A window of subliminal perception

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Abstract

Under labels such as unconscious processing and subliminal perception, identification of stimuli falling below the subjective threshold has been found remarkably accurate in some experiments while completely at chance in others. Here, we first demonstrate the existence of a window of subliminal perception in humans using different experimental paradigms and analysis methods. We then show that the standard signal detection theory (SDT) model is unable to account for this window and extend it until it is. We finally compare a range of models on empirical data. The models performing best are notable for their absence of hierarchical levels, indicating that the window could be a base property of any phenomenally conscious system. The models further explain previously incompatible findings in the literature, and they allow for estimations of peaks in subthreshold perception across the spectrum of stimulus saliency, which may be used in further studies of subliminal perception.

Significance

The study improves our understanding of subliminal perception from a model based perspective. It first provides a detailed description of where efficient subliminal perception is found across different types of tasks and analysis. It provides a model based frame for understanding this occurrence, validates the model, and uses it to explain seemingly incompatible findings in tens of previously published studies. Predictions of the model may be used as guidelines for the design of future studies studying high capacity subliminal perception. The study furthermore provides the first signal detection theory-based model of the objective process dissociation procedure for disentangling conscious and unconscious contributions to behaviour.

Introduction

Subjective reports of conscious experience are an important part of studies of visual awareness¹. In particular, reports of “seen” versus “unseen” or more detailed descriptions of awareness of a stimulus – or confidence in task performance – are common bases for examination of differences between conscious and unconscious processing^{2–7}. Often, special attention is paid to the subjective threshold which has been defined as the threshold below which participants claim not to be able to discriminate perceptual information at a level better than chance⁸ or for which they claim to have no visual experience of a stimulus⁹. The subjective threshold is thus typically defined in relation to a report criterion, and it is important to be aware that it is a separate concept from metacognitive sensitivity, which may depend on additional aspects of perception and decision making¹⁰. Furthermore, the criterion used for report may not correspond fully to the threshold for conscious perception¹¹. In fact, it remains a topic of scientific debate whether perception below the subjective threshold is generally truly unconscious (or simply reflects weak, partial, or rare instance of conscious perception), yet even if this were the case, it may be considered a special case of perception that influences behaviour but is not used for overt, strategic responses¹². Fortunately, one can remain agnostic regarding the status of perception below the subjective threshold while still examining its prevalence and capacity through empirical data and modelling.

Occasionally, it has been observed that varying stimulus parameters lead to apparent changes in the capacity of perception below the subjective threshold: Sometimes, when participants claim not to have seen a stimulus, they can detect it remarkably accurately, yet at other times they are completely at chance^{13,14}. In other words, something that can be described as a window of subliminal or subthreshold perception seems to exist. Here, we first replicate and extend earlier findings regarding the changing capacity of subthreshold perception, both using methods based on subjective ratings and a method based on objective task performance alone. Next, we identify the minimally complex model within the framework of type II signal detection theory^{15–17} able to account for this change in capacity.

From model calculations, it becomes clear that it arises as a mathematical consequence of changes in the overall performance of the system across experimental conditions. The model accomplishes this even when the subjective criteria for reporting awareness (the type II criteria) remain constant. Subsequently, we test this simple as well as more complex,

hierarchical model variants on data from human observers performing a task particularly suitable for modelling. Finally, we use the modelling results to make novel predictions for future studies, and we demonstrate that the modelling results can explain seemingly inconsistent results in the literature.

Results

The capacity of subliminal perception can be estimated using both so-called objective and subjective measures. The latter relies on participants overtly evaluating their experience or confidence whereas the first infer it from a task response. We use both methods as described below. One group of participants performed a word stem completion task in which they were instructed to complete the word stem *without* using a briefly presented prime word – what is referred to as an “exclusion task”¹⁸. They subsequently reported their awareness on the Perceptual Awareness Scale (PAS) (Figure 1). PAS has four scale steps: “1: No experience”, “2: A weak experience”, “3: An almost clear experience”, and “4: A clear experience”. PAS thus identifies the subjective threshold. A second group of participants performed a word stem completion task that was identical in all aspects, except that the participants were instructed to use the primed word to complete the word stem if possible. This type of task is sometimes referred to as an “inclusion task”¹⁸, and it is in effect a standard visual identification task (without a predefined number of response options, in this case). Subliminal perception was estimated using the three methods described below, two of which are based on inclusion task performance only.

Figure 1: Experimental design. In Experiment 1 (A), A forward and backward masked prime lasting between 0 and 200ms was presented on each trial. Following prime presentation, a three-letter word stem appeared on screen and participants had to complete the word stem either using the prime (inclusion condition) or with any

word except the prime (exclusion condition). In the example shown here, participants in the inclusion group should write “MARKET” whereas participants in the exclusion group should avoid writing “MARKET”, but could write “MARCH” or “MARS” for instance. After performing the inclusion/exclusion task, participants reported their awareness of the prime using the Perceptual Awareness Scale (PAS). In Experiment 2 (B), stimulus durations were 17, 33 and 100 ms, only the letters “b” and “h” were targets, and only a backward mask consisting of the two letters superimposed were used. In the exclusion task, the non-presented letter had to be reported.

Performance at the subjective threshold: One of the oldest methods for examining subliminal perception (in use since the 1800s) is calculating task accuracy when participants claim to have no awareness of the stimulus, i.e. below the subjective threshold¹⁹. When examining task performance as a function of stimulus intensity on trials where participants claim to have no experience of the stimulus or no confidence in the correctness of their answer, we have previously noted that task accuracy increases up to a certain point and then either stays at this peak level or drops to chance level⁹. Around the peak, a significant drop in the frequency of claims of “no awareness” (PAS1 ratings) is also observed (e.g. ¹³). As seen in Figure 2A-B, these findings were replicated by calculation of the frequency of PAS1 ratings and estimation of match rate (probability of reporting the primed word) as functions of stimulus duration in the inclusion task. Above-baseline (i.e. $t=0$) match rate was observed in the 50-150 ms time window, peaking at stimulus durations of 67-83ms (Figure 2, $p \leq 0.01$ for both time points, Bonferroni corrected for 10 stimulus durations), and match rate generally decreased at greater stimulus durations although the width of the confidence intervals increased, thus making estimation more variable (due to the decrease in the probability of reporting unseen stimuli at high objective stimulus visibility, Figure 1A). For this reason, no later differences survived Bonferroni correction.

In other words, the capability of perception below the subjective threshold appeared to change quite substantially from a baseline of around 15% (the probability of the participant and the computer reporting the same word in response to the word stem when no word was presented) to around 40% at 67-83 ms before decreasing towards baseline levels again at 200 ms. This indicates the presence of a window for accurate subthreshold perception. Next, we examined this window in the context of the psychometric functions for accuracy and awareness (i.e. in the context of how fast accuracy and awareness increases overall as a function of prime duration).

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Figure 2: Experiment 1 inclusion results. A) Frequency of PAS1 ratings (ratings of “no experience”) as a function of stimulus duration. B) Inclusion at the subjective threshold. Match probability (probability of correctly reporting the primed word) as a function of stimulus duration for the inclusion task. Error bars represent 95% confidence intervals. Note the increase above baseline (0 ms) in the 30-150 ms time window. C) Mean match rate (black dots) and mean awareness ratings (grey dots) as functions of stimulus duration. Lines represent best sigmoid function fit at the group level based on individual participant levels. Note that awareness lags behind match rate (accuracy). D) Estimation of lag between accuracy and awareness scaled to the unit interval (see Methods: Non-linear regression). Accuracy and awareness curves were simulated based on the asymptotic normal distribution of the parameter estimates defined by the estimated mean and variance–covariance matrix. The plot is based on differences between 1000 such simulated curves and empirical point wise confidence intervals. Dotted lines represent the 95% confidence interval. Note that the lag exists in the 50-150 ms time window and peaks around 80-90 ms.

Relative increase of accuracy and awareness: Both mean task accuracy and awareness ratings in visual identification tasks can be described as sigmoid functions of stimulus duration, and the awareness curve typically has a lag compared to the accuracy curve^{13,20,21}. The lag between relative accuracy and relative awareness provides a measure of subliminal perception (i.e. an estimate of the increase in accuracy that is not accompanied by a corresponding increase in awareness, see Methods: Non-linear regression)¹³. As seen in Figure 2C, match rate and awareness reports both followed sigmoid functions of stimulus

intensity in the inclusion task. Furthermore, Figure 2D identifies the lag between the accuracy and awareness in the inclusion task in the 30-150 ms time window based on 1000 simulated curves. The maximum lag was obtained at 84.2 ms (95% CI: [76.2; 93.2]) and the difference between relative accuracy and awareness at this point was statistically significant ($p \leq 0.001$).

In other words, the greatest increase in objective accuracy without a corresponding increase of awareness ratings was observed around 90 ms, but some lag was observed across the 30-150 ms interval. This corresponds well to the temporal location of the peak in subthreshold accuracy in the subjective threshold analysis above, thus indicating that the accuracy on trials with “no awareness” is greatest at the point when overall awareness lags the farthest behind overall accuracy. Both these measures of subliminal perception are nevertheless based on subjective reports, and although these have received support in recent years^{9,22–24}, we elected to also examine if the window could be demonstrated using an objective measure that avoids asking the participants about the experience: The process dissociation procedure.

Process dissociation procedure (PDP): The PDP has been proposed as an objective method for examining the influence of unconscious processing as the method does not rely on subjective ratings of awareness, but instead between the difference in exclusion and inclusion task performance^{18,25}. The reasoning is that unconscious processes are affected by the primed word, and in the inclusion task both unconscious and conscious processes will thus attempt to report the primed word. In the exclusion task, however, unconscious processes will attempt to report the primed word whereas conscious processes will attempt to avoid it. The magnitude of unconscious influences may thus be estimated by comparing performance in the two tasks (see Methods).

A peak in the influence of unconscious processing has previously been observed using the exclusion task¹⁴. Here, we replicated this finding (Figure 3). Specifically, we observed influences of unconscious processes primarily in the 30-130 ms time window, peaking at around 80 ms, thus corresponding well with the time window estimated in the two analyses above. In other words, this method avoids the use of subjective reports and quantifies unconscious processing based on objective performance alone, yet the identified window of unconscious processing coincides remarkably well with the window identified using the two subjective approaches above.

Figure 3: Experiment 1 process dissociation procedure (PDP). Match rate is plotted for both the inclusion (green) and the exclusion (blue) task, and the unconscious influence on perception is estimated using the PDP (red). Curves are based on nonlinear regression models for the inclusion and exclusion tasks and the derived nonlinear curve for unconscious influences using the PDP. Note that unconscious influences are above baseline (0 ms) in the window 30-150 ms and that they peak around 80 ms.

Summary of experimental findings: Taken together, three different methods for quantifying subliminal perception all point to the existence of a window of subliminal perception, peaking at stimulus durations of around 60-90 ms. Below, we propose a model with foundation in signal detection theory able to account for the findings. We start from the simplest imaginable model and extend it minimally until it is able to account for the experimental findings and then report the computations. Subsequently, we perform systematic model fit comparisons for a range of models (incl. hierarchical versions) on data from Experiment 2.

Type II signal detection theory (SDT) model: We propose that all three findings of a window of subthreshold perception may be understood within the framework of a signal detection model that assumes that participants have stable criteria for reporting the clarity of perception in inclusion tasks (Figure 4A) and for choosing when to exclude a primed word in exclusion

tasks (Figure 4B). The exclusion task is thus modelled following the suggestion of Snodgrass¹², i.e. within the standard type II signal detection framework with the exception that the type II criterion is not related to a report of confidence but instead as an internal criterion that determines in which cases exclusion is performed (i.e. when information is used overtly).

The purpose of the models is to demonstrate that not only the amount but also the efficiency of subthreshold processing changes as a mathematical consequence of changes in task difficulty (or more generally, as a consequence of the ability to discriminate between two signals). The paradigm used in the behavioural experiment presented above (Figure 1) was constructed to be as similar to the replicated exclusion task experiment as possible¹⁴ and to maximise the visibility of the effect through multiple response options. In order to avoid unnecessary model complexity, the models presented here are based on the simpler and more commonly studied case of distinguishing between two signals.

Figure 4: The standard type II SDT model and probabilities of interest. A) The standard SDT model for detection/identification (inclusion) tasks with type I d' and criterion (θ) as well as symmetric type II criteria ($-\tau$ and τ) representing the thresholds for subjective confidence or perception (i.e. when the signal falls below $-\tau$ or above τ , the participants reports that they are have some confidence or that they perceived the stimulus to some extent). B) The SDT model of the exclusion task given the simple case of presentation of two stimuli¹². Here, type II criteria represent the evidence levels for which exclusion is performed. The participant thus sets a criterion above which Stimulus 2 is considered seen (and is subsequently excluded) and a similar criterion below which Stimulus 1 is considered seen (and is subsequently excluded). The highlighted areas represent the cases for which the primed word is reported inadvertently.

We assume the standard Gaussian SDT model of perception (Figure 4A). The task is to distinguish between two signals presented with equal probabilities. If the evidence is above the type I threshold (θ), the response is signal 2 and otherwise signal 1 in the inclusion task. In the exclusion task, the response is also conditional on the type II threshold (as explained in the following). Confidence in the response, or awareness of the stimulus, is decided by the type II thresholds ($-\tau$ and τ), and the meaning of these thresholds vary across models. For modelling of accuracy below the type II threshold, the threshold signifies the difference between “no experience” and “something more” (e.g. 1 versus 2-4 on the PAS). For the nonlinear (sigmoid) models, the criterion reflects a more conservative “not seen” versus “seen” (e.g. corresponding to ratings 1-2 versus 3-4 on the PAS), and for the exclusion task, it reflects the clarity of perception for which the information is used strategically, i.e. θ determines the urge to report a specific stimulus, but $-\tau$ and τ determines whether the opposite of the urge is reported as instructed (see Figure 4B). It is assumed that the type I threshold lies between the lower and upper type II thresholds. For simplicity, we assume that an absence of type 1 bias ($\theta = 0$) and symmetrical type 2 criteria ($\tau_- = -\tau$, and $\tau_+ = \tau$).

This model is the simplest imaginable within an SDT framework. As we show below, it is unable to account for all findings (it predicts a steadily increasing capacity of subliminal perception), and we thus extend it until it is. The smallest imaginable extension is the inclusion of a lapse rate – e.g. small lapses of attention known to occur in psychophysical experimentation. The lapse rate is set to 2% in the sense that in 2% of the tasks, a random response is chosen no matter what the evidence is. As we show below, this minimal extension enables the model to account for all aspects of the observed experimental findings.

SDT model of performance at the subjective threshold: We first examine whether the model is able to account for the initial increase and subsequent decrease in the accuracy of subliminal perception.

The probability that the evidence level on a given trial is below the subjective threshold ($C=0$) is given by Equations (4) (general case) and (9) (simplified case) in the Methods section, and the probability of a correct response given that the stimulus intensity is classified as below the subjective threshold is given by (5) and (10). These probabilities are plotted in Figure 5A-B as functions of overall ability to discriminate between signal and noise (d') for

various subjective thresholds (τ) given a fixed metacognitive capacity and a fixed lapse rate (see Methods: Signal detection theory (SDT) model, inclusion). As d' increases, the probability of $C=0$ decreases and the rate of this decrease depends upon the τ (Figure 5A). For low d' , accuracy below the subjective criterion is close to chance, but it increases as a function of d' up until a certain point (depending on τ) from where it starts to decrease and eventually returns to chance at high d -primes (Figure 5B). These results are consistent with the experimental results presented in Figure 2A-B.

As mentioned above, the lapse rate is necessary to capture both the increase and subsequent decrease of the capacity of subliminal perception (Figure 5B). This is shown in Supplementary Results 1 where it can be seen that the influence of the lapse rate value on the results is negligible as long as it is non-zero.

Figure 5: Model of inclusion results. Model estimations given a fixed lapse rate (2%) for various subjective thresholds (τ). All results are plotted as functions of distance between two signal distributions (d'). A) Probability of responding "not seen". B) Probability of a correct response given a response of "not seen". Note that for all τ , accuracy (subliminal perception) is inversely u-shaped indicating a window of subliminal perception. C) Probability of correct answer (black dashed curve) and mean awareness rating on a dichotomous 0/1 scale for various awareness criteria (coloured curves). D) Estimation of lag between accuracy and awareness

scaled to the unit interval for various awareness criteria. Note the inverted u-shape showing the presence of the window of subliminal perception.

SDT model of the relative increase of accuracy and awareness: Next, we examined if the model can account for the lag between accuracy and awareness reported in Figures 2C-D. The overall probability of a correct response is given by (6) and (11), and the probability of reporting awareness present on a dichotomous 0/1 scale as a function of d' is given by 1 minus the expression in equation (4) and 1 minus the expression in equation (9). These probabilities are plotted in Figure 5C and 5D respectively as functions of d' for various subjective thresholds (τ) given a fixed 2% lapse rate. The model predicts that awareness and accuracy increase as sigmoid functions of d' (Figure 5C), which is consistent with the experimental data (Figure 2C). Furthermore, the model predicts a lag between accuracy and awareness (with size and peak location dependent upon τ) (Figure 5D), which is consistent with the experimental data (Figure 2D).

SDT model of process dissociation procedure: Next, we examined if the model can account for the increase and subsequent decrease in unconscious influences estimated by the PDP (Figure 3). The overall probability of exclusion is given by equation (12), and it is plotted as a function of d' in Figure 6A. The proportion of unconscious processing is given by equation (1), and it is plotted along with inclusion and exclusion probability as a function of d' in Figure 6B. The pattern observed in Figure 6B is consistent with the pattern observed in Figure 3 although it should be noted that a peak in exclusion performance is observed only for conservative criteria due to the limited number of response options (two) in the model.

Figure 6: Model of PDP results given a fixed lapse rate (2%). A) Exclusion task match rate as a function of d' for various subjective thresholds (τ). B) Match rate as a function of inclusion (green) and exclusion task (blue), and unconscious processing estimated using the PDP (red) for $\tau = 0.5$.

Further model results and predictions: In Supplementary Results 2, we present further model results and predictions that might be of use to researchers designing experiments on subthreshold perception: We present two methods to obtain an optimal trade-off between subthreshold accuracy and the number of subthreshold trials, the latter of which indicating that a d' around 2 might be optimal for studying accurate subliminal perception (Figure S2).

Test of model on new data: Finally, we tested a range of model configurations on data from a paradigm with an inclusion and an exclusion task with only two stimuli (an “h” and a “b”) in combination with awareness ratings on the 4-point PAS. In other words, the paradigm was optimised for modelling whereas the paradigm with many response options presented above was optimised for demonstrating the window of subthreshold perception (this means that the location and magnitude of the window is expected to be substantially harder to estimate in this data, and the main criterion for evaluation is thus whether the model fits the data points). Three stimulus durations (16.7, 33.3, and 100 ms) were used as pilot experiments showed that these would produce an appropriate range of d' s around 1 to 4. Several recent models of

metacognition are so-called hierarchical models^{26,27}, which include a separate noise parameter for type 2 ratings. Here, we compare a range of model configurations, including hierarchical versions.

The key parameters of our models are the standard deviation of the signal distributions (σ), the lapse rate (π), type I d' and criterion (θ) as well as the type II criteria ($-\tau$ and τ) for both inclusion and exclusion task. For hierarchical models, a metacognitive noise parameter, γ , is further added (see Methods: Signal detection theory (SDT) model, inclusion/exclusion). σ , θ and d' can be expected to be the same in the two tasks while τ is expected to differ. In addition, many parameters could vary across stimulus intensity: d' is expected to, but internal noise (reflected in σ) and subjective criteria for awareness might also change when stimuli become physically clearer. However, given the amount of data, only a limited set of parameters can be varied in order to obtain a meaningful fit. d' was set to vary as a linear function of log-duration. As there is no obvious motivation to prefer reporting one stimulus over another, we set θ to 0. This assumption appeared realistic as θ s close to zero were obtained when modelling only d' and θ for each stimulus duration separately on the inclusion data.

Figure 7 (left bars) presents a comparison of models of the inclusion task where 1) σ was 1 or free, 2) τ_- and τ_+ were non-symmetrical and fixed or allowed to be a linear function of d' , 3) π was 0 or free, 4) the model was hierarchical or not. This gives a total of $2^4 = 16$ models. Maximum likelihood estimation (MLE) based on a multinomial distribution was used for parameter estimation (i.e. individual participant levels were not taken into account). AIC was compared across models, and the non-hierarchical model with $\pi=0$, $\sigma=1$, and symmetrical τ as a linear function of d' had the lowest value overall and was marginally better than the hierarchical version. Overall, hierarchical models were thus not necessary to explain the phenomenon in theory, and they did not provide a better fit to empirical data for inclusion data. We return to how this might be interpreted in the Discussion.

Figure 8 presents the following as functions of d' for the inclusion task: the probability of reporting PAS1 (panel A, equation (9)), the probability of a correct response given a rating of PAS1 (panel B, equation(10)), the overall probability of responding correct equation (11) and of reporting $PAS > 1$ (panel C, 1 minus equation (9)), and relative lag between accuracy and awareness. The fit of the winning model is shown. In all cases, it is clear that the model

370 provides a good fit to the data and that the curves are qualitatively similar to those presented
 371 in Figure 5.

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 373 **Figure 7: Model comparison.** AIC for each model (lower is better). π : the lapse rate; σ : standard deviation of
 374 the signal distributions; τ : type II criteria, i refers to the type 2 criterion and can be τ_- or τ_+ .

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 376 **Figure 8: Model/Experiment 2 inclusion results.** All results are plotted as functions of distance between two
 377 signal distributions (d'). A) Probability of responding "not seen" ($PAS = 1$). B) Probability of a correct response

given a response of “not seen” ($PAS = 1$). C) Probability of correct answer (black) and reporting $PAS > 1$ (red). D) Lag between accuracy and awareness scaled to the unit interval. Curves represent the winning SDT based model.

Unlike in the inclusion task where participants provide direct information on τ through awareness ratings, τ has to be inferred through the type 1 response in the exclusion task. This results in substantially less data upon which to base models, and only model comparisons with substantially fewer parameters than for inclusion provided meaningful results. For that reason, we present in Figure 7 (right bars) a comparison of a hierarchical and non-hierarchical exclusion model where 1) σ was 1, 2) τ was symmetrical, and 3) π was 0. Again, the non-hierarchical model was marginally better than the hierarchical version. Figure 9 presents the following as functions of d' for the winning model: Match rate (accuracy) in the inclusion task, match rate in the exclusion task, and the proportion of unconscious processing. Again, it is clear that the model provides a good fit to the data and that the curves are qualitatively similar to those presented in Figure 6B, although a very liberal exclusion criterion makes the window of subliminal perception hard to detect.

Figure 9: Model/Experiment 2 PDP results. Match rate is plotted for the inclusion (green) and exclusion (blue) tasks, and the unconscious influence on perception is estimated using PDP (red). Curves represent the fitted SDT based model.

Subliminal perception in other studies: Finally, we conducted a re-analysis of data from 10 previously published studies with a total of 249 participants to shed further light on why the window of subliminal perception is rarely reported/examined. Supplementary Results 3 confirm the pattern of our model results, but also show that the majority of data is collected for low d' values where subliminal perception is very weak and only a very small proportion of data is collected at or after the peak.

Discussion

Using stimulus material similar to that typically utilised in inclusion/exclusion tasks, we replicated previous findings of a peak in the impact of subthreshold processing on behaviour. Specifically, we observed: 1) a peak in inclusion accuracy for stimuli reported to be below the subjective threshold, 2) a peak in task accuracy without a corresponding increase in reports of clarity of perception, and 3) a peak in the estimated capacity of unconscious processing using PDP methods. All three effects were found at similar stimulus durations, indicating that they reflect a general peak in the occurrence and capacity of subthreshold perception.

Calculations based on a minimally extended type II signal detection model showed that these observations can be viewed as a mathematical consequence of changes in the overall capacity of the system to discriminate between signal two signals, the type I d' . In other words, the model shows that a window of efficient subliminal perception is to be expected even if observers maintain stable thresholds for which perceptual information is considered perceived. It should be noted that changes in the metacognitive capacity of the observers across different perceptual scenarios were not necessary to account for the empirical findings.

A range of model configurations, incl. hierarchical versions, were subsequently tested on data from a paradigm designed specifically for the purpose, and we found the strongest evidence for a relatively simple, non-hierarchical model, which provided and excellent fit to the data. This shows that even in human observers, a simple SDT-based model can account for the phenomenon (while of course not ruling out that hierarchical models might provide better fits in other experiments).

Our modelling results appear to explain inconsistencies in the findings of several previous experiments using the Perceptual Awareness Scale (PAS). A number of studies have found accuracy to be at or very close to (and not significantly different from) chance level on trials for which participants claim to have no experience of the stimulus^{28–33} whereas the present study and others^{9,34,35} found accuracy to be above chance in some cases. In one of the latter studies, above-chance accuracy was reported for a mix of very different stimulus intensities³⁵ and for the others, a very wide range of stimulus durations was used, and overall accuracy varied between chance and ceiling across these. Assuming relatively non-biased type I criteria, this corresponds to type I d' 's in the range from 0 to at least 4 (at which point it becomes difficult to obtain reliable d' estimates without hundreds of trials per participant per stimulus duration). Above-chance performance on subthreshold trials was found primarily for stimulus durations with midrange to high overall accuracy levels (before dropping to chance again at very long stimulus durations). In contrast, the former studies used stimulus durations resulting in overall low accuracy levels, typically corresponding to d primes between 0 and 1. The difference between the studies is thus consistent with the model, which predicts that high accuracy for subthreshold trials is expected for mid-range and high d primes, but to a much smaller degree or not at all for low and very high d primes.

This conclusion is supported by an analysis of an additional 6 studies (10 experiments, total $N = 249$) for which the raw data were available to us, and which used two type 1 response options in combination with the PAS^{36–41}. For these, accuracy for PAS1 increased for overall d' 's ranging from 0–2 as predicted by the model calculations presented in Figures 5B and 8B. Interestingly, these studies and the ones mentioned above exemplify that subliminal perception is typically studied at around $d'=1$, yet our work shows that this is just at the edge of the window of subliminal perception, and researchers would likely be better able to examine subliminal perception at higher d' 's of around 2.

Other results of previous studies are also consistent with our model predictions. For instance, Overgaard et al.²⁸ found different accuracy levels for subthreshold stimuli when participants were instructed to distinguish between “seen”/“not seen” only and when they reported experience using PAS. It appears straightforward that a more liberal criterion is adopted when even a “weak glimpse” counts as a conscious experience compared to when the stimuli has to be “seen”, and following Figure 5B, subthreshold perception is thus expected to be more accurate in the latter case, reflecting the fact that weak experiences are likely to be

classified as “not seen”. Interestingly, exactly such a “not seen”/“seen” dichotomy was used by Boyer et al.⁴² who demonstrated that participants were able to rate confidence meaningfully on subthreshold “not seen” trials. However, in our model framework, this could be explained as applying subsequent liberal criteria where first only a conservative criterion was set, and our model calculations show that different accuracy levels should be expected across the subsequent more liberal criteria. Furthermore, consistent with our model, the mean accuracy level for subthreshold perception (by the conservative criterion) in the two experiments of that study (75% versus 81%, corresponding to d-primes around 1.4 and 1.8 respectively) lead to apparent differences in the accuracy at the liberal criterion.

On a separate note, an SDT model of the exclusion task was first proposed by Snodgrass¹², and our model calculations confirm the predictions made by the author that conservative criteria cause more failures to exclude. This could be taken as support for the claim¹² that improved exclusion performance under conditions of monetary reward⁴³ could be evidence of criterion shift although additional empirical work is needed to demonstrate that such criterion shifts are actually possible and to separate the impact of d' and criterion changes.

Regarding our model, it may be noted that our single evidence axis is likely an abstraction, and the model does not specify the smallest meaningful unit of sensory evidence (e.g. whether it is a neuron, coalition of neurons in a specialised area, or network of connected sensory neurons). Nor does the model exclude a role of network dynamics, such as synchronisation between areas processing the same object or attentional amplification of the object as these could be seen as methods to shift the position on the evidence axis or modulate the variance magnitude/shape of the signal/noise distributions. Nevertheless, the model is notable for its simplicity (e.g. the absence of noise specifically for awareness), and it thus demonstrates that the apparent discrepancies between objective accuracy and awareness can be accounted for without taking into account separate (e.g. higher-order) processes outside sensory processing. Note that this of course does not exclude the obvious existence of higher-order systems capable of introspection and/or of using suprathreshold information for overt, strategic actions.

Taken together, we thus find support for a window of subliminal perception from various analyses of inclusion and exclusion tasks, and we show that this can be understood within a framework based on signal detection theory. The window is found around the time that task

accuracy first starts to increase and increases until overall accuracy reaches its peak (as measured by percent correct). In other words, subliminal capabilities appear with the appearance of minimal perceptual discrimination capacity and increase until the upper plateau of the psychometric function is reached. This interval is likely to be a somewhat unusual (but not necessarily rare) case of visual processing in everyday life as individuals are generally able to sample for longer in cases of uncertainty before initiating behaviour (i.e. looking more closely, or simply not rushing). However, in cases where fast reactions are necessary (e.g. during sports), perception may fall within this window more frequently, in line with the subjective intuition that perception is less conscious in these cases and feelings of automatic actions are common.

One might resultingly hypothesise that the window exists in order to allow for faster actions where consciousness would be too costly to summon, but our model would suggest that this is not necessarily the case. Instead, it could be something that arises naturally in a system for perceptual discrimination that can be described by the presented model, and it would in fact be a challenge to avoid this situation (note that this of course does not rule out the existence of multiple processing pathways, some of which could be entirely unconscious). For this reason, any perceptual capacity below the subjective threshold could be a consequence of the natural build of such systems rather than an added feature.

Methods

Two empirical experiments were conducted. In Experiment 1, one group of participants performed an inclusion task and one group performed an exclusion task. Data from the exclusion task has been used in a previous article on a different topic²². In Experiment 2, all participants performed both an inclusion and an exclusion task. The difference between tasks is explained below.

Participants

All participants had normal or corrected-to-normal vision and gave informed consent to participate. For Experiment 1, 16 healthy participants (9 females) performed an inclusion task (mean age = 23.3 years, SD = 3.22), and 16 participants (9 females) performed an exclusion task (mean age = 24.9 years, SD = 1.67). For Experiment 2, 20 healthy participants (14 females) performed both an inclusion and an exclusion task (mean age = 25.2, SD = 3.49). Experiments

were designed so that they had either around twice as many trials or 25% more participants than previous studies examining similar effects (e.g. ^{9,14}).

Apparatus and stimuli

Stimuli were generated and displayed in Spyder 2.1.11 (<http://code.google.com/p/spyderlib>) using Python 2.6.6 (www.python.org) and PsychoPy v.1.74.01 (www.psychopy.org). They were displayed on a 14" LED monitor with a screen resolution of 1366x768 at a refresh rate of 60Hz.

For Experiment 1, stimuli consisted of 308 four to six letter Danish words, and masks were rows of six pseudorandom letters. Words were found using a Danish frequency dictionary, and it was confirmed that at least two four to six letter words could be constructed using the first three letters of any individual target word. For Experiment 2, only the letters 'h' and 'b' were used, and the mask was an overlapping presentation of the two letters.

Procedure

In Experiment 1, participants performing the inclusion task were asked to complete a three-letter word stem *using* a briefly displayed primed word (Figure 1). Participants performing the exclusion task were asked to complete the word stem *without using* the primed word. In Experiment 2, only one of the letters 'h' and 'b' was presented on a given trial, and in the inclusion task, participants were asked to report the presented letter, whereas they had to report the *other* letter in the exclusion condition.

For Experiment 1, at the onset of each trial, a fixation mark appeared for 500ms. The fixation mark was followed by a forward mask consisting of six pseudorandom letters displayed for 50ms. Next followed the prime word with a duration pseudorandomly selected between 11 possibilities between 0 and 200ms with no possibilities in the interval between 150 and 200ms: {0, 16.7, ..., 133.3, 150, 200}. For prime durations of 0ms, no prime was presented. The prime was followed by a backward mask consisting of six pseudorandom letters displayed for 50ms. A word stem consisting of the first three letters of the target word followed the backward mask and remained on screen until participants had completed the word stem or until 10 seconds had passed. Finally, a graphical representation of the Perceptual Awareness Scale (PAS)²⁹ appeared on screen, and participants were asked to indicate their experience of the prime word using the keyboard number keys. The response

options were: “1: No experience”, “2: A weak experience”, “3: An almost clear experience”, and “4: A clear experience”. Stimuli were presented in black on a white background.

The experiment consisted of a practice block and six experimental blocks. For all blocks (including practice), each of the 11 prime durations was used four times in a pseudorandom order, resulting in a total of 44 trials per block. The experiment consisted of 308 trials in total for each participant.

For Experiment 2, the same procedure was used with the following exceptions. No forward mask was used, the stimuli were only the letters ‘h’ and ‘b’, and the backwards mask consisted of an overlapping presentation of the letters ‘h’ and ‘b’. Only the stimulus durations 16.7, 33.3, and 100 ms were used. The experiment consisted of a practice block and 10 experimental blocks for each of the inclusions and exclusion conditions. For all blocks (including practice), each of the three prime durations was used eight times in a pseudorandom order, resulting in a total of 24 trials per block. The experiment consisted of 480 trials in total for each participant.

Statistical analysis and model calculations

Estimations of the influence of unconscious processing were made using three different methods.

Performance below the subjective threshold: One of the oldest methods for examining unconscious processing is calculating task accuracy when participants claim to have no awareness of the stimulus¹⁹. Here, we used logistic regression to model match rate (the probability of correctly completing the word stem with the primed word) for trials where participants reported “no experience” (PAS1) in the inclusion task. Match (1 if the prime word/letter was reported and 0 otherwise) was considered as the dependent variable and stimulus duration was the independent variable. A random participant effect was also included in the analysis. Likelihood Ratio (LR) tests were used to assess systematic differences. Data were analysed using Stata ver. 15.1.

Non-linear regression: It has recently been proposed²⁰ and demonstrated¹³ that not only task accuracy but also awareness reports can be described as sigmoid functions of stimulus intensity (x below) in visual identification (inclusion) tasks:

$$f(x) = a + \frac{b - a}{1 + e^{\frac{c-x}{d}}}$$

Where a denotes the lower plateau, b denotes the upper plateau, c denotes the x-value of the centre point of the slope, and d is a measure of the steepness of the slope. Furthermore, it has been demonstrated that awareness (as estimated by various rating scales) lags accuracy and that the lag can be estimated by scaling to the unit interval using the following function¹³:

$$f(y) = \frac{y_{accuracy} - a_{accuracy}}{b_{accuracy} - a_{accuracy}} - \frac{y_{awareness} - a_{awareness}}{b_{awareness} - a_{awareness}}$$

Process dissociation procedure (PDP): Jacoby and colleagues¹⁸ proposed PDP as a method to disentangle conscious (intentional) and unconscious (automatic) contributions to performance in a given task without relying on subjective reports. The key rationale is that unconscious processes are affected by the primed word, and in the inclusion task, both unconscious and conscious processes will thus attempt to report the primed word. In the exclusion task, however, unconscious processes will attempt to report the primed word whereas conscious processes will attempt to avoid it. The relative contribution of conscious and unconscious processes may thus be estimated by comparing performance in the two tasks. Specifically, by combining Equations 3 and 4 from Jacoby et al.²⁵, we find that unconscious/automatic influences, A , is given by:

$$A = \text{Exclusion} / (1 - (\text{Inclusion} - \text{Exclusion})) \quad (1)$$

Signal detection theory (SDT) model, inclusion: The standard SDT type II model was used. Following the notation of Barrett et al.:

$$S = \begin{cases} 1 & \text{Signal} \\ 0 & \text{Noise} \end{cases}$$

$$R = \begin{cases} 1 & \text{Answers Signal} \\ 0 & \text{Answers Noise} \end{cases}$$

$$T = \begin{cases} 1 & \text{Correct answer} \\ 0 & \text{Incorrect answer} \end{cases}$$

$$C = \begin{cases} 1 & \text{Confidence in answer} \\ 0 & \text{No confidence in answer} \end{cases}$$

626 We assume that signal and noise are equally likely, $P(S = 1) = P(S = 0) = \frac{1}{2}$, and that the
 627 evidence X follows a normal distribution:

$$628 \quad X \sim \begin{cases} N(-\frac{d'}{2}, 1) & \text{Noise} \\ N(\frac{d'}{2}, 1) & \text{Signal} \end{cases}$$

629 We consider two different sets of thresholds:

630 **Type 1** (θ):

$$631 \quad X < \theta \Rightarrow R = 0, \quad X \geq \theta \Rightarrow R = 1$$

632 **Type 2** (τ_- and τ_+):

$$633 \quad X < \tau_- \text{ or } X > \tau_+ \Rightarrow C = 1, \quad \tau_- \leq X \leq \tau_+ \Rightarrow C = 0$$

634

635 We make the natural assumption that $\tau_- < \theta < \tau_+$. For hierarchical models, X is replaced by X
 636 $+ \gamma$ where γ is independent from X and is normally distributed around 0 with a variance, ω .

637

638 Within this setup we can calculate the probabilities of interest. For example, the probability
 639 of answering correctly and not being confident about the answer is given by:

$$640 \quad P(T = 1, C = 0) = P(C = 0 | R = 0, S = 0) \cdot P(R = 0, S = 0) + P(C = 0 | R = 1, S = 1) \cdot P(R = 1, S = 1)$$

$$641 \quad = \frac{1}{2} \left(\Phi(\theta + \frac{d'}{2}) - \Phi(\tau_- + \frac{d'}{2}) + \Phi(\tau_+ - \frac{d'}{2}) - \Phi(\theta - \frac{d'}{2}) \right) \quad (2)$$

642

643 In a similar way we get

$$644 \quad P(T = 0, C = 0) = \frac{1}{2} \left(\Phi(\tau_+ + \frac{d'}{2}) - \Phi(\theta + \frac{d'}{2}) + \Phi(\theta - \frac{d'}{2}) - \Phi(\tau_- - \frac{d'}{2}) \right)$$

645

646 so that the difference becomes

$$647 \quad P(T = 1, C = 0) - P(T = 0, C = 0) =$$

$$648 \quad \frac{1}{2} \left(2\Phi(\theta + \frac{d'}{2}) - \Phi(\tau_- + \frac{d'}{2}) - \Phi(\tau_+ + \frac{d'}{2}) - 2\Phi(\theta - \frac{d'}{2}) + \Phi(\tau_+ - \frac{d'}{2}) + \Phi(\tau_- - \frac{d'}{2}) \right) \quad (3)$$

649

650 Finally the probability of no confidence in the answer is given by

$$P(C = 0) = \frac{1}{2} \left(\Phi(\tau_+ + \frac{d'}{2}) - \Phi(\tau_- + \frac{d'}{2}) + \Phi(\tau_+ - \frac{d'}{2}) - \Phi(\tau_- - \frac{d'}{2}) \right) \quad (4)$$

The probability of answering correctly given no confidence in the answer is

$$P(T = 1 | C = 0) = \frac{P(T = 1, C = 0)}{P(C = 0)} = \frac{\Phi(\theta + \frac{d'}{2}) - \Phi(\tau_- + \frac{d'}{2}) + \Phi(\tau_+ - \frac{d'}{2}) - \Phi(\theta - \frac{d'}{2})}{\Phi(\tau_+ + \frac{d'}{2}) - \Phi(\tau_- + \frac{d'}{2}) + \Phi(\tau_+ - \frac{d'}{2}) - \Phi(\tau_- - \frac{d'}{2})} \quad (5)$$

and the probability of answering correctly is

$$P(T = 1) = \frac{1}{2} \left(1 + \Phi(\theta + \frac{d'}{2}) - \Phi(\theta - \frac{d'}{2}) \right) \quad (6)$$

making plots illustrating the consequences of the model and when fitting the model to the data of Experiment 2, we use a slightly simplified version. In this situation where

$$\theta = 0, \tau_- = -\tau, \text{ and } \tau_+ = \tau$$

we have that

$$P(T = 1, C = 0) = \Phi(\frac{d'}{2}) + \Phi(\tau - \frac{d'}{2}) - 1 \quad (7)$$

and

$$P(T = 0, C = 0) = \Phi(\tau + \frac{d'}{2}) - \Phi(\frac{d'}{2})$$

so that

$$P(T = 1, C = 0) - P(T = 0, C = 0) = 2\Phi(\frac{d'}{2}) + \Phi(\tau - \frac{d'}{2}) - \Phi(\tau + \frac{d'}{2}) - 1 \quad (8)$$

Similarly we get

$$P(C = 0) = \Phi(\tau + \frac{d'}{2}) + \Phi(\tau - \frac{d'}{2}) - 1 \quad (9)$$

$$P(T = 1 | C = 0) = \frac{\Phi(\frac{d'}{2}) + \Phi(\tau - \frac{d'}{2}) - 1}{\Phi(\tau + \frac{d'}{2}) + \Phi(\tau - \frac{d'}{2}) - 1} \quad (10)$$

And

$$P(T=1) = \Phi\left(\frac{d'}{2}\right) \quad (11)$$

673

674 If we want to incorporate a lapse rate, denoted by π , then all probabilities entering the
 675 equations in this section and the one below should be replaced by $\pi/8 + (1-\pi)$ *probabilities.

676

677 *Signal detection theory (SDT) model, exclusion:* We consider the simple situation where one
 678 of two words is shown. People are given the task of indicating the other word than what they
 679 think they saw. We introduce

$$W = \begin{cases} 1 & \text{Word 1 is shown} \\ 2 & \text{Word 2 is shown} \end{cases}$$

$$A = \begin{cases} 1 & \text{Word 1 is answered} \\ 2 & \text{Word 2 is answered} \end{cases}$$

682

683 If X is the evidence, then we assume that

$$X \sim \begin{cases} N(-\frac{d'}{2}, 1) & \text{Word 1 is shown} \\ N(\frac{d'}{2}, 1) & \text{Word 2 is shown} \end{cases}$$

685 or in other words

$$X | W = w \sim N(-\frac{d'}{2} + (w-1) \cdot \frac{d'}{2}, 1)$$

687 Note that for hierarchical models, X is replaced by $X + \gamma$ where γ is independent from X and is
 688 normally distributed around 0 with a variance, ω .

689

690 We consider the threshold value τ such that

$$\begin{aligned} X < -\tau & \Rightarrow A = 2 \\ -\tau \leq X < 0 & \Rightarrow A = 1 \\ 0 \leq X < \tau & \Rightarrow A = 2 \\ X \geq \tau & \Rightarrow A = 1 \end{aligned}$$

692 The match probability (that is the probability of inadvertently answering the same word as
 693 shown) is given by

694

$$695 \quad P(T = 0) = P(A = 1, W = 1) + P(A = 2, W = 2)$$

$$696 \quad = \frac{1}{2} P(A = 1 | W = 1) + \frac{1}{2} P(A = 2 | W = 2)$$

$$697 \quad = \frac{1}{2} (P(X \geq \tau | W = 1) + P(-\tau \leq X < 0 | W = 1) + P(X < -\tau | W = 2) + P(0 \leq X < \tau | W = 2))$$

$$698 \quad = \frac{1}{2} (1 - \Phi(\tau + \frac{d'}{2}) + \Phi(\frac{d'}{2}) - \Phi(-\tau + \frac{d'}{2}) + \Phi(-\tau - \frac{d'}{2}) + \Phi(\tau - \frac{d'}{2}) - \Phi(-\frac{d'}{2}))$$

$$699 \quad = \Phi(\frac{d'}{2}) + \Phi(\tau - \frac{d'}{2}) - \Phi(\tau + \frac{d'}{2}) \quad (12)$$

700

701 **Supplementary Material**

702 In this section, a number of additional model results and predictions are presented.

703

704 **Supplementary Results 1**

705 It should be noted that all model calculations assume that participants fail to pay attention to
 706 the task on a small proportion of trials independently of d' . On such trials, participants
 707 perform at chance and report “no experience”. Here, we show the consequences of this
 708 assumption for the model. As seen in Figure S1, the proportion of inattentive trials has two
 709 important consequences. First, it determines the asymptote for the proportion of trials for
 710 which participants report no awareness (Figure S1A). The explanation is that as d' increases,
 711 ordinary reports of no awareness become increasingly rare whereas reports of no awareness
 712 due to lack of attention remain stable and thus become a larger proportion of the total
 713 proportion of reports of no awareness. Second but most importantly, the proportion of
 714 inattentive trials causes the accuracy on trials below the subjective threshold to peak and
 715 return to chance at high d' s, and the shape of the accuracy curve depends upon the proportion
 716 of inattentive trials (Figure S1B).

Figure S1: The impact of the proportion of inattentive trials on model estimates at $\tau=1$. A) The impact on the proportion of subthreshold reports. B) The impact on subthreshold accuracy. C) The impact on the proportion of the total trials that are subthreshold but on which the reply to the type I task is correct. D) The impact on the proportion of trials that are incorrect and below the subjective threshold subtracted from the proportion of trials that are correct and below the subjective threshold.

Supplementary Results 2

Studies of conscious/unconscious perception or metacognition generally use procedures to ensure certain task accuracy levels or a certain distribution of “seen”/“not seen” responses^{5,44,45}. Experimenters in such studies may also be interested in optimizing above-chance accuracy at very low τ (i.e. when participants are instructed to report higher than “not seen” even when they have seen just a brief glimpse of the stimulus but are not aware of its identity). This is relevant because arguments that subthreshold information is unconscious are stronger in these cases, yet it can be difficult to obtain above-chance accuracy. As seen in Figure 2B based on Equation (8), a peak in subthreshold accuracy is achieved at midrange to high d primes (around 2-4) whereas it may be difficult finding any indication of subliminal perception at lower d -primes. Of course, at high d primes, the probability of responding “not seen” decreases as shown in Figure 2A (7) and for this reason, experimenters may not simply want to ensure the highest accuracy at the subjective threshold, but also a substantial number

of trials on which to base their statistics. This can be achieved by estimating the proportion of the total trials on which a participant reports “not seen” but is correct, or the difference in the proportion of correct and incorrect trials given a response of “not seen”. These two probabilities are plotted in Figure S2 as a function of d' . Note that the first probability peaks at $d'=\tau$ as is seen by differentiating (7) and noting that τ is a root for the resulting function. Note also that the impact of lapse rate on the proportions reported in Figure S2 is negligible (Figure S1C-D).

Figure S2: Model of accurate subthreshold perception as a function of d' for various subjective threshold criteria (τ). A) The proportion of the total trials that are below the subjective threshold but on which the reply to the type I task is correct. B) The proportion of trials that are incorrect and below the subjective threshold subtracted from the proportion of trials that are correct and below the subjective threshold.

Supplementary Results 3

Finally, a supplementary analysis of accuracy at the subjective threshold was made using data from an additional 6 published studies (10 experiments) for which the raw data were available to us. These studies all had two type 1 response options and used the PAS. Some used multiple stimulus intensities, some only one. For each experiment, we fitted a generalized linear mixed-effects model (GLMM) predicting accuracy (using stimulus intensity and experimental conditions as predictors when available) with participant as a

random effect. This gave us a predicted accuracy for each participant (for each condition and intensity available). The predicted accuracy was then converted to an estimated d' using the `dprime.mAFC` function from the `psyphy` r package. Next, all datasets were merged into one containing accuracy (1 or 0) for each trial, a unique participant id, the estimated d' , pas rating and experiment. We then subset the data to contain trials with PAS1 ratings alone. This left us 16800 observations based on 249 participants. We fitted a logistic generalized linear mixed model predicting accuracy as a function of estimated d' with participant and experiment as random effects.

This gave us an estimated logistic slope of 0.38 (95CI:0.26;0.49) with an (inversed logistic) intercept of 0.44 (95CI: 0.36;0.52). This has been plotted in Figure S3 in red on top of the predicted data based on the same model in grey. The raw mean PAS1 accuracy for each bin of d' in 0.25 increment steps that had at least 100 observations, and a line shows a smoothed moving average. Both the statistical model that takes into account the different experiments and participants as well as the smoothed moving average on the raw data indicate that a d' of 0 corresponds to roughly chance level on PAS 1 accuracy and that this accuracy is expected to rise towards roughly a d' of 2 as predicted by the models presented in Figure 5B and 7B.

Figure S3: Accuracy below the subjective threshold as a function of d' in 10 experiments (N=249). Each grey dot represents one stimulus intensity condition for participants. Black dots represent averaged values for binned d' values (bins of $\frac{1}{4} d'$). The blue dashed line plots a moving average, and the red dashed lines plots a logistic generalized linear mixed model predicting PAS1 accuracy from overall d' with a 95% confidence interval.

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Author contributions

KS conceived the study, experiments and the base model approach at the conceptual level. All authors discussed the design. BMB and KS developed and applied the modelling approach. SHDP programmed and piloted the experiments and collected data. Data was analysed by BMB and KS. The manuscript was drafted by KS. MO, SHDP and BMB provided edits, recommendations and corrections on the manuscript.

Competing interests

The authors declare no competing interests.

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