Motivational trade-offs as evidence for sentience in bees: a critique

Jenny Read[1] & Vivek Nityananda[1]

1. Biosciences Institute, Newcastle University, Henry Wellcome Building, Framlington Place,

Newcastle Upon Tyne, NE2 4HH, UK

Corresponding authors:

Jenny Read

Email: jenny.read@newcastle.ac.uk

Orcid ID: 0000-0002-9029-5185

Vivek Nityananda

Email: vivek.nityananda@newcastle.ac.uk

Orcid ID: 0000-0002-2878-2425

Abstract

Establishing if insects feel pain can have far-reaching consequences for insect husbandry, commercial

pollination and scientific research. Research in this field therefore requires careful experiments and

strong evidence. One important criterion proposed for measuring insect sentience is the ability to

show a motivational trade-off, in which "the negative value of a noxious or threatening stimulus is

weighed (traded-off) against the positive value of an opportunity for reward". A recent paper

investigated motivational trade-offs in bumblebees and concluded that bees can trade-off heat

against high sugar rewards. In this paper, we develop a signal detection model to highlight which

features would be key to supporting the argument that motivational trade-offs are evidence of the

capacity for experience pain. We then re-analyse the data from the original paper and find several

limitations. Our own re-analysis finds no support for the final conclusions made by the paper. We

therefore provide recommendations for future studies investigating the ability of insects to feel pain.

Introduction

Establishing if insects feel pain can have far-reaching consequences for insect husbandry, commercial

pollination and scientific research. Research in this field therefore requires careful experiments and

strong evidence. Recent approaches to investigate this question test whether insects fulfil a list of

eight criteria, such as nociception, sensory integration, and flexible self-protection, mostly assessed

behaviourally (1, 2). One important criterion is the ability to show a motivational trade-off, in which

"the negative value of a noxious or threatening stimulus is weighed (traded-off) against the positive

value of an opportunity for reward" (1).

Motivational trade-offs as evidence for sentience

For a motivational trade-off to be evidence of sentience, "enough flexibility must be shown to

indicate centralized, integrative processing of information involving a common measure of value" (1).

Even microbes could make *behavioural* trade-offs (e.g. (3)). They might, for example, move away

from heat when the sugar concentration is uniform but move towards heat if there was a sufficient

high sugar concentration (Figure 1A). However, information may only be combined in the final

chemical pathways onto the motor system, e.g. if an increase in sucrose concentration or a decrease

in temperature causes the microbe's flagellum to move it forward, while a decrease in sucrose or

increase in temperature causes it to change direction randomly. The negative value of heat and the

positive value of sugar are combined into a common measure of value ("S-H" in Figure 1), but this is

hard-wired through the interaction of chemotaxis and thermotaxis proteins with the flagellar motor.

The microbe's trading off of heat for sugar would therefore not be considered evidence of sentience.

A recent paper (4) investigated motivational trade-offs in bumblebees. The bees were first trained to

associate high sucrose (40% solution) with one colour and another concentration (either 10%, 20%,

30% or 40%, one value per bee) with a different colour. The high-sucrose feeders were then heated.

When both colours of feeder offered the same high-sucrose concentration, bees avoided feeding

from the heated feeders. However, when the unheated colour offered low-sucrose, bees became

relatively more likely to feed from the heated, high-sucrose feeders. This suggests they were trading

off aversive heat for rewarding sucrose (Figure 1C and D, Figure 2).

This behaviour cannot be fully hard-wired, since the bees made choices based on the colour of the

feeder without sensing the sucrose directly. The bees must have been generating their reward signal

via an internal representation of the reward associated with each colour (Figure 1B). The authors

conclude that "the trade-off [between heat avoidance against sucrose preference] is mediated in the

central nervous system".

This does not however follow from the data. In honeybees, neuronal activity correlated with the

prediction of reward has been observed in the suboesophageal ganglion (5). The neuron involved

projects to more central regions including the lateral protocerebrum and the mushroom bodies. But

it doesn't follow that the trade-off of predicted reward with nociception *also* occurs flexibly and

centrally. It could, for example, occur peripherally through a fixed chemical pathway, as in the

microbe example. Thus, avoidance of heat and a choice of higher reward would not in themselves

represent new evidence about bee sentience. We already know that bee behaviour is guided by

predicted future reward (6), as when they fly to a distant flower, rather than direct sensing of sucrose

as in microbe chemotaxis. We also already know that bees can learn to associate reward with

arbitrary stimuli when making these predictions (6).

Maybe the interaction between nociception and reward is what is critical? Figure 1C and 1D shows a

simple situation in which the common value of a given heat/sugar combination is fixed, and bees

make decisions between two options based on the differences between these fixed values. In this

case, there would be no interaction between heat and sucrose concentration.

Figure 1. A: Even unicellular organisms can trade off stimuli of different value. For example, if sensed

changes in heat and sugar both control flagellar rotation by the same ultimate molecular pathway,

then both are effectively combined into a common value. B: In bees, behaviour can be controlled by

 an internal representation of predicted reward only recently learnt from an arbitrary mapping. This

reward signal could be combined with signals about noxious stimuli to produce a common value

signal that controls behaviour, but it is not yet clear whether the creation of common value is itself

flexible or central. C, D: Simple signal detection theory account of how bees might decide between

two options, based on their differing values. C: When both colours offer 40% sucrose but one is

heated, bees are more likely to choose the unheated colour (purple) since this has the higher total

value. D: When the 40% sucrose is heated but the other colour offers only 10% sucrose, bees reliably

choose the heated colour (brown). We use Δ to represent the difference in value relative to the noise

on the signal.

Underlying signal detection theory

To explore the interaction further, we ran an analysis using signal detection theory.

In the original paper, the authors fitted their binary data with a logit link function. Their fixed-effects

model was

"proportion ~ Concentration *Temperature",

where "proportion" is the proportion of high-value choices, Temperature codes whether any feeders

were heated or not (reference level = unheated), and "Concentration" is the sucrose concentration of

the varying feeders (10%, 20%, 30%, 40%). It's helpful to think through the underlying signal-

detection theoretic model implied by this. Effectively, we are modelling the expected difference in

net value between the two choices, Δ, as sketched in Figure 1C and D.

This difference in expected value presumably declines as the concentration of the varying feeder

approaches that of the high-value feeder, falling to zero when neither feeder is heated and both

contain 40% sucrose (blue line in Figure 2B). The difference in value is also reduced when the high-

value feeder is heated (red line in Figure 2B is below the blue line). This explains why bees tend to

avoid the heated feeder when both feeders offer 40% sucrose.

Figure 2. The signal detection theory implied by fitting a logistic function to this data. (A) The model

assumes bees base their decisions on a noisy signal about the difference in value between the two

choices (Figure 1C). We'll write the mean difference, relative to the standard deviation of the noise,

as Δ. The GLMM models the proportion of high-value choices as a logistic function of Δ,

corresponding to the shaded region of the distribution. (B) The GLMM models the difference in value

Δ as a function of Concentration and Temperature. α represents the model intercept, β_C the main

effect of Concentration, β_H the main effect of Temperature, and β_{int} the interaction term.

Interpretation of an interaction term

If there is a negative interaction between Temperature and Concentration, the decline would be

steeper in the heated condition (red line steeper than blue line, as shown in Figure 3B). This would

mean that bees treat heat as effectively less aversive when the relative reward is higher, potentially

representing a motivational trade-off. Note that a positive interaction term does not make sense

from this point of view, as it would mean bees treat heat as more aversive when there is more to be

gained by enduring it.

Interestingly, an interaction term rules out the simple decision model sketched in Figure 1C and 1D.

There, we assumed that each combination of sucrose S and heat H had a distinct value to the bee,

say V(S,H). In Figure 1, we further represented this as linear, V(S,H) = S-H, but we can relax that

assumption and write V as an arbitrary function of S and H. We assumed that the expected value of

the difference between two choices was just the difference in these fixed values, $\Delta = V(S1,H1) - V(S2,$

H2). If this were valid, then for the bees' decisions in the experiment we would have

Δ (Unheated) = V(40%,0) - V(C,0) : bees choose between unheated feeders offering 40% or

concentration C

Δ(Heated) = V(40%,H) - V(C,0) : bees choose between a heated feeder offering 40% or an

unheated feeder offering concentration C

By subtracting these, we can see that [Δ(Unheated)−Δ(Heated)] would be constant, equal to

[V(40%,0)-V(40%,H)]. This is consistent with a GLMM with no interaction term. In that case, the

difference is equal to β_H (following terminology in Fig 3B). However, it is not consistent with an

interaction term.

Thus, an interaction term means that we can't model each option as having a fixed value to the bee,

so that the difference between these options is just the difference in these fixed values. Rather, the

relative value between the choices depends on the particular choices being made. Thus, a significant

interaction term could be viewed as showing bees are making the sort of flexible motivational trade-

off taken as evidence for sentience.

Re-analysis of experimental data

The original paper claimed a marginally significant interaction term (p=0.04, Figure 3A). This would

imply that the aversive effect of a noxious stimulus is not fixed but depends on the relative value to

be gained by enduring it. Some might consider this "enough flexibility to indicate centralized,

integrative processing of information involving a common measure of value" (1). However, the claim

of a significant interaction depends on a flawed statistical analysis. We detail the key results of our

re-analysis here and present a detailed discussion in the statistical analyses section.

The authors excluded nearly a third (9 out of 31) bees tested in the crucial "trade-off" conditions

comparing high and low sucrose because, during the initial unheated trials, these bees did not show

a statistically significant preference for high sucrose. But bees were *not* excluded based on their

performance in the heated conditions, or in the equal-sucrose condition. This is a problem because it

could introduce bias. The paper's conclusion requires that the proportion of high-value choices is

lower in the heated condition than the unheated. Excluding bees that didn't make enough high-value

choices in the unheated condition, without applying such a criterion to the heated condition, risks

printing an effect of temperature into the chosen data, whether or not it was there to begin with.

Another result of excluding the data is that this leaves only two data points for the 30% condition.

Additionally, the analysis included a complex set of random effects which it did not have enough data

to assess (random effects for subject nested within colony, and a random slope as well as intercept

for Temperature, even though there were only 32 subjects from 7 colonies, each with 2 values of

Temperature). The fitted model was therefore singular. The significance of the interaction effect in a

simpler model also depends on a single data point.

This is a shaky analysis on which to rest any conclusion. We have re-run the analysis including all

bees, and with a simpler random-effects model (Figure 3B). We find main effects both of

concentration and temperature, which are substantially more significant than the marginally

significant interaction reported in the paper. We find no evidence to support an interaction term, still

less a negative one as required for a motivational trade-off.

Figure 3. Authors' analysis and our re-analysis. A: The authors' included data and statistical model.

8/10 bees tested with 30% sucrose are excluded because, in the unheated condition, they did not

show a significant preference for 40% over 30%; 1/10 bee in the 20% condition was also excluded.

The model includes a complex set of random effects (1 +Temperature | colony / subject) and is

singular. Statistical analysis finds no main effect of temperature (p=0.1) and a marginally significant

interaction with concentration (p=0.04). B: Our re-analysis including all 41 bees tested and simpler

random effects. We find no evidence for an interaction between temperature and concentration, but

we do find highly significant main effects of both temperature and concentration ($p<10^{-5}$). Dots show

data for individual bees. There are two dots for each bee: heated and unheated. Lines show

predictions of the fitted model, formula shown on the plot, using function glmer of R package lme4.

Note that the model in B is fitting more data with fewer parameters. Shaded regions show 95%

confidence intervals obtained using function of bootMer of lme4 with 100 samples.

Statistical analysis:

We analysed all data in R Studio (2024.04.2).

Model fitting

In both the original paper and our reanalysis, models were fit with the package lme4 (version 1.1-31)

using the command glmer. The code used in the paper fitted the formula

"proportion ~ Concentration *Temperature + (1+Temperature|colony/subject)",

where "proportion" is the proportion of high-value choices, Temperature codes whether any feeders

were heated or not (reference level = unheated), and "Concentration" is sucrose concentration of the

varying feeders (10%, 20%, 30%, 40%). This formula fits random effects for subject nested within

colony, and also fits not only a random intercept but also a random slope (i.e. it allows the effect of

heat to vary between bees). With only 2 results for each subject and <5 subjects per colony, there is

not enough data to fit both random intercepts and slopes for Temperature within subject and colony,

and so glmer warns that the model is singular. The results of this singular fit are shown in Figure 1A,

which matches the results given in the paper (interaction: z=-2.068, P=0.039; main effect of

Temperature : z = 1.627, P=0.104, n=32). The main effect of temperature is not significant, but the

marginally significant negative interaction term indicates that bees become progressively less likely

to select the heated feeder as the concentration in the unheated feeder approaches the high value

of the heated feeder, consistent with a trade-off between desirable sucrose and undesirable heat.

To avoid the warning about singularity, we simplified the model to

"proportion ~ Concentration * Temperature + (1|subject)".

With the same bees excluded as in the paper, we now find a stronger interaction between

Concentration and Temperature (z = 2.651, P= 0.008, n = 32), plus a significant main effect of

Temperature (z= -3.727, P=0.0002, n=32). Since the reference temperature is Unheated, the negative

main effect of Temperature indicates that bees are less likely to choose high-quality sucrose when

these feeders are heated, as expected. However, the positive value of the interaction term means

that the aversive effect of heat becomes actually becomes *less* as the concentration in the unheated

feeder approaches the 40% available from the heated feeder, which is the opposite of what we

would expect from a motivational trade-off.

The interaction term was driven entirely by one subject (bee ID40) that was tested with 20% sucrose

and never selected the 40%-sucrose feeder in the heated condition. With this bee removed, there

was no significant interaction between Temperature and Concentration (interaction: z=-0.545,

P=0.586, n=31) although both had significant main effects when a model was fitted without an

interaction term. This is true both for our model with simpler random effects, and for the original

singular model: removing bee 40 abolished the interaction. Thus, the interaction term depends on

excluding 9/41 bees, and even after that on just one of the remaining 32 bees. It is then significantly

negative only when the model is singular due to overfitting the random effects, and is significantly

positive for a non-singular model where subject is the only random effect. This is not evidence for

any interaction, still less the negative interaction implied by a motivational trade-off.

If we run the "Concentration * Temperature + (1|subject)" model but including all 41 bees, again

neither the interaction nor the main effect of Temperature are significant (interaction: z=-0.481,

P=0.631 ; main effect : z=-0.543, P=0.587 , n=41, AIC=473.6). If we drop the interaction term and fit

"proportion ~ Concentration + Temperature + (1|subject)" , we obtain the model shown in Figure 1B

(main effect of Temperature: z = -4.462, P=8e-6, n=41, AIC=471.8).

Conclusions

The question of insect sentience is important both scientifically and for its implications. Given this, it

is vital that we rely on strong evidence. Unfortunately, the present paper does not provide this.

Recommendations for future studies include pre-registering the statistical analysis and any planned

exclusion criteria. Criteria that introduce bias or result in the exclusion of 80% of subjects should be

avoided. Physiological studies examining the mechanisms underlying behaviour will also be

important in order to answer questions about where a common value signal is neurally constructed

and how flexible it really is. Certainly, any implications for policy should rely on robust replications

from multiple labs.

Data availability statement: Our code is provided as supplementary material. We thank the original

authors for making the data and code available to us. These are uploaded at this link:

https://doi.org/10.6084/m9.figshare.c.6066371.v4.

Declaration of Interest: none

Author's contributions: VN and JR re-analysed the data and wrote the paper. VN developed the
signal detection model.

Ethical note: This article is based on a re-analysis of previous data and did not involve any
experimentation on animals or humans.

Acknowledgements: VN is funded by a BBSRC David Phillips fellowship BB/S009760/1 and a
Leverhulme Trust Research Project Grant RPG-2021-358

References

1.   A. Crump, H. Browning, A. Schnell, C. Burn, J. Birch, Sentience in decapod crustaceans: A
general framework and review of the evidence. *Animal Sentience* **7** (2022).

2.   M. Gibbons, L. Chittka, A framework for evaluating evidence of pain in animals. *Animal
Sentience* **7** (2022).

3.   A. Paulick, *et al.*, Mechanism of bidirectional thermotaxis in Escherichia coli. *eLife* **6**, e26607
(2017).

4.   M. Gibbons, E. Versace, A. Crump, B. Baran, L. Chittka, Motivational trade-offs and
modulation of nociception in bumblebees. *Proceedings of the National Academy of Sciences of the
United States of America* **119**, 3–5 (2022).

5.   C. J. Perry, A. B. Barron, Neural Mechanisms of Reward in Insects. *Annual Review of
Entomology* **58**, 543–562 (2013).

6.   A. Avarguès-Weber, *et al.*, Visual cognition in social insects. *Annual review of entomology* **56**,
423–43 (2011).

268