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Biased pain reports through vicarious information: A computational approach to investigate the role of uncertainty

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ABSTRACT

Expectations about an impeding pain stimulus strongly shape its perception, yet the degree that uncertainty might affect perception is far less understood. To explore the influence of uncertainty on pain ratings, we performed a close replication of the study of Yoshida, Seymour, Koltzenburg, and Dolan (2013), who manipulated vicarious information about upcoming heat pain and found evidence for uncertainty-induced hyperalgesia. In our study, we presented eight fictitious ratings of previous participants prior the delivery of electrocutaneous pain. The vicarious information was either biased to over- or underreport pain levels based on the participant's psychometric function. We induced uncertainty by manipulating the variation of the vicarious information. As in Yoshida et al. (2013), four computational models were formulated, such that each model represented a different way of how the pain ratings might have been generated by the physical stimulus and the vicarious information. The four competing models were tested against the data of each participant separately. Using a formal model selection criterion, the best model was selected and interpreted. Contrary to the original study, the preferred model for the majority of participants suggested that pain ratings were biased towards the average vicarious information, ignoring the degree of uncertainty. Possible reasons for these diverging results are discussed.

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1. Introduction

The potential of expectations to affect pain perception has been well-established, although precise mechanisms are not yet fully understood (Wiech, 2016; Wiech, Ploner, & Tracey, 2008). Inspired by successful perception models from other domains, such as vision (e.g., Friston, 2012; Kersten, Mamassian, & Yuille, 2004), pain researchers have only recently started to consider pain perception as active inference, with sensory information and expectations jointly driving the experience of pain (De Ridder, Vanneste, & Freeman, 2014; Hechler, Endres, & Thorwart, 2016; Wiech, 2016; Zaman, Vlaeyen, Van Oudenhove, Wiech, & Van Diest, 2015). Through the use of computational models, insights into cognitive pain-modulatory mechanisms are starting to emerge (Roy et al., 2014; Seymour et al., 2005; Wiech et al., 2014). For example, a biased decision-making towards the expected pain intensity was recently shown (Wiech et al., 2014). However, it remains unclear to which degree the uncertainty associated with expectations influences cognitive pain modulatory processes.

In a recent study, Yoshida et al. (2013) manipulated expectations about the intensity of an upcoming painful heat stimulus through the presentation of vicarious information. Prior to stimulus presentation, each participant ($n = 13$) observed 8 ratings of (ficticious) *previous participants* that were either located above or below the predicted rating of the participant based on their psychometric function. The uncertainty of this information was manipulated by changing the variance of the fictitious ratings. Yoshida et al. (2013) found strong evidence for an adapted Bayesian model, assuming that people's ratings were influenced by both the nociceptive input as well as by the prior expectation induced by the vicarious information, augmented with an additional uncertainty bias. Thus, overall pain ratings were pulled towards the direction of the vicarious information, and uncertainty further boosted pain ratings.

These findings are in line with previous work, in which similar uncertainty driven hyperalgesia is observed (Carlsson et al., 2006;

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Lin, Hsieh, Yeh, & Niddam, 2014; Meulders, Vansteenwegen, & Vlaeyen, 2012; Oka et al., 2010; Yoshida et al., 2013). However, opposite findings have found that uncertainty is associated with hypoalgesia (Brown, Seymour, Boyle, El-Deredy, & Jones, 2008; Quelhas Martins, Mcintyre, & Ring, 2015), or found no difference between predictable and unpredictable pain as well (Carlsson et al., 2006; Clark, Brown, Jones, & El-Deredy, 2008; Crombez, Baeyens, & Eelen, 1994; Lorenz et al., 2005; Rubio et al., 2015). Most likely methodological differences in the operationalization of uncertainty with regard to either stimulus onset or stimulus properties, such as intensity or duration (Miller, 1981), and expectations through either conditioning, instructions or vicarious learning, likely contribute to these conflicting findings. In addition, most of those studies used rather small sample sizes (below 15 participants). In light of these conflicting findings, we decided to perform a close replication study of the behavioral part of the experiment conducted by Yoshida et al. (2013).

In the current study, we presented vicarious information prior to the delivery of noxious electrocutaneous stimuli (i.e., five different intensities between pain threshold and pain tolerance). During three experimental blocks, we presented vicarious information in the form of eight fictitious ratings from so-called 'previous participants'. These rating were based on the participant's psychometric function, as determined in the pre-experimental phase. In a within-subjects design, the amount of variation of the eight ratings was manipulated (SD 6 or 16 on the 0–100 scale) as well as the direction of the average vicarious ratings (plus 8 or minus 8, again on the same scale).

We tested the hypothesis that the expectation of more or less pain biases pain perception towards the vicarious information and that uncertainty would increase pain ratings as observed in Yoshida et al. (2013). All data and Matlab code are publically available at the Open Science Framework (osf.io/6bw6x).

2. Material and methods

2.1. Participants

After the study was approved by the Local Ethics Committee (G-2015 12 404), volunteers were recruited through local advertisement boards. Exclusion criteria based on self-report were: (1) a history of cardiac, breathing or cardiovascular disorders, neurological disorders, chronic pain, psychiatric disorders, (2) pregnancy, hearing difficulties, acute pain, use of recreational drugs, ongoing recovering from severe trauma, advice from general practitioner to avoid stress, any type of electronic implant (e.g., pacemaker), pain or discomfort located at the wrist, arm or fingers. All participants provided their written informed consent and were paid 16 euros. Of the forty-four healthy volunteers who participated in the study, 38 were included in the final sample. Six participants were dropped due to either technical problems ($n = 5$) or electrode detachment ($n = 1$). Nine out of 38 participants were male and the mean age was 22.6 years (SD = 5.2).

2.2. Electrocutaneous stimuli

The stimuli were applied to the dorsal end of the ulna at the left wrist using a commercially available electric stimulation device (Constant Current Stimulator, model DS5; Digitimer©, Hertfordshire, UK) delivering a 252 ms monopolar alternating squared waveform (4 ms, with 2 ms in between) pulses via two surface electrodes (V91-01, 8mm, Coulbourn©) filled with K–Y gel. Electrical stimulation levels were determined for each individual based on a pre-experimental threshold and tolerance setting procedure (see Section 2.3).

2.3. Procedure

2.3.1. Pre-experimental phase

The goal of the pre-experimental phase was to determine for each participant the psychometric function of how intensity relates to perceived pain.

Threshold and tolerance setting procedure: For each participant, pain threshold and tolerance were determined using the Ascending Methods of Limits approach (Fruhstorfer, Lindblom, & Schmidt, 1976). Participants were instructed to rate the intensity of the electrocutaneous stimulus on an intensity visual analogue scale (VAS) with the following anchors: *'0 – no sensation at all', '30 – just painful electrocutaneous sensation', '100 – the worst imaginable pain'*. During this phase, the participants communicated their VAS rating orally to the experimenter. Stimulation intensity gradually increased until participants indicated their tolerance threshold was reached (i.e., either a VAS score of 100 or the intensity at which a higher intensity would no longer be tolerable by the participant). A variable inter-stimulus interval of minimum 10 s was used. Based on this information, threshold and tolerance levels are determined as follows, for each individual separately: the intensity corresponding to a rating of 30 is used as pain threshold, whereas pain tolerance corresponds to the intensity at which a higher intensity would no longer be tolerable by the participant (see Fig. 1A).

Estimation of the psychometric curve: After the initial threshold and tolerance setting procedure, participants proceeded to a pre-experimental stimulus-rating procedure, in which they rated a sequence of electrocutaneous stimuli of various intensities. The goal of this phase was to estimate the participant's *psychometric curve*. In this phase, for each participant individually 13 different stimulus intensities were used. These stimulus intensities were created as follows. All stimuli were located between participants' pain threshold and tolerance. The most intense stimulus corresponded to the participant's pain tolerance, whereas the other stimuli were distributed equally across the threshold-tolerance range using the following equation: tolerance – $f \times$ (tolerance – threshold), where f stands for fraction and takes values from 0 (tolerance) to 0.9, in steps of 0.075 (thus creating 13 stimuli in total, with the tolerance–threshold stimulus included, and the lowest stimulus near to but above pain threshold). For example, the level of the second most intense stimulus was then calculated as tolerance – 0.075 × (tolerance – threshold), which means that this stimulus is 7.5% below the tolerance level.

Each of the 13 stimuli was presented four times, resulting in a pseudo-randomized sequence of 52 stimuli as no more than two consecutive trials with the same stimulus intensity were allowed. Upon presentation of the stimulus, the previously described VAS appeared and participants were asked to indicate their perceived intensity using key presses to alter the location of the cursor. The starting point of the cursor was randomized across trials.

Using a maximum likelihood procedure (code obtained from Yoshida et al. (2013), Matlab ©), we fitted the participant's psychometric function operationalized as a sigmoid function defined by three parameters to describe the relationship between VAS ratings and stimulation intensity (expressed in milliampere or mA):

$$H(x) = \alpha\left(1 - 2^{-\left(\frac{x}{\lambda}\right)^k}\right) \quad (1)$$

where $H(x)$ is the VAS rating for a stimulus intensity x, α is the asymptote, λ is the latency parameter and k is an abruptness parameter. The asymptote α is the maximal VAS rating if the stimulus intensity becomes very large. The parameter k determines the steepness of the Weibull and λ determines the inflection point. An examples is given in Fig. 1B.

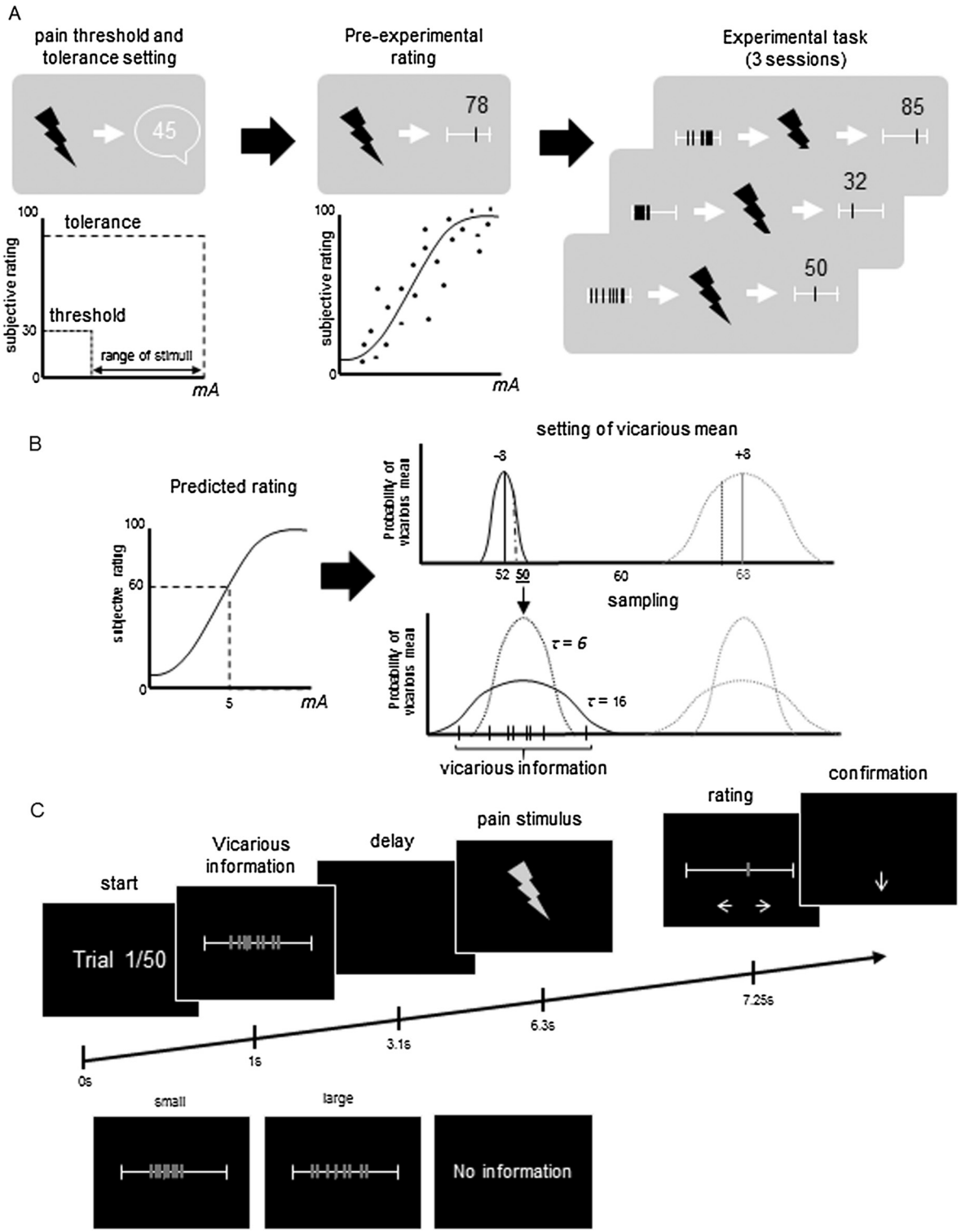


Fig. 1. The experimental protocol. (A) Overview of the experimental flow. First, pain threshold and pain tolerance were assessed using a series of ascending electrocutaneous stimuli. Next, 13 different stimuli located in between pain threshold and pain tolerance were presented repeatedly in order to estimate the participants' psychometric function. Based on this function vicarious information was generated and presented prior to stimulus onset during three sessions. (B) Illustration of the generation of vicarious information. Based on the predicted rating (in this case 60) for a given intensity (5 mA), either 8 points are added or subtracted based on the condition. In this example, vicarious information is generated below the participant's predicted rating (in this case 52). Next, based on a Gaussian distribution with mean 52 and SD 1, 1 sample was drawn (in this case 50). This value is used as the mean of a Gaussian distribution from which the vicarious information is drawn with a SD of 6 or 16 depending on the condition. The eight drawn samples are then represented as lines on the rating scale. In this example, we assumed large uncertainty. The dotted lines on the middle/right panels show the putative distributions for low uncertainty trials, as well as high and low uncertainty ratings when vicarious information is located above the participant's rating. (C) Trial structure. Adapted with permission from Yoshida et al. (2013).

2.3.2. Experimental phase

In the experimental phase, there were 5 conditions: the no information condition and four different information conditions. In the no information condition, no vicarious information but the words "no information" were displayed before stimulus presentation. In the four information conditions, ratings were displayed before stimulus presentation. Participants were led to believe that the displayed ratings were the true ratings of people who had previous come to our lab. However, they were generated by the experimenter using eight draws from a normal distribution as follows: $v \sim N(H(x) + \theta + R, \tau^2)$, with v being a single vicarious rating, $H(x)$ the participant's predicted rating (see Eq. (1)), θ an additional constant, R additional standard normal noise (i.e., $R \sim N(0, 1)$) and τ^2 the variance. The additional constant θ was either negative or positive (-8 or 8); and the standard deviation τ was either low or high (6 or 16). Thus, for each stimulus intensity four different types of vicarious information were possible: vicarious info generated based on either plus or minus 8 and with a low or a high variation (see Fig. 1B).

Each participant performed three experimental sessions. In each session, 5 different stimulus intensities were each presented 2 times in each of the 5 conditions, totaling 50 trials. The intensities were again created for each participant individually, as in the pre-experimental procedure, using the following fractions: 0% (tolerance), 20%, 40%, 60% and 80%. The adopted intensities [mean (SD)] were: 3.32 (1.35), 3.85 (1.45), 4.39 (1.58), 4.92 (1.46), 5.45 (1.95) mA (see Fig. S3).

A trial started with the visual presentation of the trial number vs. the total number of trials within the current session (see Fig. 1C). This information was presented for 1 s. Next, a rating bar appeared for 2.1 s during which 8 ratings emerged (263 ms between ratings) or in the no information condition "no information" was presented on screen for a similar time period. Next, the screen remained black for 3.2 s after which the electrocutaneous stimulus was presented for 252 ms. Then, 0.7 s after stimulus offset, the rating scale appeared. Participants rated the perceived intensity, using key presses to alter the location of the cursor. The starting point of the cursor was randomized across trials. Hereafter, they pressed another button to continue to the next trial.

Within each session, a pseudorandomized presentation order was used with the restriction of no more than 2 consecutive trials of the same stimulus intensity. In between sessions, the intensity-response function of Eq. (1) was re-estimated to control for potential habituation or sensitization effects using all previous trials (see Fig. S2). After each session, a break of 5 min was foreseen. At the end of the experiment participants filled in the Dutch version of the Fear of Pain questionnaire (FPQ-III, (McNeil & Rainwater, 1998) which is a self-report measure of pain-related fear.

2.4. Data analysis

The data are shown in Fig. 2A. The data from the no information condition are displayed as reference only and were not included in analyses. In order to explore the influence of the vicarious information on pain ratings, we calculated the difference between the participant's actual rating and the predicted rating based on their updated psychometric curve. This difference score was then standardized within participants as we transformed it to z-scores to account for inter-individual differences. Next, we averaged these values for the five different conditions. A repeated measures ANOVA was ran with the factors Bias (+8 or -8) and Uncertainty (6 or 16) and their interaction.

2.4.1. Computational modeling analysis

We compared the performance of four competing perceptual models, following Yoshida et al. (2013). In particular, for each participant separately, we evaluated the generalizability (i.e., the balance between fit and complexity) of each model using the Bayesian Information Criterion (BIC), using the global search algorithm in MATLAB© that ran until three equal solutions were found. The analysis was independently double checked in R (using the differential evolution global optimizer that was run five times, unless there were less than three equal solutions, in which case five more runs were started; the solution with the largest loglikelihood was selected and from this point a local optimizer was started to check whether the found minimum could be improved). The MATLAB and R solution were very similar. To assess uncertainty of the estimates, 100 nonparametric bootstrap replications were computed. This BIC value was converted to the posterior model probability.

All four models assume the data are normally distributed, but differ in what they assume to be the mean (μ) and variance (σ^2) of this distribution.

Absolute model – The first model is based on the sigmoid function $H(x)$ from Eq. (1), which maps the intensity of the noxious electrocutaneous stimulus, to a participant's rating, allowing for some unexplained variation around the fitted function (denoted as σ^2_{m1}). Its shape is determined by three parameters; the asymptote (α), the latency (λ) and the abruptness (k). This model ignores the potential influence of the vicarious information, as it assumes that only the noxious input determines the perceived intensity and that this judgment is unaffected by expectations.

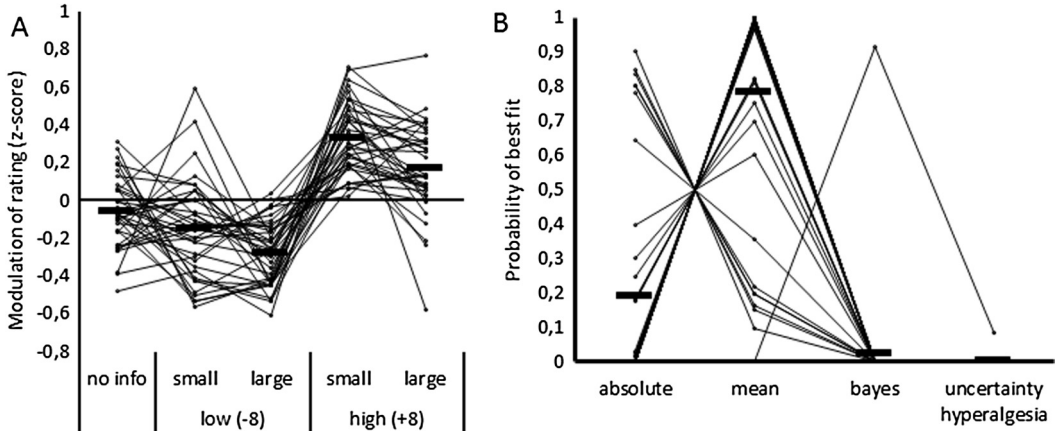


Fig. 2. Modulation of ratings. (A) Modulation of ratings per condition, averaged over participants (black bars). The difference between the participant's actual rating and the estimated rating based on their (updated) psychometric curve was calculated and transformed to z-scores. (B) Posterior probability for each of the four models under comparison, averaged over participants.

$$\mu_{abs} = H(x)$$

$$\sigma^2_{abs} = \sigma^2_{m1}$$

Mean-only model – The second model, is an extension of the first model from a four-parameter to a five-parameter model. It assumes that participant's ratings are a linear combination of the output of the sigmoid function plus the difference between this value and the average rating of the vicarious info (μ_{vic}), again allowing for some unexplained variation (denoted as σ^2_{m2}). The difference between the expected value based on the psychometric function and the average vicarious information is weighted so that the extent to which the participant's rating are biased towards the vicarious info is determined by this factor (ρ), with ρ restricted to positive integers:

$$\mu_{mean} = \mu_{abs} + \rho(\mu_{vic} - \mu_{abs})$$

$$\sigma^2_{mean} = \sigma^2_{m2}$$

Bayesian model – In this four-parameter model, the participant's rating is driven by the combination of a likelihood (the stimulus) and the prior distribution (the vicarious information) according to Bayes' rule (see e.g., Kruschke & Vanpaemel, 2015, Chapter 16). The larger the variance of the vicarious information, the smaller its influence on the mean. Thus, the more uncertain people are about their expectations, the less they are influenced by these expectations:

$$\mu_{Bayes} = \frac{\sigma^2_{vic} H(x) + \sigma^2_{m3}\mu_{vic}}{\sigma^2_{vic} + \sigma^2_{m3}}$$

$$\sigma^2_{Bayes} = \frac{\sigma^2_{vic}\sigma^2_{m3}}{\sigma^2_{vic} + \sigma^2_{m3}}$$

where σ^2_{vic} is the variance of the eight ratings and σ^2_{m3} the unexplained variation.

Uncertainty-Hyperalgesia model – The last model is a five parameter model that builds further upon the Bayesian model, by including an additive effect of the posterior uncertainty on the mean of the participant's ratings:

$$\mu_{uncertain} = \mu_{bayes} + \beta\sigma^2_{\text{Bayes}}$$

$$\sigma^2_{uncertain} = \sigma^2_{\text{Bayes}}$$

where β is restricted to be positive.

3. Results

Analyses of variance of the transformed rating modulations revealed a main effect of Uncertainty [$F(1,37) = 11.65$, $p = 0.002$, $\eta^2_p = 0.24$] with higher ratings during the trials with little variation compared to trials with large variation (see Fig. 2A). There was also a significant effect of Bias [$F(1,37) = 116.59$, $p = 0.001$, $\eta^2_p = 0.76$], as ratings were higher when the vicarious information was biased towards higher ratings compared to a bias towards lower ratings (see Fig. 2A). There was no evidence for an interaction [$p = 0.51$].

Fig. 2B shows the posterior model probabilities for each of the four models, averaged over participants. Inspection of this figure reveals a clear preference for the mean only model. No evidence for the uncertainty-hyperalgesia model was found. In Table 1, the parameter estimates (averaged over persons) are provided.

We exploratory correlated the impact of the vicarious info (i.e., indexed by ρ) with Fear of pain scores assessed by the FPQ-III but did not find any correlation ($p = 0.57$).

4. Discussion

We attempted to replicate Yoshida et al.'s (2013) finding that uncertainty about the intensity of an upcoming stimulus exerts a strong hyperalgesic effect. To this end, we presented vicarious information (i.e., eight fictitious ratings of previous participants) prior to the onset of noxious stimuli located between pain threshold and pain tolerance. Both the variation and a bias towards higher or lower pain ratings of the vicarious information, based on the individual's psychometric function, were manipulated. Pain ratings were obtained on a trial-by-trial basis. Contrary to the original study, we did not find any support for increased pain ratings under conditions of high uncertainty. Model comparison revealed most support for the mean-only model, that assumed that the perceived intensity is influenced by the mean of the vicarious information but not by the uncertainty of the vicarious information.

Some differences between the current and the original study should be acknowledged. First, we used noxious electrocutaneous stimuli applied at the left wrist whereas the original study used thermal stimuli at the left ankle. Second, in the original study a fixed sequence of different stimuli were used based on the participant's pain tolerance due to practical reasons. The difference between the lowest and highest stimulus (i.e., pain tolerance) was 8 degrees (as steps of 2 degrees were used) (Yoshida; personal communication). As a consequence, several of the presented stimuli were probably located below pain threshold as differences between pain threshold and pain tolerance of ±4 degrees have been reported (Chalaye, Goffaux, Lafrenaye, & Marchand, 2009; Edwards & Fillingim, 2007). In order to ascertain that all stimuli were above pain threshold in the current experiment, we selected stimuli between pain threshold and pain tolerance. However, as visible in Fig. S1, this was not always the case. Third, in the original study, stimulus duration varied between 200 and 250 ms (depending on the temperature), whereas in our study this was fixed to 252 ms.

It may be possible that these methodological differences combined affected the precision of the afferent input, due to for example recruitment of different fibers (Baumgärtner, Greffrath, & Treede, 2012), or lower pain acuity at the leg relative to the wrist (Mancini et al., 2014), resulting in less precise nociceptive input in the Yoshida study compared to our experiment. Less precise nociceptive input implies a likelihood with a large variance. Such a broad likelihood increases the effect of the prior, whereas a narrow likelihood reduces the impact of the prior. Hence, the pain ratings in the Yoshida study might be better explained by a Bayesian model that takes changes in the prior into account, while the pain ratings based on less sensory uncertainty (i.e., for electrical stimuli)

Table 1
Mean estimated parameters and standard errors of the mean.

Model	α	λ	k	ρ	β	σ^2
Absolute	86.08 (4.26)	5.59 (1.78)	4.70 (0.46)	–	–	8.42 (0.67)
Mean-only	85.87 (4.21)	5.61 (1.75)	6.15 (1.77)	0.32 (0.04)	–	7.48 (0.51)
Bayesian	84.58 (4.36)	4.28 (0.41)	8.77 (3.67)	–	–	9.23 (0.84)
Uncert.-Hyp.	80.82 (4.83)	5.22 (1.13)	13.81 (6.04)	–	0.39 (0.14)	9.46 (0.96)

Mean estimated parameters for each of the four models and standard errors of the mean between brackets. Uncert.-Hyp. = uncertainty-hyperalgesia model.

would not require a Bayesian model because changes in the prior have relatively less effect. In future studies, it would be interesting to estimate sensory uncertainty using a perceptual (intensity) discrimination procedure.

Another difference with the study of Yoshida et al. (2013) is that we did not exclude participants from data analyses based on the variation criteria adopted in the original study (i.e., if the variance during pre-experimental session is larger than mean variance across participants plus 1 SD, then participants were excluded; Yoshida: personal communication). However, re-analyzing the data with the same criteria led to the exclusion of 6 participants without affecting the results. A final difference with the original study is that it remains unclear to which extent differences in gender ratio might contribute to the findings as our sample consisted predominant of females whereas in the original study gender ratio was more balanced.

Our findings contribute to a growing body of research that investigates the potential role of uncertainty in pain perception. As it stands, support for increased pain reports during uncertain pain conditions is rather limited as the majority of studies found no difference between predictable and unpredictable pain (Carlsson et al., 2006; Clark et al., 2008; Crombez et al., 1994; Lorenz et al., 2005; Rubio et al., 2015) or even lower pain ratings during unpredictable conditions (Brown et al., 2008; Quelhas Martins et al., 2015). Most likely, manipulation of expectations either about the intensity of an impending stimulus (i.e., event predictability) or the onset of a stimulus (i.e., onset predictability) or a combination of both contribute to the differential findings (Miller, 1981), as for example most studies that found no difference between predictable and unpredictable pain have manipulated stimulus onset. However, one of the few studies that did report hyperalgesia during unpredictable pain (Lin et al., 2014), suggests that it is due to a decrease in reported pain over time in the predictable context. In a conditioning paradigm, one of two cues always preceded a low painful stimulus whereas the other cue was associated with either a high or low painful stimulus (50–50%). During the first 30 trials, no difference between both pain conditions was observed, whereas for the last 30 trials, pain ratings decreased for predictable pain but did not change for unpredictable pain, suggesting that differences between both conditions were driven by predictability. However, as a condition with a high pain predictive cue was lacking, inferences should be made cautiously. For example, Brown et al. (2008) used four word cues ('low', 'medium', 'high', 'unknown') preceding a stimulus of either a low, medium or high intensity. They found lower pain ratings for the high intensity stimulus during the predictable compared to the unpredictable condition, no difference for the medium intensity stimulus and the opposite for the low intensity stimulus. These findings fit with a Bayesian observer model where the prior is updated through experience (Brown et al., 2008; Petzschner, Glasauer, & Stephan, 2015). In each of the predictable conditions, the same stimulus is presented repeatedly. As a consequence, the prior will converge to this stimulus value. In the unpredictable condition different stimuli are equally likely and hence the prior covers a wide range of stimuli with a mean located at the center of the spectrum. As a consequence higher values are rated as lower, whereas lower values are rated as higher (Petzschner et al., 2015). However, this regression to mean effect would also be expected in the study of Martins et al. (2015) where different stimuli were presented in blocks of either fixed stimulus intensities or randomly, but overall higher ratings during the unpredictable condition were found for all stimuli. These and our findings that the Bayesian model did not perform better was somewhat surprising given the wealth of evidence favoring perception as Bayesian inference (Petzschner et al., 2015). However, these findings are not necessarily incongruent with this view, they may merely suggest that expectations and uncertainty induced through vicarious information or though experience might be differently mapped onto a prior then cue-induced expectations (through experiential learning).

Furthermore, given the large body of research on the behavioral sequela of unpredictable aversive events (Abbott, Schoen, & Badia, 1984; Foa, Zinbarg, & Rothbaum, 1992; Maier & Seligman, 1976; Miller, 1981; Mineka & Kihlstrom, 1978) it might be interesting in future studies to include indices of stress or anticipatory anxiety in order to relate emotional changes to perceptual changes as large inter-individual differences can be expected on how people respond to predictability. Furthermore, certain traits as for example scores on the intolerance of uncertainty scale (Buhr & Dugas, 2002; Freeston, Rhéaume, Letarte, Dugas, & Ladouceur, 1994) might moderate pain modulatory effects of uncertainty. In sum, we did not find increased pain reports under conditions of uncertainty but found strongly biased ratings towards the direction of the vicarious information.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.cognition.2017.07.009.

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