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Attenuated sensory precision and contextual prediction error in persistent
depression

Anna Bevan^{1,2*}, Caitlin Hitchcock¹, Daniel J Mitchell¹, Tim Dalgleish^{1,2}

¹ MRC Cognition and Brain Sciences Unit, University of Cambridge, Cambridge, United Kingdom
² Cambridgeshire and Peterborough NHS Foundation Trust

* Corresponding author
Email: anna.bevan@mrc-cbu.cam.ac.uk (AB)

Abstract

Chronic and recurrent forms of clinical depression can persist for a lifetime and often respond poorly to intervention. Psychological formulations implicate rigid, negative expectations of self and world which are resistant to updating with new information, a phenomenology consistent with a Bayesian account of brain function. Bayesian predictive processing models suggest that sensory data which is represented with low precision (high uncertainty) in the brain cannot exert much influence on existing beliefs, giving rise to the hypothesis that persistent forms of depression may be characterised by disturbances in sensory precision optimization. We optimized a computational model with data from a cross-modal (visual, auditory, somatic) covert attention task to estimate sensory precision in persistently depressed participants relative to healthy controls. Results suggested that both sensory precision and the salience of attentional targets were attenuated in depressed participants across sensory modalities, contributing to a suppression of contextual prediction error in this group. These outcomes provide support for a novel theoretical account of depression chronicity and suggest avenues for enhancing the effectiveness of psychological interventions for this population.

Introduction

Clinical depression is a debilitating disorder associated with high levels of disability and burden worldwide [1]. Although the majority of episodes of major depression remit within a year [2], a substantial minority become chronic, often following a fluctuating course which may include recurrent episodes of major depression interspersed with periods of dysthymia or residual symptomatology [3-5]. Once depression persistence is established, treatment response to both antidepressant medication and psychological intervention is poor [6-9]: a more detailed understanding of the mechanisms contributing to the maintenance of persistent depression is needed to facilitate the development of more targeted and effective interventions. At a phenomenological level, psychological formulations

of depression persistence implicate rigid, negative beliefs about self and world which are resistant to updating with new information [10, 11]. This phenomenology appears potentially explicable in terms of predictive processing accounts of information processing [12-14].

According to predictive processing formulations [12-14], perception arises from a process of Bayesian inference, in which prior beliefs ('priors') regarding the causes of sensory data are updated with incoming sensory prediction error (those aspects of sensory data that remain unexplained by the prior) to produce a posterior probability distribution over possible causes of sensory experience. The confidence with which these causes can be inferred is reflected in the breadth of the distribution, with lower variance corresponding to higher certainty. This certainty, defined as the precision (inverse variance) of the posterior distribution over causes, is a function of the precision of both prior and prediction error, and their relative precisions act as weights determining their relative influence on the resulting percept [15]. The role of attention in this kind of formulation is to optimize the precision of prediction error arising within relevant sensory channels relative to each other and to the prior in order to allow the most informative data to update predictions [16, 17]. This system is thought to be a hierarchical one in which higher-level beliefs (for example, regarding the nature of the environment and the contingencies that depend on that environment) constrain lower-level predictions, and where precision-weighted prediction errors originating at a perceptual level cascade up the hierarchy to update high-level beliefs when environmental contingencies change: new learning about a changing context thus depends on precision optimization at lower levels of the hierarchy. Attentional disturbance is a well-established feature of depression [18, 19], and disturbed precision optimization could theoretically account for the intransigence of negative predictions regarding the internal and external environment in its more persistent manifestations.

The proposal that the precision of sensory prediction error is attenuated in persistent depression is broadly consistent with a number of existing theories which posit that disruptions to precision

estimation within allostatic and interoceptive systems lead to a reduced influence of interoceptive prediction error and related failures of model updating in depressed individuals, with negative consequences for both interoceptive experience and allostasis [20-23]. Our own hypothesis generalises this disruption to the whole range of sensory modalities, although it remains plausible that interoceptive or bodily signals may nevertheless constitute a special or extreme case within this broader framework. In line with this, we have previously found that somatic cues assume disproportionate salience for persistently-depressed samples in cross-modal attentional capture [24].

A paradigm which can potentially offer insight into individual differences in precision optimization [16, 25] is the Posner covert attention task [26]. In this task, a target can appear on either the left or the right side of space and is preceded in each trial by a cue which predicts its location with a probability that remains constant throughout the task. ‘Valid’ cues (accurately indicating the target location) are associated with facilitated response latencies, while ‘invalid’ cues (indicating the incorrect location) are associated with slowed responses. The latency difference between responses to valid and invalid cues is sometimes known as a ‘validity effect’, and is robustly elicited regardless of the sensory modality of the cue or target [27]. It has been proposed [28] that smaller validity effects in the Posner task reflect a relative potentiation of bottom-up sensory prediction errors (high sensory precision), while larger validity effects conversely index a relative reliance on prior predictions arising from the cue (high precision of the prior). In line with the hypothesis advanced here, disproportionately large validity effects have been observed in depressed samples, relative to non-depressed control participants, in this task [24, 29].

An established computational model developed by Feldman and Friston [16] provides a framework for modelling sensory precision in the context of the Posner covert attention task. This model allows hidden states to bias sensory precision towards the left or right side of space prior to target presentation, depending on the laterality of the cue, and has succeeded in simulating validity effects

in the Posner task on this basis. The same model also offers insight into context updating when predictions regarding the probabilistic structure of the environment are not fulfilled [16].

According to the model, attention infers state-dependent sensory precision given context-specific probabilistic contingencies, and a mismatch between this inferred precision and the true state-dependent precision driven by incoming sensory data generates a contextual prediction error, signalling the need to update contextual beliefs. For example, in the Posner task, a cue on one side of space establishes an implicit probabilistic context, represented by the hidden states, which predicts the occurrence of informative sensory data on that side of space and redistributes precision accordingly. A target occurring on the opposite side (following an invalid cue) elicits sensory prediction errors with unexpectedly low precision, causing large contextual prediction errors on the hidden states themselves. Therefore, the model predicts that the probabilistic context established by an invalid cue should drive an attenuation of precision-weighted sensory prediction error, and an inflation of contextual prediction error relative to the context established by a valid cue.

Feldman and Friston suggest that these dynamics may be reflected in early and late components of event-related brain potentials (ERPs): responses to stimuli presented during electroencephalogram studies. Like the model-derived precision-weighted sensory prediction error, early (P1 and N1) ERP components are positively modulated by attention [30] while, like the model-derived contextual prediction error, the later (P3) ERP component is amplified in response to novel or unexpected stimuli. More broadly, the P3 has an amplitude that is inversely related to the probability of the stimulus, and positively related to its salience [31], and is thus thought to index context updating [32].

Of interest, a substantial literature [33] suggests that depressive disorders are associated with attenuation in the amplitude of the P3 component in relevant tasks: this literature and model assumptions, therefore, give rise to the hypothesis that contextual prediction error derived from

estimated model parameters should be suppressed in depressed participants relative to healthy controls.

In the current study, an adapted version of Feldman and Friston's [16] computational model was optimized with empirical data derived from a cross-modal version of the Posner covert attention task to estimate the underlying model parameters for persistently-depressed participants relative to healthy controls. Estimated model parameters included a parameter representing baseline capacity for sensory precision, perhaps reflecting arousal or alertness; and a salience parameter representing stimulus-specific potentiation of state-dependent sensory precision. The task included visual, auditory and somatic stimuli which varied across blocks in their designation as either target or cue, allowing stimulus salience to be estimated in term of both bottom-up (modality) and top-down (task-relevance) influences on attentional capture. The adapted model is described in detail in the Method section.

We predicted that overall sensory precision and salience estimates would be attenuated among persistently-depressed participants, and that contextual prediction error in response to unexpected stimuli would be suppressed, consistent with the existing EEG literature. We also predicted, following our previous studies [24], that the relative salience of somatic stimuli would be exacerbated in the persistently-depressed group in comparison to healthy controls.

Results

Participant characteristics

All 16 depressed participants were diagnosed with chronic or recurrent forms of depressive illness. Six individuals (37.5%) met criteria for chronic depression and 10 (62.5%) met criteria for recurrent depression. Of these, two participants described respective histories of 9 and 15 past episodes of depression; the remainder reported that they had experienced too many depressive episodes to

count. Nine participants (56.25%) reported that their first depressive episode occurred in childhood. Mean age of onset was 19.00 years old (SD 6.81) and the mean number of years since first diagnosis was 18.19 (SD 12.49). Eleven individuals (68.75%) met criteria for at least one comorbid Axis 1 disorder (5 met criteria for one anxiety disorder, 3 met criteria for two anxiety disorders, and 1 met criteria for three anxiety disorders. One participant met criteria for an anxiety disorder and an eating disorder). Nine depressed participants (56.25%) were prescribed psychotropic medication at the time of testing (n=3 were prescribed an SSRI, n=1 an SSRI and a sedative-hypnotic; n=1 an SNRI; n=1 a tetracyclic; n=1 a sedative-hypnotic, n=1 an atypical antipsychotic and a sedative-hypnotic; and n=1 a mood stabiliser, an SNRI and a neuroleptic).

Two members of the control group ($n=16$) were also prescribed psychotropic medication, for sleep (a sedative-hypnotic) and pain (unspecified), respectively.

A series of t-tests demonstrated that there were no significant group differences with respect to the matched characteristics of age and years of education (Table 1). As expected, however, depressed participants differed significantly from never-depressed controls with respect to self-reported symptoms of depression and anxiety.

Table 1: Demographic Characteristics and Mood Ratings

Characteristic	Depressed group ^a Mean (SD)	Control group ^a Mean (SD)	Group difference
Sex	14 women	14 women	-
Age (years)	37.19 (16.56)	38.44 (17.27)	$t(30) = -0.21, p = 0.84$
Education (years)	16.31 (2.30)	15.81 (3.41)	$t(30) = 0.49, p = 0.63$
Depression (BDI-II)	31.75 (12.06)	2.81 (2.59)	$t(16.38^b) = 9.39, p < 0.001$
Anxiety (BAI)	24.13 (14.88)	1.69 (1.78)	$t(15.43^b) = 5.99, p < 0.001$

BDI-II=Beck Depression Inventory-II; BAI= Beck Anxiety Inventory.

^an=16 for each group, ^bdegrees of freedom adjusted due to unequal variances.

Posner task

For simplicity, only cued trials were included in the analyses (18,432 trials). Reaction times (RTs) shorter than 200ms or longer than 1500ms were assumed to result from anticipations or misfires and removed from the dataset (197 observations; 1.07%). An additional 73 errors (0.4%) were also removed.

A mixed-design ANOVA confirmed that a validity effect was present in both groups and exacerbated in the depressed group relative to healthy controls (Supplementary Materials, Section 1). The model (see Method) was fit to the data and parameters estimated employing a Bayesian Markov Chain Monte Carlo (MCMC) procedure. Model variations, nested within the overall model, were developed and subjected to a model comparison procedure (Supplementary Materials, Section 2) to identify the most probable source of the group difference in validity effect identified in the ANOVA. The most probable model, given the data, located group differences in the salience parameters γ and the basal precision parameter τ .

Salience and precision model parameter estimation

The salience and precision model was fit to the data γ averaged by group, cue modality, cue validity and SOA and pooled over target modality given that the design was not fully crossed. Modality-specific estimates of target salience were derived by fitting the model independently to the data for each cue modality, averaged by group, target modality, cue validity and SOA, while holding τ and ϑ constant at the most probable values derived from the pooled analysis to ensure consistency. Figure 1 shows the resulting parameter estimates.

Figure 1: Model parameters by group. Salience and precision model parameter estimates for depressed versus healthy participants. Upper left: salience estimates by stimulus category (cue versus target, averaged over stimulus modality); upper right: salience estimates by modality (auditory versus somatic, averaged over stimulus category). Lower left: basal precision estimates by group; lower right: decay rate parameter θ estimated for the whole sample. Points represent the mean of the posterior distribution for each parameter: error bars are 95% credible intervals.

The depressed group and the control group differed credibly in stimulus salience (γ) as a function of both stimulus category (cue vs target) and modality (auditory vs somatic). When compared by stimulus category, averaging over modality, the γ estimates indicate that depressed participants assigned higher salience to cues and lower salience to targets relative to healthy controls; suggesting, perhaps, a deficit in the ability to discriminate or amplify stimuli according to behavioural relevance. When compared by stimulus modality (averaging over category) the γ estimates suggest that depressed participants assigned disproportionate salience to somatic stimuli in the context of a weakened influence of auditory stimuli relative to healthy controls, consistent with our prediction.

Estimates for the basal precision parameter τ also differed between groups, with a credibly smaller estimate for the depressed group relative to healthy controls.

Consequences for perception and action. The consequences of the identified group differences in target salience and basal precision for perception and action in the context of a covert attention trial are illustrated in Figure 2. The upper row of panels in Figure 2 shows the consequences for a trial when the target is preceded by a valid cue (not shown), while the lower row shows the consequences when the cue is invalid. The depicted trial is one in which the SOA is 100ms; parameters are averaged over cue and target modality.

Figure 2: Consequences for perception of group differences in salience and precision. Targets are represented following valid cues (top row) and invalid cues (bottom row). Targets s (black lines), target predictions v (unbroken coloured lines) and absolute prediction error ϵ (dashed lines) are shown by group in the leftmost panels; log-precision by group over the course of the trial in the central panels, and the estimated precision of the target predictions (90% confidence regions) by group in the rightmost panels. The depicted trial represents an SOA of 100ms, and parameters are averaged over target and cue modality. Cues are not shown for greater readability of the plots.

The leftmost panels of Figure 2 show the target s (black line) together with the target predictions v as perceived by healthy controls (red line) and depressed participants (blue line). Absolute prediction error ϵ for the respective groups is shown by dashed lines. When cues are valid, absolute prediction error is relatively small for both groups; when they are invalid it is increased for both groups, but

disproportionately so for depressed participants. This impact on perception is driven by reduced precision of the prediction error which dampens its ability to influence posterior beliefs.

The reduction in log sensory precision in depressed participants relative to healthy controls is depicted in the central panels of Figure 2. Regardless of cue validity, sensory precision is attenuated in the depressed group due to the combination of a reduction in the basal sensory precision level τ together with reduced influence of the target salience parameter γ_{target} . When the cue is invalid, sensory precision suffers yet further in the depressed group due to the disproportionate influence of γ_{cue} in reallocating precision to the opposite side of space. The rightmost panels of Figure 2 combine the target predictions from the leftmost panels with the sensory precision estimates of the middle panels to show the target predictions v surrounded by 90% conditional confidence regions which are inversely proportional to the estimated precision of the sensory data over time. Conditional confidence is reduced for the depressed group relative to healthy controls regardless of cue validity, but the reduction is disproportionately large when cues are invalid, necessitating a compensatory increase in evidence accumulation which can account for the group x validity effects in RT observed in the ANOVA (Supplementary Materials, Section 1).

Consequences for context updating. The consequences of these group differences in salience and precision for context updating are shown in Figure 3. Upper panels show precision-weighted sensory prediction errors ξ on the hidden causes v , and lower panels show the contextual prediction error on hidden states x . In the control group, we see a similar pattern to that observed by Feldman and Friston: invalid cues suppress precision-weighted sensory prediction error and enhance contextual prediction error given unexpectedly low state-dependent sensory precision. In the depressed group, precision-weighted prediction error in response to validly-cued targets is almost comparable to that seen in healthy controls, although its suppression in response to invalid cues is greater. The most marked group differences are seen in contextual prediction error, which is suppressed in the depressed group

relative to healthy controls, particularly in response to invalidly-cued targets. This suppression results from low target salience in the depressed group, causing an absolute reduction in state-dependent sensory precision, but reducing its predicted expectation commensurately more. According to the theory advanced by Feldman and Friston [16], this is analogous to a reduced or suppressed P3 amplitude in depressed participants, consistent with literature demonstrating similar outcomes in real EEG tasks [33].

Figure 3: Consequences for prediction error of group differences in salience and precision. Control participants show a facilitation of precision-weighted sensory prediction error (ξ) in response to validly-cued relative to invalidly-cued targets. However, contextual prediction error (prediction error on the hidden states x encoding state-dependent precision) is exacerbated following an invalid cue, reflecting the failure to optimize stimulus precision. Depressed participants show a similar facilitation of precision-weighted sensory prediction error (ξ) in response to validly-cued targets; but a relative attenuation of contextual prediction error, particularly following invalidly-cued targets. Given model assumptions, this outcome is consistent with ERP evidence in this population.

Participant-level parameter estimates

As a check on the conclusions, the model was independently fit to the individual data of each of the 32 participants and participant-level parameter estimates derived using an identical procedure to that

used to derive the group-level estimates. The participant-level estimates (Supplementary Materials, Figure S3) suggest that the conclusions drawn from the group-level estimates are robust.

Medication-free analyses

The ANOVA and group comparisons based on participant-level parameter estimates were repeated, including only the 21 participants who were medication-free at the time of the study. No substantive differences in outcomes were identified (Supplementary Materials, Section 4).

Additional analyses

Somatic salience and interoception. A regression analysis was undertaken to identify influences on relative somatic salience (the ratio of somatic to auditory salience) which could account for the observed increase in somatic salience among the depressed group relative to healthy controls. One potential hypothesis suggests that somatic stimuli are more salient among depressed participants due to relatively high levels of anxiety in this group [34], in which case anxiety symptomatology across the sample should be positively associated with somatic salience. An alternative hypothesis suggests that if depressed individuals habitually suppress or attenuate endogenous interoceptive or bodily signals, exogenous somatic or bodily prediction error arising from a novel task may be relatively unexpected and hence more surprising. In this case interoceptive awareness should be negatively associated with relative somatic salience.

Self-reported interoceptive awareness, also known as interoceptive sensibility [35] was estimated using the total score of the Multidimensional Assessment of Interoceptive Awareness (MAIA) [36]. Interoceptive sensibility was reliably decreased in the depressed group relative to controls ($t(30) = -5.54$, $p < 0.001$). Interoceptive sensibility (total MAIA score) and anxiety (BAI score) were then simultaneously regressed onto relative somatic salience. Both interoceptive sensibility ($\beta = -0.26$, $p = 0.011$) and anxiety ($\beta = 0.008$, $p = 0.03$) predicted unique variance in relative somatic salience, in the

expected directions. With respect to overall model fit, adjusted $R^2 = .37$. Relationships are shown in Figure 4 (upper panels).

Figure 4: Influences on sensory precision and somatic salience Upper panels: partial correlation plots. On the left, interoceptive sensibility is negatively associated with relative somatic salience, controlling for the influence of anxiety severity. On the right, anxiety severity is positively associated with relative somatic salience, controlling for the influence of interoceptive sensibility. Lower panel: despite relatively low basal precision on average in the depressed group, a positive relationship between participant-level estimates of basal precision and anxiety severity is apparent among depressed participants; the same relationship is not present in healthy controls.

Basal sensory precision and anxiety. Assuming that the basal precision parameter τ reflects a tonic level of arousal, external focus, or scanning attention, a question of interest was the relationship between this parameter and anxiety levels. Figure 4 (lower panel) shows individual τ estimates plotted against BAI scores for depressed participants (in blue) and controls (in red). Although τ estimates in the depressed group are in general smaller than those in controls, higher levels of anxiety in depression are associated with higher τ ($r(16) = 0.54$, $p = 0.033$). Although the range of anxiety scores is limited in the controls, the same association is not present and the non-significant trend is in the opposite direction ($r(16) = -.41$, $p = 0.11$). These results may suggest that depression and anxiety exert

opposing influences on basal precision, although the numbers here are too small to draw firm conclusions.

Discussion

We estimated underlying precision and salience parameters of a computational model optimized by RT data from a cross-modal Posner task, and found that, given model assumptions, depressed participants demonstrated reduced sensory precision, reduced target salience, and increased somatic salience relative to controls. Contextual prediction error (possibly analogous to the P3 ERP) derived from these parameter estimates was suppressed in the depressed group relative to healthy controls, consistent with real electroencephalogram data in this population [33]. Each of these findings is discussed in turn below.

Sensory precision

Attenuated sensory precision in the depressed group was underpinned by a generic reduction in basal sensory precision regardless of the modality or salience characteristics of the stimuli in any given trial. This finding is consistent with predictive processing models which posit that depression is characterised by an underweighting of sensory prediction error in the interoceptive realm [20, 23], but generalises reduced precision to other sensory modalities including the somatic, auditory and visual modalities. Of interest, although estimates of basal precision were reduced on average in depressed participants relative to healthy controls, among the depressed group they were positively associated with anxiety scores. This may suggest that high arousal or hypervigilance associated with anxiety has an opposing influence on basal sensory precision relative to the dampening effect of longstanding depression; however, a larger study better able to disaggregate different presentations of anxiety and depression symptomatology will be required to confirm such a hypothesis. Importantly, these findings indicate that attenuated sensory precision in persistent depression may generalise across sensory modalities.

347

348 At a neural level, it has been proposed that the optimization of sensory precision is underpinned by
349 the cholinergic system [17, 25]. Acetylcholine (ACh) transmission regulates the gain control of sensory
350 channels in selective attention, enhances cortical sensitivity to salient sensory information, and
351 contributes to top-down cortical control under conditions of attentional challenge [37-39]. Prefrontal
352 cholinergic signalling has been associated with both slow volume transmission and fast phasic activity,
353 perhaps contributing to maintenance and switching of task set, respectively [40, but see 41], and while
354 thalamic cholinergic signalling may enhance the processing of salient sensory signals [42], cortical
355 cholinergic circuits may have the opposing function of inhibiting irrelevant sensory information and
356 reducing distractibility and behavioural flexibility in order to maintain existing context representations
357 and task set [43, 44].

358

359 There is evidence that both stress and depression modulate cholinergic activity [45-47]; in particular,
360 an extensive literature implicates chronically elevated central cholinergic signalling in depression.
361 Although both the causes and consequences of a putative hypercholinergic state in depression remain
362 unclear, it is possible to speculate that such a state could be consistent with excessive top-down
363 control of afferent sensory inputs, or with the effort required to maintain the task-set associated with
364 an outdated context by habitual suppression of inconsistent sensory evidence, consistent with an
365 overemphasis on prior precision at the expense of sensory precision. An interesting simulation of a
366 related situation [48] tracked interactions between noradrenaline (NA) and ACh in an agent
367 undertaking a behavioural task involving both expected and unexpected uncertainty. A simulated
368 lesion to the NA system was found to lead to perseverative errors resulting from failures in context
369 updating, which also contributed to an increase of PFC activity and to persistently elevated ACh levels
370 which no longer accurately tracked uncertainty.

371

372 **Target salience**

A striking finding of the current study was the attenuation of target salience relative to cue salience among depressed participants in comparison to healthy controls, suggestive of a disturbance in the discrimination or amplification of behaviourally-relevant signals. Importantly, attenuated target salience contributed to an attenuation of predicted state-dependent precision, suppressing contextual prediction error, particularly in response to unexpected targets. The current study, therefore, suggests (given model assumptions) that disturbed salience processing may contribute to failures in context updating in depressed participants, consistent with our predictions and also with evidence that the amplitude of the P3 wave, thought to reflect context updating, is typically blunted in depression [33, 49].

The finding that stimulus salience exerts a powerful influence on context updating in the current study is consistent with existing predictive processing theory [50-52]. To register and adapt to shifting environmental contingencies in the maintenance of an online inferential working model of that environment, the brain must monitor a constant stream of incoming sensory information and to amplify those aspects of it that are relevant for model updating; particularly information that is motivationally significant, novel or unexpected. It has been proposed that locus coeruleus (LC) activity underpins such activity through noradrenaline (NA) release, dynamically reconfiguring neural networks in response to such stimuli in order to facilitate flexible belief updating [50-52] and rapid behavioural adaptation [53]. It has also been proposed that the P3 ERP component is an electrophysiological marker of such LC-mediated context updating [31, 32].

NA plays a central role in detecting and responding to both threat and potential reward [54], and the noradrenergic system is therefore extremely responsive to stress [e.g., 55]. During acute stress, NA is released both centrally and peripherally, and high tonic LC activity may disengage task-focused attention and promote bottom-up sensory signals in a manner consistent with hypervigilance or scanning for threat [56]. Over the longer-term, both acute and chronic stress induce plasticity in the

NA system with likely implications for mood and anxiety disorders [57], and although the precise relationships between chronic stress, changes in NA signalling and depression are not yet clear [58], there is robust evidence for noradrenergic system disruption in individuals with depressive illness [59, 60].

Somatic salience

In contrast to the attenuation of top-down salience, there was evidence that depressed participants found the bottom-up characteristics of somatic stimuli disproportionately salient in comparison to healthy controls. The finding that somatic cues are uniquely distracting or salient for depressed participants replicates our previous findings [24], but requires some explanation, particularly given a body of literature indicating *reduced* bodily awareness in depressive disorders [34, 61-63]. Relative somatic salience was positively associated with physiological anxiety symptom severity, perhaps reflecting heightened threat value of bodily signals in anxious individuals; and negatively associated with interoceptive sensibility, suggesting that individuals who reported less awareness of interoceptive sensation day-to-day were more surprised (in a Bayesian sense) by somatic stimuli in our task. It is possible that increased surprise at novel bodily sensations can result from habitual downregulation of interoceptive and other bodily signals, an explanation which can accommodate both the increased salience of the novel stimuli employed in the current studies, and the reduced salience of endogenously-occurring interoceptive signals such as heartbeats observed in tasks indexing interoceptive awareness [61, 62]. Alternatively, higher salience of unwanted bodily signals may motivate more habitual cognitive and behavioural avoidance of such signals [e.g., 10, 64, 65], reflected in lower interoceptive sensibility. A targeted approach, employing a wider range of interoceptive measures [35], is needed to investigate this question further. In theoretical terms, our finding that somatic stimuli are disproportionately salient in the context of attenuated generic sensory precision is broadly consistent with the proposal [21] that bodily signals are both noisy and amplified in depressive disorders.

Clinical implications

The finding that persistently depressed individuals may be at a disadvantage in model updating due to a pervasive attenuation of sensory precision has clinical implications, particularly with respect to psychological therapies for this population. For example, Cognitive Behaviour Therapy [66] provides a powerful rationale for identifying, examining and updating rigid and entrenched high-level prior beliefs regarding the internal and external context, but places much less overt emphasis upon the related necessity to amplify data quality and sensory precision commensurately. Explicit practice in the amplification of sensory precision (for example, through the use of attention training or meditation practices) may be of benefit for this population [67-70].

Evidence for the disproportionate salience of somatic signals in persistently depressed individuals also has potential clinical relevance, particularly if high somatic salience arises from a combination of threat and emotional avoidance or downregulation associated with somatic signals. Current CBT practice explicitly formulates beliefs, predictions and avoidance behaviours in the external milieu, but is to some extent lacking in a language and rationale for bringing the same lens to bear on the internal milieu, despite the likely relevance of interoceptive and bodily experience to depression and its persistence. Nevertheless, relevant techniques could very easily be generalised, much as techniques for the updating of verbal beliefs have been generalised to accommodate beliefs and meanings instantiated in visual imagery [71]. The current findings may also indicate an increased emphasis on body-focused interventions such as relaxation practices and body-focused meditation practices with persistently-depressed populations.

Limitations and future research

Although adequately powered, the study is limited by a modest sample size, and replication with larger samples would be an advantage to consolidate the conclusions. The study includes only behavioural

data: model predictions could be more fully tested in future research employing a wider range of methods including electrophysiological recording and pharmacological manipulations. The suggestion that depression and anxiety may exert opposing influences on sensory precision deserves further investigation with dedicated samples, and the relationship between disproportionate somatic salience in the current study and existing interoceptive theories of depression persistence remains to be elucidated.

In summary, this study presents novel evidence of attenuated sensory precision, generalised across sensory modalities, contributing to failures in context updating in persistently depressed participants. These findings are both theoretically and clinically important and open up new avenues for future research in the domain of persistent depressive disorders.

Method

Participants

Participants were sixteen persistently-depressed individuals and sixteen never-depressed controls, matched to the depressed group on age, sex and years of education. Major Depressive Disorder (MDD) was diagnosed via a Structured Clinical Interview for DSM-IV Axis I disorders (SCID-1) [72] administered by a trained research assistant, and a SCID mood module administered on the same day as testing by a registered clinical psychologist. Depression and anxiety severity were estimated using the Beck Depression Inventory (BDI-II) [73] and the Beck Anxiety Inventory (BAI) [74], respectively. Inclusion criteria for the depressed group were a diagnosis (determined by the SCID) of either chronic or recurrent MDD in the context of a current Major Depressive Episode of at least moderate severity, defined as scoring 20 or above on the BDI-II [75]. Exclusion criteria included current alcohol or substance dependence or a history of psychosis, bipolar disorder, traumatic brain injury, intellectual disability or dementia. Exclusion criteria were similar for the control group, with the additional specification that controls had no significant history of anxiety or depression, and scored within the

'minimal' range on both self-report measures at the time of testing: i.e., a score of less than 14 on the BDI-II [75] and a score of less than 8 on the BAI [76].

Participants were recruited via email from an established volunteer database. All participants provided written informed consent before taking part in the study and received compensation of £6 per hour for their participation. The study was conducted in accordance with ethical approval from the Cambridge Psychology Research Ethics Committee (PRE.2013.72).

Materials

Figure 5 shows the layout of the experimental materials. Cues and targets were auditory, somatic or visual stimuli presented well above perceptual threshold for 400ms intervals. Visual stimuli consisted of 400 ms illuminations of one of two 3 mm white light emitting diodes (LEDs) positioned to the left and right peripheries of the participant's visual field. Somatic stimuli consisted of 400 ms bursts of 210 Hz vibration, delivered by one of two 10mm vibrating tactors (310-131, Precision Microdrives) affixed to the participants' left and right ventral forearms using surgical tape. Auditory stimuli consisted of 400 ms 440 Hz tones (60dB LAeq) delivered via one of two 50mm mylar speakers positioned to participants' left and right, close to the LEDs. LEDs and tactors were connected via a parallel port to a desktop PC running MATLAB R2009a (Mathworks). All stimuli were controlled via a program written using the psychophysics toolbox [77, 78] to ensure precise stimulus onset and offset latencies.

498

499 **Figure 5: Layout of the experimental materials for the Posner task.** Participants are seated at a table,
500 with forearms resting against small pads affixed to the table and outer surface of the speakers, and
501 eyes resting on a fixation dot positioned between them. Tactors are affixed to the participant's left
502 and right ventral forearms using surgical tape. LEDs are embedded in the padding, clearly visible and
503 close to the ipsilateral speaker and tactor. Foot pedals are adjusted to a comfortable position under
504 the table and lights dimmed during the task.
505

506 In each trial, a target was presented to either the right or left side of fixation, and participants indicated
507 the location of the target using a spatially congruent foot pedal response. A spatially valid, neutral or
508 invalid cue was presented immediately before the target. Trials began with cue onset followed by
509 target onset at one of three possible stimulus onset asynchronies (SOAs: 100, 300 or 500 ms). Uncued
510 trials began with target onset. Following target offset, the program paused until a response was made,
511 triggering an inter-trial interval, randomly varied between 1000 and 1500 ms. Participant responses
512 were made using foot pedals for the left and right feet, connected to the PC via the parallel port, and
513 reaction latencies and error data were collected by the program. Cues were valid (appearing at the
514 same location as the target), invalid (appearing at the opposite location), or neutral (simultaneous
515 cues at both locations), with equal probability.

516

517 **Procedure**

518 Participants were instructed to maintain fixation on the dot while responding as quickly and as
519 accurately as possible to targets. Four brief practice blocks (reflecting the 4 experimental blocks) were
520 completed to check participants' understanding of the task and to familiarise them with the
521 equipment. The experimenter observed the participant throughout the task to ensure that central
522 fixation was maintained.

523

524 Eight trials were presented for every combination of SOA (3 levels), validity (3 levels) and laterality (2
525 levels) and there were additionally eight uncued trials for each laterality, totalling 160 trials per block.

526 Trial types were presented within blocks in a randomized order, and in total participants completed

four blocks counterbalanced using a Latin Square. In one block, targets were auditory and cues were somatic; in a second, targets were somatic and cues were auditory. In the remaining two blocks, targets were visual and cues were auditory or somatic respectively. During all blocks, continuous white noise was delivered via the peripheral speakers to mask any sound associated with tactor vibration. Participants were given opportunities to rest between blocks.

Model

The model was derived from Feldman and Friston's [16] predictive coding model of covert attention. This model allows hidden states to bias sensory precision towards the left or right side of space prior to target presentation depending on the location of a cue. Evidence for the presence of a target is accumulated through an updating process utilising precision-weighted prediction errors. A response is triggered once the posterior probability that the target is present reaches a given level (80% in the original model). This probability is a function of both the expectation and the scale (i.e., inverse precision) of the target estimate. Therefore, the hidden states encoding precision affect both target recognition and the confidence associated with it, with a consequent effect on reaction times.

Because our experimental paradigm differed slightly from the canonical Posner paradigm modelled by Feldman and Friston, some adaptations were made to the model framework. First, we replaced the single precision gain-control parameter γ with modality-specific parameters γ_{target} and γ_{cue} intended to reflect bottom-up salience attributes of the different stimuli in addition to top-down salience reflecting their role as cue or target in a given block. Second, given that all cues in our study were exogenous, we omitted the high-precision central channel which produced endogenous cueing in the original model. The basic form of our adapted model is illustrated in Figure 6.

Simulated cue and target

Figure 6: Cue, target and target probability over time. The upper left panel shows a simulated cue and target (SOA=300ms) situated within a single trial. y represents the point at which 80% confidence in the presence of the target is achieved. Speed of processing components (SoP) contribute to the remainder of the RT. The lower left panel shows the same simulated target (s) and the associated prediction of the underlying hidden cause (v). This prediction is a gaussian function, varying over time, with mean shown by the dotted line, and standard deviation shown by the surrounding grey area. The uncertainty associated with the expectation of v reflects the estimated precision of the sensory data, which is affected by cue validity: here the target follows a neutral cue. The right panel shows the resulting posterior confidence in the presence of the target (the probability that v is greater than 0) over time.

For the purposes of the model all stimuli were simulated using a Gaussian function with a standard deviation of 67 ms and with the mean (μ) located at the midpoint of the veridical stimulus (i.e., 200 ms from the start of the trial for a cue, and 300, 500 or 700 ms for a target depending on SOA). This generated simulated stimuli of approximately 400 ms duration with an onset appropriate to their category and condition (Figure 6, upper left panel). Each trial was modelled as lasting for 1 second and was comprised of one thousand 1ms time-bins.

Sensory data s resulting from cue or target presentation is compared to the representation of its cause v , inducing prediction error ϵ . Prediction error, weighted by its precision Π , drives changes in the

572 representation of v over time. The denominator $\Pi + C$ (where C is a positive constant) corresponds to
 573 posterior precision and reflects constant prior precision. Sensory precision Π is derived from the log-
 574 precision π which is the sum of hidden state x and basal sensory precision parameter τ . Hidden state
 575 x represents state-dependent sensory precision, and its changes over time are driven by the causes v
 576 weighted by salience parameters γ , and decay at rate ϑ . A spatial component is introduced by the
 577 validity indicator which determines the impact of an invalid, neutral or valid cue on x , given that x
 578 represents the side of space containing the target.

$$s = v + \varepsilon \quad (1)$$

$$\xi = \varepsilon \left(\frac{\Pi}{\Pi + C} \right) \quad (2)$$

$$\dot{v} = \xi \quad (3)$$

$$\Pi = e^{\pi} \quad (4)$$

$$\pi = x + \tau \quad (5)$$

$$\dot{x} = \gamma_{target} v_{target} + \text{validity}(\gamma_{cue} v_{cue}) - \vartheta x \quad (6)$$

$$\text{validity} \in -1, 0, 1 \quad (7)$$

579

580 Priors for the parameters to be estimated were flat and broad relative to the posterior estimates as
 581 follows:

$$\tau \sim \text{Uniform}(0,5) \quad (8)$$

$$\gamma_{cue} \sim Uniform(0,1) \quad (9)$$

$$\gamma_{target} \sim Uniform(0.01,1) \quad (10)$$

$$\vartheta \sim Uniform(0,0.01) \quad (11)$$

582

583 The limits on the priors for γ_{target} and ϑ reflect the model constraint that x 's decay must be slower than
584 its accumulation [16].

585

586 A parameter recovery procedure demonstrated adequate estimation precision for the model
587 parameters (Supplementary Materials, Figure S5).

588

589 **Data standardization.** Given model assumptions, the raw RTs can be thought of as the result of a
590 mixture of processes, including the perceptual recognition process captured by the model, the
591 additional contribution of modality-specific perceptual speed-of-processing lags, and the latencies
592 associated with motor preparation and motor response implementation. The sum-total of all
593 perceptual and motor speed-of-processing factors SoP (Figure 6, upper left panel) was estimated as
594 follows:

595

$$SoP = RT - y \quad (12)$$

596 where y represents the process of perceptual recognition described in the model and specifically the
597 point in peristimulus time at which 80% confidence in the presence of the target is achieved. Although
598 neither SoP nor y are known, the estimation is rendered more tractable by adding a constant d to both
599 RT and y , where d is defined as the difference between the point of 80% confidence and target mean
600 μ . Equation 12 can therefore be rearranged as

601

$$SoP = RT + d - \mu \quad (13)$$

602 d is determined by the underlying model parameters and therefore can be estimated by fixing those
 603 parameters at reasonable values. For the purposes of this estimation we used only neutrally-cued data
 604 and followed the original model in fixing confidence at 80% and basal precision (τ) at 2. Decay
 605 parameter ϑ was fixed at 0.01. SoP can be estimated in this way either for the sample as a whole, or
 606 independently by group. Estimates for the whole sample are shown in Table S6 (Supplementary
 607 Materials).

608

609 **Model optimization.** Feldman and Friston [16] simulated RTs by finding the point in peristimulus time
 610 at which the posterior probability of the target reached 80%, i.e., finding t where

611

$$P(v_t > 0) = 0.8 \quad (14)$$

612 This timepoint can be identified by applying the CDF of the standard normal distribution to a z-score
 613 derived from the mean and standard deviation of v_t

614

$$P(v_t > 0) = 1 - \Phi\left(\frac{0 - v_t}{\sqrt{\exp(-\pi)}}\right) = 0.8 \quad (15)$$

615 Rearranging, we can derive an estimate of precision at the point of 80% confidence from the data y :

616

$$\hat{\pi}_y = -\log\left(\left(\frac{v_y}{-\Phi^{-1}(0.8)}\right)^2\right) \quad (16)$$

where y enters the model as an index indicating the timepoint at which 80% confidence, and hence (ultimately) a response, is achieved. The model is optimized by minimizing the difference δ between each estimate of precision derived from the data and its counterpart derived from the model parameters:

$$\delta = \hat{\pi}_y - \pi_y \quad (17)$$

hence δ can act as an informal index of model fit.

The model was fit to the data and parameters estimated employing a Bayesian Markov Chain Monte Carlo (MCMC) procedure conducted using JAGS [79], running with R [80] and the runjags [81] and coda [82] packages. For each parameter estimate, four chains were initialised at a range of starting points and run until convergence, assessed visually and according to the potential scale reduction factor $\hat{R}$ [83]. Once adequate convergence was identified, chains were subsequently run until an effective sample size near or above 10,000 samples was collected for each parameter of interest [84]. Model fit was assessed using a posterior predictive check (Figure S7, Supplementary Materials).

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Supplementary Materials

Section 1. Analysis of Variance

The data (Figure S1) were subjected to a mixed ANOVA (IBM SPSS Statistics for Windows, version 25) with a between-participants factor of Group and within-participants factors of Cue Modality, Cue Validity, SOA and Target Laterality. The data were pooled across target modalities for simplicity and because the design was not fully crossed. A Greenhouse-Geisser correction was employed where the assumption of sphericity was not met.

Figure S1: Reaction times by group and cue validity. RTs (ms) are panelled by cue modality, SOA and target laterality. Error bars represent 1 standard error of the mean (between-groups error).

Within-participants effects. There was a marked effect of cue validity, $F(1.57, 60) = 65.76$, $p < 0.001$, $\eta_p^2 = 0.69$, in the expected direction, indicating that participants displayed robust validity effects (see Figure S1). A large effect of SOA, $F(1.68, 60) = 243.23$, $p < 0.001$, $\eta_p^2 = 0.89$, indicated that RTs decreased as SOAs increased. An interaction between cue modality and SOA, $F(2, 60) = 23.13$, $p < 0.001$, $\eta_p^2 = 0.44$, suggested that responses to targets with auditory cues were speeded relative to

targets with somatic cues but only at longer SOAs; and an interaction between validity and SOA, $F(4, 120) = 8.92$, $p < 0.001$, $\eta_p^2 = 0.23$, indicated that validity effects were smallest at the longest SOA. An interaction between validity and laterality, $F(2,60) = 3.29$, $p = 0.044$, $\eta_p^2 = 0.10$, suggested that responses to left-sided targets were speeded relative to right-sided targets only when cues were neutral; and, finally, an interaction between SOA and laterality, $F(1.65, 60) = 7.13$, $p = 0.002$, $\eta_p^2 = 0.19$, suggested that left-sided responses were slightly quicker at shorter SOAs while right-sided responses were slightly quicker at the longest. There was also a non-significant trend towards a main effect of modality, $F(1,30) = 3.96$, $p = 0.056$, $\eta_p^2 = 0.12$, suggesting that responses to targets with auditory cues were (unreliably) faster than responses to targets with somatic cues. There were no other significant main effects or interactions (all $ps > 0.1$).

Group effects. There was a statistically significant interaction between group and cue validity, $F(1.57, 60) = 4.37$, $p = 0.026$, $\eta_p^2 = 0.13$, indicating exacerbated validity effects in the depressed group relative to healthy controls, as predicted. There was no main effect of group, $p > 0.5$, and no other significant interactions between group and any other factors (all $ps > 0.08$).

Section 2. Model comparison

1. Salience model: group difference in γ . In the first model, speed of processing (SoP) estimates were based on the sample as a whole; confidence was fixed at 80%; and a single estimate of basal precision parameter τ was derived for the whole sample. Salience parameters γ were estimated independently for each group.

2. Basal precision model: group difference in τ . In the second model, SoP estimates were based on the sample as a whole, confidence was fixed at 80%, and salience parameters γ were estimated for the whole sample. Basal precision parameter τ was estimated independently for each group.

3. Confidence model: group difference in α . The preceding models both posit group differences in mechanisms contributing to perceptual precision. An alternative hypothesis suggests that depressed participants differ from healthy controls not in terms of perception itself, but in requiring a higher level of confidence (i.e., more time for evidence accumulation) before being willing to commit to a response. In the third model, therefore, a confidence parameter α was estimated for each group as follows:

$$\alpha \sim \text{Uniform}(0.5, 1) \quad (18)$$

The confidence parameter α overlapped substantially with basal precision parameter τ , due to their similarity in roles. An increase in τ increases the precision of the conditional confidence in the target, pulling the lower bound of the confidence estimate away from 0. Similarly, a reduction in α , by definition, pulls the lower bound of the confidence estimate in the same direction, reducing the amount of precision required to attain the cut-off. Only the unique contribution of τ to the prediction of cue and target differentiates the two parameters. Due to this overlap, attempts to estimate the two parameters simultaneously were found to lead to difficulties with convergence, and so τ was fixed at 2 for both groups. SoP estimates and salience parameters γ were estimated for the sample as a whole.

4. Speed of processing model: group difference in SoP. The fourth model assumed that confidence and precision parameters did not differ by group, and that group differences were solely accounted for by differences in perceptual and motor speed of processing. SoP and its consequences for data y were estimated independently for the two groups. Confidence was fixed at 80%, and precision parameters γ and τ were estimated for the whole sample.

Combination models. All possible combinations of these models were also considered (a total of 15 models). Models in which both τ and α varied by group were discarded following initial runs which

demonstrated that these functionally similar parameters traded off each other when both were allowed to vary within the same model, causing difficulties with convergence. It was observed that the addition of a group difference in SoP to any other group difference or combination of differences worsened the fit of the model (estimated using the difference δ between log-precision estimates derived from the model and log-precision estimates derived from the data, averaged over all data points), without any compensatory gains in terms of reduced model complexity. Five models which included group differences in SoP and at least one other parameter were discarded for this reason. Six models remained: the four index models described above, and two combination models as follows:

5. Salience and precision model: group differences in γ and τ . This model assumes that group differences are present in both state-dependent and basal precision parameters (i.e., salience parameters γ and basal precision parameter τ). These parameters were allowed to vary by group, while confidence was held constant at 80% and SoP was estimated for the whole sample.

6. Salience and confidence model: group differences in γ and α . This model locates group differences in the salience parameters γ and the confidence parameter α . Basal precision was held constant at 2 and SoP was estimated for the whole sample.

Model comparison. All six models were entered into a Bayesian model comparison using the product space method [85]. The model comparison proceeded by fitting each model to the data y averaged by group, cue modality, cue validity and SOA; i.e., pooled over target modality as in the ANOVA (and for the same reasons). Posterior model probabilities are shown in Table S2. The best-fitting model was the salience and precision model, which provided a better description of the data by a Bayes factor of 13.02 relative to its nearest competitor.

Table S2: Model posterior probabilities

	Model	Location of group difference	Posterior probability
5	Salience and precision model	γ and τ	0.93
6	Salience and confidence model	γ and α	0.07
2	Basal precision model	τ	2.70×10^{-12}
1	Salience model	γ	1.28×10^{-14}
3	Confidence model	α	8.63×10^{-18}
4	Speed of processing model	SoP	8.34×10^{-23}

Figure S3. Participant-level parameter estimates

Figure S3. Participant-level parameter estimates. Points represent group averages for participant-level estimates, error bars are 1 standard error of the mean (between-groups error). Independent-samples t-tests were carried out on the individual estimates for τ and for the ratio of somatic to auditory salience and the ratio of target to cue salience. Welch's t-tests correcting for unequal variances confirmed that τ was reliably smaller in the depressed group than in healthy controls, $t(18.75) = -3.00$, $p = 0.007$, Cohen's $d = 1.03$, as was the ratio of target γ to cue γ , $t(15.81) = -2.60$, $p = 0.02$, $d = 0.92$. A standard t-test confirmed that the ratio of somatic γ to auditory γ was reliably larger in depressed participants than in healthy controls, $t(32) = 4.10$, $p < 0.001$, $d = 1.44$.

Section 4. Medication-free analyses

Nine depressed participants (56.25%) and two healthy controls (12.5%) were prescribed psychotropic medication at the time of the study, and were excluded from the medication-free analysis.

Analysis of Variance. As in the main analysis, the data were subjected to a repeated-measures ANOVA with the factors of Group, Cue Modality, Cue Validity, SOA and Target Laterality. The data were pooled across target modalities and a Greenhouse-Geisser correction was employed where the assumption of sphericity was not met.

Within-participant effects. The key outcomes remained highly significant in the medication-free analysis, including the effect of cue validity, $F(1.29, 24.45) = 72.81$, $p < 0.001$, $\eta_p^2 = 0.79$, and the effect of SOA, $F(1.24, 23.46) = 182.35$, $p < 0.001$, $\eta_p^2 = 0.91$. The interactions between cue modality and SOA, $F(2, 38) = 18.00$, $p < 0.001$, $\eta_p^2 = 0.49$, and between validity and SOA, $F(4, 76) = 8.42$, $p < 0.001$, $\eta_p^2 = 0.31$, also remained. However, the interactions between validity and laterality, and between SOA and laterality, no longer met criteria for statistical significance ($ps > 0.1$).

Group effects. The interaction between group and cue validity was strengthened by the exclusion of medicated participants, $F(1.29, 24.45) = 8.41$, $p = 0.005$, $\eta_p^2 = 0.31$. As in the main analysis, no main effect of group was observed, $p > 0.8$, nor interactions between group and any other factor ($ps > 0.1$).

Salience and precision model parameter estimation. The participant-level estimates for the medication-free participants are plotted in Figure S4. Independent-samples t-tests were carried out on the individual estimates for τ and for the ratio of somatic to auditory salience and the ratio of target to cue salience. Although the group difference in τ was no longer statistically significant due to a loss of power, the effect size was in fact increased relative to the whole-sample analysis: $t(6.82) = -2.31$, $p = 0.055$, $d = 1.21$; Welch's t-test. The group difference in the ratio of target γ to cue γ remained

statistically significant, $t(16.36) = -3.20$, $p = 0.005$, $d = 1.25$; Welch's t-test, as did the group difference in the ratio of somatic to auditory salience, $t(19) = 2.36$, $p = 0.029$, $d = 1.16$.

Figure S4: Participant-level parameter estimates for medication-free participants. Points represent group averages for participant-level estimates, error bars are 1 standard error of the mean (between-groups error).

Figure S5. Parameter recovery

Figure S5. Parameter recovery. Simulated data was derived from 3 input constants for each of the three parameters of interest ($\tau = 1.5, 2, 2.5$; $\gamma_{\text{cue}} = 0.005, 0.0075, 0.01$; $\gamma_{\text{target}} = 0.015, 0.035, 0.055$); the γ weights for cue and target were covaried as in the true design. The input constants were chosen to reflect the range of probable parameter values given the real data. The model was then fit to the simulated data to assess how precisely the known parameters could be estimated. “True” parameter values used to simulate data are shown in red. Black points represent the mean of the posterior distribution for each parameter estimate: error bars are 95% credible intervals. In general the estimates reflect the true input parameters accurately and with reasonable estimation precision.

Table S6. Estimated sum of perceptual and motor speed of processing components by target modality and SOA.

SOA	Perceptual and motor SoP components (ms)		
	<i>Auditory target</i>	<i>Somatic target</i>	<i>Visual target</i>
100	478	452	287
300	432	394	244
500	430	357	222

Figure S7. Posterior predictive check on salience and precision model

Figure S7. Posterior predictive check on salience and precision model. The mean posterior estimates of the salience and precision model parameters for each group and condition were used to generate predicted RTs which are plotted against observed RTs averaged over group and condition. RTs are calculated from the beginning of the trial (rather than from target presentation) to allow comparison across SOA categories. Although examination of the plot suggests that some variance due to effects of group and condition may be unaccounted for by the model (for example, RTs in response to the longest SOA condition are slightly underestimated; there may be signs of an interaction between group and SOA) on the whole the model has succeeded in predicting average response times for both groups within each condition within a few ms.