes and are not to scale

121 average accuracy of 0.25–0.5° when a chinrest is used, according to the manufacturer. A nine-  
122 point calibration of the eye-tracker was performed prior to each block and whenever necessary.

123 Each trial started with a central black fixation object, presented until an online gaze-  
124 contingent procedure verified 1000 ms of stable fixation (gaze was placed within a radius of  
125 1.5° of screen center). Following this, the edges of the fixation object changed color for 200  
126 ms to represent a spatial informative or uninformative cue. After a varying foreperiod (500 /  
127 900 / 1300 / 1700 / 2100 ms) the target was briefly (33 ms) presented at 4° to the left or right  
128 of center, with target being congruent to a spatially-informative cue direction in 50% of trials  
129 (valid condition), incongruent in 25% of trials (invalid condition), or neutral with respect to a  
130 spatially-uninformative cue in the remaining 25% of trials (uninformative condition).  
131 Participants were requested to press a key with their dominant hand, as quickly as possible and  
132 after no longer than 1000 ms, upon target detection. Between groups, participants were  
133 presented with the five foreperiods in either a uniform distribution (20% probability for each



**Figure 2.** Target probability (bars) and hazard-rate (conditional probability, dashed line) for the uniform and inverse-U foreperiod distributions

134 foreperiod) or an inverse-U-shaped distribution (a ratio of 1:2:3:2:1 between the five  
135 foreperiods, leading to trial percentages of approximately 11%, 22%, 33%, 22%, and 11%,  
136 respectively). These prior distributions resulted in different time-dependent conditional  
137 probabilities, i.e. different hazard-rate functions, as depicted in **Fig. 2**. The manipulation of  
138 hazard-rate was required to differentiate its effect from other foreperiod effects related to the  
139 WS, such as arousal (Steinborn and Langner, 2012; Weinbach and Henik, 2012). The different  
140 distributions were examined in separate participant groups, in order to avoid carry-over effects  
141 of distribution learning (Mattiesing et al., 2017). Fixation was monitored throughout the  
142 foreperiod, using an online gaze-contingent procedure, and trials that included  $\geq 1.5^\circ$  gaze-  
143 shift for more than 10 ms during this period were aborted and repeated at a later stage of the  
144 session. An error feedback tone was sounded when participants responded before target onset  
145 or did not respond within 1000 ms following target onset. These trials were not included in the  
146 analysis. The trial procedure is depicted in **Fig. 1**.

147 Participants of the uniform distribution group performed 10 blocks of 160 trials each,  
148 divided into two sessions of approximately 1.25 hours each. Participants of the inverse-U-



149 shaped distribution group performed 18 blocks of 144 trials each, divided into three sessions  
150 of approximately 1.25 hours each. This number of repetitions guaranteed that we have a  
151 minimum of 50 trials in all conditions and for all foreperiods in each of the two distributions,  
152 and a large enough number of trials conduct a sequential analysis on pairs of consecutive trials.  
153 A short break was given after each block. Feedback on performance in each block was provided  
154 at the end of each experimental block and included: mean RT and number of error trials  
155 (including both missed trials or premature responses). Starting from the 2<sup>nd</sup> experimental block,  
156 participants were also presented with a message that encouraged them to perform faster if the  
157 current block's mean RT fell below their global mean RT of the entire session. A practice block  
158 of 10 trials with random conditions was administered at the beginning of each session.

159 *Statistical analysis*

160 A negligible amount of trials with no response (< 1% of all trials; mean 0.7% of trials per  
161 participant, range 0-2.16% of trials) were discarded from analysis. Additionally, trials with  
162 response time below 150 ms were considered unlikely to represent genuine target-related  
163 responses (Keele and Posner, 1968; McLeod, 1987) and were likewise discarded from analysis  
164 (< 1% of all remaining trials; mean 0.3% of trials per participant, range 0-2.2% of trials).

165 The reaction times (RTs) of the remaining trials were modeled using a generalized  
166 linear mixed model (GLMM), assuming a gamma family of responses with an identity link (see  
167 explanation below) (Baayen and Milin, 2010; Lo and Andrews, 2015). Unlike analysis of  
168 variance (ANOVA), GLMM is suited for non-normally distributed variables, like the positively  
169 skewed RT distribution, while also allowing to model trial-level covariates, thus increasing the  
170 analysis' power (Baayen and Milin, 2010). Hierarchical models are also well suited for  
171 unevenly distributed trial numbers among conditions, as is the case with the Inverse-U shaped  
172 distribution and the sequential effect in the current study, by weighting the population-level  
173 mean according to the number of samples included in the subject-level means for each

174 condition. An assumption of this analysis is that the RTs follow Gamma distribution. Gamma  
175 distributions are suited to describe continuous responses that are zero-bounded and have a  
176 unimodal and rightward-skewed distribution (e.g., RTs). We further assumed that the  
177 predictors are linearly related to the predicted RT, thus an identity link was used (i.e., no  
178 transformation was made on the value produced by the predictors) (Lo and Andrews, 2015).

179       The following fixed effects were modeled: (1) linear and quadratic terms for Foreperiod  
180 duration, to model the slope of the foreperiod effect; (2) Cue (valid / invalid / uninformative),  
181 to model the effect of spatial attention; (3) the Foreperiod (FP)-Distribution (uniform / inverse-  
182 U-shaped), to model the effect of the hazard-rate function; (4) linear and quadratic terms for  
183 the Sequential effect, calculated as the difference between the current trial foreperiod and the  
184 previous trial foreperiod, such that positive values indicate the previous trial was longer than  
185 the current trial, and vice-versa for negative values; (5) The interaction terms between  
186 Foreperiod duration, Cue and FP-Distribution, and between Sequential effect, Cue and FP-  
187 Distribution. For simplicity, we assumed no interaction between sequential effect and  
188 foreperiod duration, e.g. we assumed that the cost in performance for a current trial of 900 ms  
189 and previous trial of 500 ms equals the cost of a 1300 and 900 ms pair of trials. To reduce  
190 computational complexity, all continuous factors were Z-scaled. To allow the computation of  
191 Sequential effects, the first trial of each session for each participant was discarded from analysis  
192 (total of 100 trials). Treatment contrasts coding scheme was used for Cue, with the  
193 uninformative condition set as the reference level, and sum contrasts coding scheme was used  
194 for FP-Distribution. Statistical significance for main effects and interactions was determined  
195 via a likelihood-ratio (LR) test against a reduced nested model excluding the fixed term (i.e.  
196 type-II sum of squares, SS). Statistical significance for parameter coefficients was determined  
197 according to Wald z-test (Fox, 2016).

198           In addition to the fixed effects, we considered the Z-scaled current trial number (i.e. the  
199 running trial identifier for the given session) as a covariate, in order to capture effects of fatigue  
200 and training along the experiment (Baayen and Milin, 2010). Since the different experimental  
201 groups may have experienced different fatigue or training effects, we additionally considered  
202 the interaction between FP-Distribution and trial number. Covariates were added to the model  
203 if the extended model converged and was found to significantly improve fit ( $p < .05$ ) in an LR  
204 test against the model without the covariate (Bates et al., 2015a).

205           The model's random effect structure was selected according to the model that was  
206 found to be most parsimonious with the data, i.e. the fullest model that the data permits while  
207 still converging with no singular estimates (Bates et al., 2015a), in order to balance between  
208 type-I error and statistical power (Matuschek et al., 2017). This was achieved by starting with  
209 a random intercept-by-subject-only model, and continuing to a model with random slopes for  
210 fixed terms by subject and their correlation parameters, and from there to a random interaction  
211 slopes by subject model, testing for model convergences in each step. Models that failed to  
212 converge were trimmed by the random slope with the least explained variance and were  
213 retested. Finally, we tested whether the model supports random slopes for the aforementioned  
214 covariates.

215           To provide support for null results ( $p < .05$ ), we additionally modeled the data using a  
216 Bayesian GLMM, with weakly informative priors (Gelman et al., 2017) on the model's fixed  
217 and random effects ( $N(0, 10)$ ) and correlation ( $LKJ(2)$ ) parameters, using the default mean for  
218 the intercept (298), and using informative shape parameters ( $gamma(0.02, 12.0)$ ) according to  
219 Lo & Andrews (2015). Posterior distributions were constructed using four Markov chain  
220 Monte-Carlo (MCMC) chains and 20,000 iterations per chain, with the first 2,000 samples used  
221 as warmup. The large number of iterations was required in order to calculate a stable Bayes  
222 Factor (BF). BFs were calculated by comparing the marginal likelihood between the full model

223 and a nested null model, with marginal likelihood estimated by 100 repetitions of bridge  
224 sampling (Gronau et al., 2017). BFs are reported with the null results in the nominator ( $BF_{01}$   
225 or  $\log BF_{01}$  for  $BF_{01} > 100$ ), representing by how much the data is supported by the null model  
226 relative to the full model, along with range and the proportional estimation error (as in Morey  
227 & Rouder, 2018).

228 Analyses were performed in R v4.0.3 using R-studio v1.3.959 (R Core Team, 2018).  
229 Frequentist modeling was performed using the lme4 (Bates et al., 2015b) package, Bayesian  
230 modeling was performed using the brms package (Bürkner, 2017), and additional model  
231 diagnostics were performed using the performance package (Lüdtke et al., 2020). An R-  
232 markdown file describing all the model fitting steps and diagnostic checks on the final model  
233 is available at the project's OSF repository (see Data Availability statement)

234

235

## Results

236 Reaction times (RTs) were modeled using a GLMM with FP-Distribution (uniform / inverse-  
237 U-shaped) as a between-subject fixed term and FP-Duration (continuous), Sequential effect  
238 (continuous), and Cue (valid / invalid / uninformative) as within-subject fixed terms, as well  
239 as the full interaction terms between FP-Duration, FP-Distribution, and Cue, and between  
240 Sequential effect, FP-Distribution, and Cue. Trial number and the interaction between trial  
241 number and FP-Distribution were added as covariates, and we allowed for a random intercept  
242 and a random slope for the linear term of FP-Duration and Cue by participant.

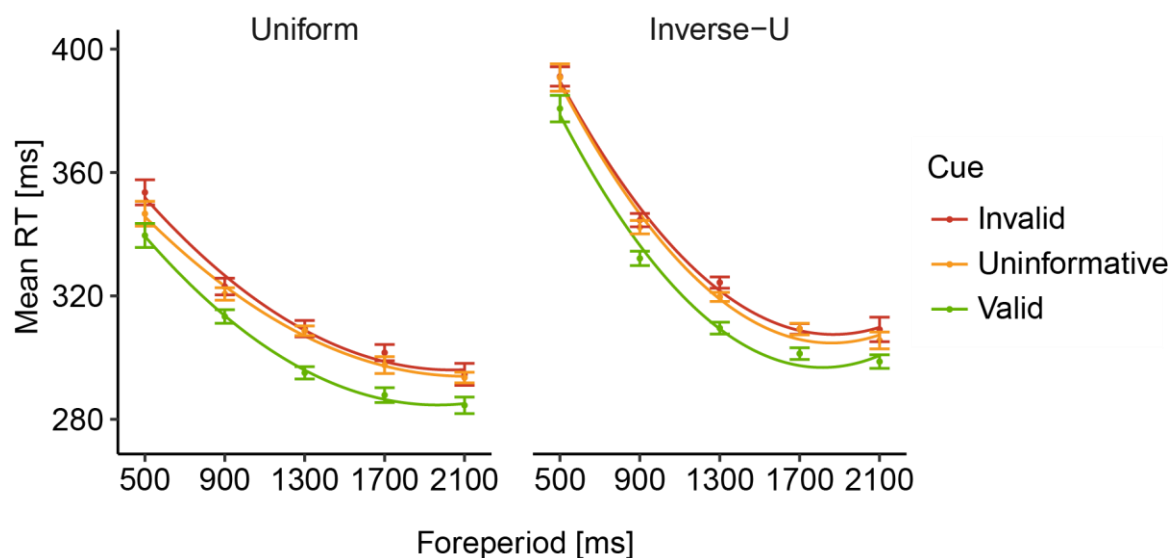
### *Effects of foreperiod and spatial attention*

244 Results showed that the *FP-RT slope*, the decrease in RT as foreperiod increases, changed with  
245 distribution, for each of the cues (see **Fig. 3**). We observed a significant main effect for FP-  
246 duration ( $\chi^2(2) = 864.59, p < .001$ ), with negative linear and positive quadratic terms,

247 consistent with the classic effect of foreperiod on RT and its expected shape, thought to reflect  
248 the increasing conditional probability along with the increase in the temporal uncertainty as the  
249 foreperiod duration becomes longer (Niemi and Näätänen, 1981). We additionally observed a  
250 main effect for Cue ( $\chi^2(2) = 19.90, p < .001$ ), indicating the expected effect of spatial  
251 attention on RT. This effect was reflected by a large benefit in RT for valid vs. uninformative  
252 cues ( $\beta = -10.146, t = -12.582, p < .001$ ) as well as a smaller but significant cost for  
253 invalid vs. uninformative trials ( $\beta = 2.666, t = 2.530, p = .011$ ). Most importantly for the  
254 purpose of this study, we found no significant interaction between Cue and FP-Duration  
255 ( $\chi^2(4) = 5.862, p = .210$ ), indicating that the effect for cue did not vary with foreperiod and  
256 supporting the hypothesis that spatial attention does not affect the FP-RT slope.

257 *Effects of the hazard-rate function*

258 The between-group variable of FP-Distribution (uniform / inverse-U-shaped) was used to  
259 assess the involvement of expectations based on the hazard-rate function on the foreperiod  
260 effect, and the relation of this effect to spatial attention. Findings showed no main group effect  
261 of FP-Distribution on RT ( $\chi^2(1) = 0.601, p = .435$ ), indicating that both groups had similar

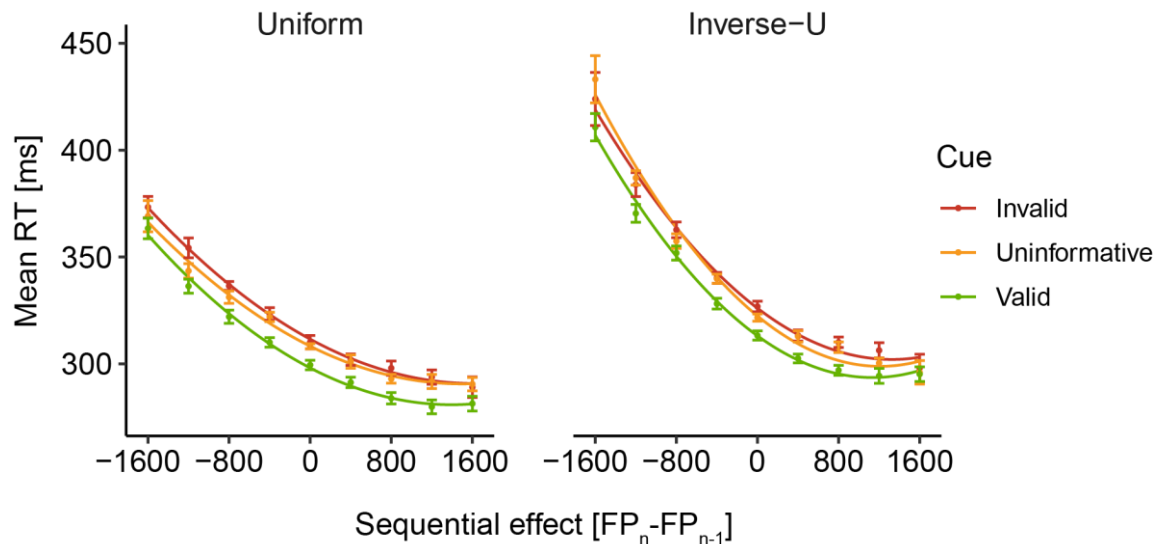


**Figure 3.** *Effect of hazard-rate function on RTs.* Mean reaction time (RT) for the uniform (left) and inverse-U-shaped (right) distributions. Each graph depicts group averaged mean reaction time (colored dots) with 2<sup>nd</sup> degree polynomial fit (colored lines). Error bars represent  $\pm 1$  standard error from the group mean, corrected to within-subject variability (Cousineau & O'Brien, 2014).  $N=20$  for each group

262 overall RT. However, there was a significant interaction between FP-Distribution and FP-  
263 Duration ( $\chi^2(2) = 102.68, p < .001$ ), indicating that, consistently with previous findings  
264 (e.g., Cravo et al., 2011; Trillenberg et al., 2000), the effect of foreperiod on RT was modulated  
265 by the prior distribution from which they originated, i.e. by their hazard-rate functions.  
266 Importantly for the goal of this study, there was no evidence that this effect of FP-Distribution  
267 on FP-Duration was modulated by the validity of the cue, as reflected by an insignificant  
268 interaction between Cue, FP-Distribution, and FP-Duration ( $\chi^2(4) = 4.699, p = .320$ ). This  
269 suggests that the effect of the hazard-rate function on foreperiod, was independent of spatial  
270 attention. As expected, no significant interaction was found between Cue and FP-Distribution  
271 ( $\chi^2(2) = 0.050, p = .975$ ).

#### 272 *Sequential effects*

273 To test for the existence of sequential effects, we calculated the difference between the FP-  
274 Duration of one trial and the FP-Duration of the previous trial ( $FP_{current} - FP_{previous}$ ).  
275 Consistently with previous studies (Alegria and Delhaye-Rembaux, 1975; Niemi and  
276 Näätänen, 1981), results showed an asymmetrical sequential effect on RTs, such that RTs were  
277 slower when the current trial was shorter than the previous trial (negative values in **Fig. 4**), but  
278 were not affected when the opposite was true (positive values in **Fig. 4**), leading to a quadratic  
279 relation with RT ( $\chi^2(2) = 1644.5, p < .001$ ). The lack of effect when a trial is longer than  
280 its previous trial is thought to result from the combined contribution of sequential and hazard-  
281 rate effects: sequential effects erroneously guide expectations toward an early timing leading  
282 to lower performance; but, given that the target has not appeared at the earlier time, the  
283 conditional probability increases and expectation grow following the hazard rate function,  
284 leading to higher performance. Combined, the result is no enhancement or decrement of  
285 performance at late time points. Additionally, results revealed that this effect was significantly



**Figure 4.** *Sequential effect on RTs.* Mean reaction time (RT) for the uniform (left) and inverse-U-shaped (right) distributions, with x-axis depicting the sequential effect (difference between current (FP<sub>n</sub>) and previous (FP<sub>n-1</sub>) trial foreperiod). Each graph depicts group averaged mean reaction time (colored dots) with 2<sup>nd</sup> degree polynomial fit (colored lines). Error bars represent  $\pm 1$  standard error from the group mean, corrected to within-subject variability (Cousineau & O'Brien, 2014).  $N=20$  for each group.

286 modulated by the FP-Distribution ( $\chi^2(2) = 28.924, p < .001$ ), with linear component being  
287 more negative for the inverse-U compared to the uniform distribution. This finding, also  
288 consistent with previous findings (Niemi and Näätänen, 1981), supports the involvement of the  
289 hazard rate function in this effect. Generally, these findings demonstrate that expectations  
290 based on the hazard-rate function and sequential effects each had a unique contribution to the  
291 resulting RTs, along with a synergetic effect between them.

292 We next tested whether these effects were modulated by spatial attention, by examining  
293 the interaction between them and Cue. Results showed no significant interaction between  
294 Sequential effect and Cue ( $\chi^2(2) = 1.177, p = .882$ ), nor a significant three-way interaction  
295 between Sequential effect, FP-Distribution, and Cue ( $\chi^2(4) = 2.585, p = .630$ ). Both  
296 results suggest that, as the hazard-rate effects, sequential effects are independent of the spatial  
297 locus of attention.

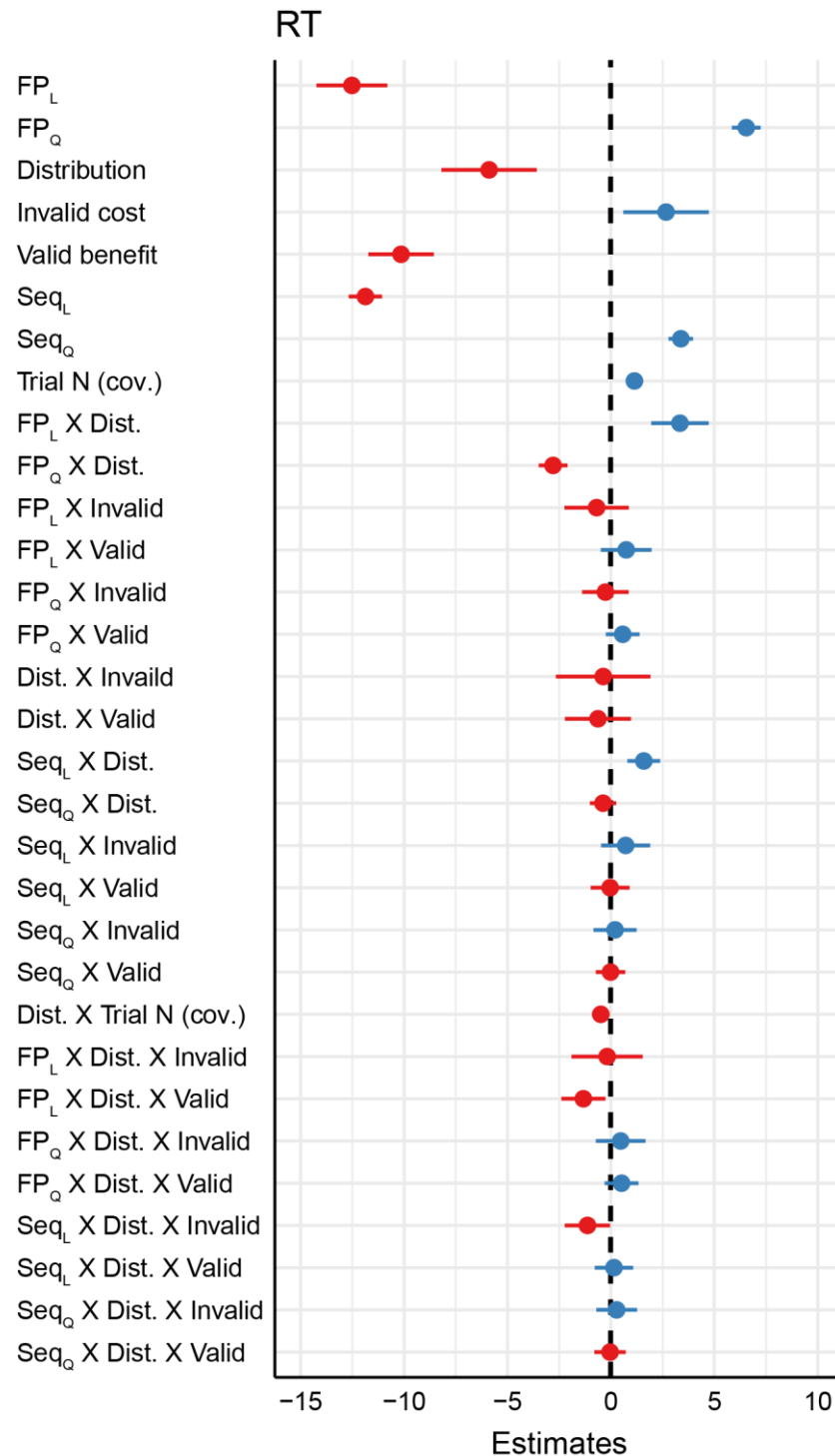
298 Model estimates for all fixed factors described are depicted in **Fig. 5**. Model estimates  
299 for covariates and additional model information can be found online in the project OSF  
300 repository (see Data Availability statement).

301 *Bayesian modeling*

302 Our results indicated that there was no evidence for a three-way interaction between Cue, FP-  
303 Distribution, and FP-Duration, as well as no three-way interaction between Cue, FP-  
304 Distribution, and Sequential effect. To examine whether the evidence supports these null  
305 results, we constructed a Bayesian GLMM using the same model terms. Model estimates  
306 closely resembled the coefficients found in the frequentists model. We compared the resulting  
307 Bayesian model with two nested models, each lacking the corresponding three-way interaction  
308 term. Results showed large support for the null model lacking the FP duration three-way  
309 interaction term compared to the full model (mean  $\log BF_{01} = 8.483 \pm 0.002\%$ , range 8.289-  
310 8.681), and similarly large support was observed for the null model lacking the Sequential  
311 effect three-way interaction term compared with the full model (mean  $\log BF_{01} = 9.969 \pm <$   
312  $.001\%$ , range 9.731-10.146). Both results support the conclusion that temporal expectations  
313 based on hazard-rate function and sequential effects are independent of spatial attention.  
314 Additional modeling information can be found online (see Data Availability statement).



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**Figure 5. Model estimates.** Forest plot of fixed factors estimates, modeled using a GLMM assuming a gamma response family and identity link function (estimates are given in ms units), and depicting mean in respect to the reference level (uninformative cue type). All continuous factors were scaled and centered. Positive values depicted in blue and negative values in red. Horizontal lines depict 95% Wald confidence intervals. Dashed vertical line centered at zero-sized estimate. Valid and invalid terms are relative to uninformative cue condition.  $FP_L$  = linear component of Foreperiod duration;  $FP_Q$  = quadratic component of Foreperiod duration; Dist = FP-Distribution;  $Seq_L$  = linear component of Sequential effect;  $Seq_Q$  = quadratic component of Sequential effect; Interaction terms denoted by X

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## Discussion

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In this study, we examined whether the spatiotemporal model which was proposed to account for cue-based temporal expectation also carries for temporal expectation based on contextual information, i.e. the hazard-rate function and sequential effects. By varying the foreperiod, we observed the established FP-RT slope effect, with RT decreasing as foreperiod increases. This FP-RT slope changed according to the hazard-rate function, which was manipulated by varying the foreperiod distribution. In addition, we found the expected asymmetrical sequential effect: slower RTs for trials in which the foreperiod was *longer* than their previous trial, and no opposite effect for trials in which the foreperiod was *shorter* than the previous trial. Critically, all these effects were unaffected by spatial attention – similar modulations of expectations were found in both attended and unattended spatial locations. This indicates that temporal expectations based on contextual information – the hazard-rate function and recent previous experiences – are independent of spatial attention.

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### *The spatiotemporal model of temporal expectation*

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Doherty et al. (2005) were the first to demonstrate an interaction between cue-based temporal and spatial attention in early visual event-related potentials (ERP) components. They presented participants with moving objects that disappeared behind an occluder and reappeared in an expected or unexpected location and/or time. Participants were requested to indicate whether a target dot was presented on the reappearing object. Findings showed that when a target appeared at an expected location, the early visual P1 component was increased relative to an unexpected location, and this effect was enhanced when the target also appeared at the expected time. However, when a target appeared at the expected time but not the expected location, there was no enhancement relative to its appearance at an unexpected time and

340 location, suggesting that early perceptual benefits of temporal attention depend on the  
341 allocation of spatial attention. This spatiotemporal synergism was not found in later ERP  
342 components, such as the P3, considered to be less affected by perceptual processes and more  
343 by response requirements, and also not in RTs.

344 In a later study by Rohenkohl et al. (2014), symbolic spatial and/or temporal cues  
345 predicted 80% validity the time and location of a grating-patch target, for which participants  
346 were requested to perform a non-speeded orientation discrimination task. Findings showed that  
347 valid temporal cues improved both RT and perceptual sensitivity relative to invalid cues, but  
348 that this effect was limited to trials where spatial attention was focused at the target's location.  
349 These findings provided, again, evidence for a strong synergistic interaction between temporal  
350 and spatial expectations in a discrimination task. Consistently, recent evidence by Seibold et  
351 al., (2020) showed that temporal attention boosts the effect of spatial attention on early ERP  
352 components in a visual search task.

353 This evidence of a tight link between spatial attention and cue-based temporal  
354 expectation led Nobre and van Ede (2018) to propose their spatiotemporal neurophysiological  
355 model, which can account for these findings. According to this model, the interaction between  
356 spatial and temporal processes stems from time-specific synchronization of spatially-specific  
357 neural populations at the attended retinotopic receptive-fields. These neurons, coding the  
358 attended location and relevant features, acquire a temporal structure from repeated exposure to  
359 the temporal cues, which affects them but not populations outside the receptive-field (Nobre  
360 and van Ede, 2018). This model was developed based on evidence on cue-based expectation  
361 but was never before examined for other sources of temporal expectations. The present  
362 evidence indicates that hazard-rate and sequential effects do not depend on spatial attention,  
363 suggesting that these forms of expectation cannot be explained by the spatiotemporal  
364 mechanism proposed by Nobre and van Ede. This further suggests that cue-based temporal

365 expectation and temporal expectation that are driven by contextual information, which are often  
366 described as two manifestations of the same expectation process, likely rely on distinct neural  
367 mechanisms. This evidence is consistent with studies that dissociated hazard rate effects and  
368 cue-based temporal expectation and found that these two sources of expectations share some,  
369 but not all, of their underlying brain networks (Lima et al., 2011; Coull et al., 2016; Amit et  
370 al., 2019). More generally, this conclusion is compatible with the increasing recognition in this  
371 field that there is no single unified expectation mechanism, but that distinct sources of temporal  
372 expectations facilitate performance via distinct neural mechanisms (van Ede et al., 2020).

373 *Spatiotemporal synergism and cue-based expectations*

374 It is important to note, however, that evidence regarding the dependency, or lack  
375 thereof, of cue-based temporal expectation on spatial attention, is ambivalent. In addition to  
376 the supporting evidence described above, a few studies provided evidence challenging this  
377 interaction. For example, MacKay & Juola (2007) used a visual search task in a rapid stimulus  
378 visual presentation (RSVP) stream of letters. Visual cues were provided to indicate the time,  
379 location, or both of the target letters, and a discriminate task was performed on the cued targets.  
380 Findings showed that both types of cues were effective on their own and their combined effect  
381 was additive, indicating that there was no interaction between temporal and spatial attention.  
382 In a later study, Weinbach et al. (2015) used a spatiotemporal cueing paradigm and showed  
383 that temporal cueing improves RT even when coupled with an invalid spatial cue. Moreover,  
384 there was no interaction between the effect of the temporal and the spatial cues, indicating that  
385 enhancement resulting from temporal attention was not affected by spatial attention. The  
386 authors noted that the discrepancy between their findings and previous findings could have  
387 stemmed from differences in task demands: whereas most previous studies used demanding  
388 perceptual discrimination tasks, they used a speeded-RT detection task. Another study by  
389 Rolke et al (2016) investigated the combined influence of temporal, spatial, and feature-based

390 attention and found no synergetic effects between spatial and temporal attention when spatial  
391 attention was manipulated. In that study, temporal expectations were manipulated implicitly,  
392 whereas spatial attention was manipulated explicitly using symbolic attentional cues. Findings  
393 showed no spatiotemporal interaction, and therefore it was suggested that this interaction  
394 occurs only when attention is manipulated similarly in both modalities (Seibold et al., 2020).

395 *Temporal attention and temporal expectation*

396 The apparent discrepancies among different findings on spatiotemporal dependency  
397 could be accounted for by the dissociation between attention and expectation processes.  
398 According to one view, described in Summerfield & Egnér (2009), expectation reflects the  
399 narrowing down of the probability space of possibilities, constructed according to prior  
400 knowledge; whereas attention is the selection of specific, goal-relevant information that should  
401 be prioritized. Both attention and expectation coexist and are often entangled – e.g., cueing to  
402 the left visual field increases our expectation of encountering a target at that location, and  
403 induces a shift of attention that prioritizes information on that particular visual space. Tailored  
404 experimental designs can dissociate attention and expectation, as was demonstrated in visual  
405 spatial attention and feature attention studies (Summerfield and Egnér, 2009, 2016; Kok et al.,  
406 2012).

407 Similar to spatial cues, temporal cueing paradigms often create a symbolic association  
408 between a certain cue and a specific target onset time. Thus, the onset of the cue induces an  
409 attentional shift which prioritizes information processing around the cued time interval. In  
410 addition, in these designs, the repeated exposure to target onset after a cue changes the  
411 probability space and induces *temporal expectation*, which is independent of attention  
412 according to the definition described above (Summerfield & Egnér, 2009; but see Nobre & van  
413 Ede (2018) for a different approach). Therefore, according to this view, in these designs,  
414 temporal attention often coincides with temporal expectation, although specific experimental

415 designs can dissociate these functions (Denison et al., 2019, 2021). Importantly, according to  
416 this definition, both hazard-rate function and sequential effects can be viewed as forms of  
417 temporal expectation, as they narrow down the probability space.

418 We hypothesize that this proposed dissociation between expectation and attention could  
419 account for the discrepancies between previous studies on the spatiotemporal dependency, with  
420 temporal attention being spatially-specific, while temporal expectation remaining independent  
421 of the spatial locus of attention. This, in turn, could explain the results observed here – since  
422 the hazard rate and sequential manipulations affect only temporal expectation and not attention,  
423 their manifestations were free of spatial constraints.

#### 424 *Conclusions*

425 This study examines the relation between spatial attention and two forms of temporal  
426 expectation – those based on the hazard-rate function, the moment-by-moment increase in a  
427 target's conditional probability over time, and those based on sequential effect. Our results  
428 showed that both forms of temporal expectations are independent of spatial attention. We  
429 conclude that the benefit from these forms of expectation is not spatially-specific, but rather  
430 reflects a general non-specific enhancement that is not accompanied by shifts of attention.  
431 Furthermore, we suggest that the spatiotemporal neurophysiological model proposed by Nobre  
432 and van Ede (2018) to explain cue-based expectation cannot account for hazard-rate and  
433 sequential expectation effects. Future studies are encouraged to examine the dissociation  
434 between different mechanisms of temporal expectation, and to refine the terminology to reflect  
435 this dissociation.

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437 **Data availability.** The datasets generated by this study and an R-markdown file that  
438 reproduces all the reported modeling, statistical analyses and graphs within the paper are  
439 uploaded to the Open Science Foundation repository and are available at: <https://osf.io/25gzj>

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