# Title

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## Abstract

tendrá una extensión máxima de 300 palabras

## Identification and Reflection about the Sustainable Development Goals

Definición de cuales ODS se ajustan al TFM, máximo 2 páginas, después del

resumen, que no contabilizarán a efectos de paginado

## List of Abbreviations

ordenadas alfabéticamente.GLMHMM: Generalized Linear Model with Hidden Markov Model

## Index

## 1.- Introduction and Objectives

Perceptual decision-making is far away from being completely understood; it is of course influenced by the characteristics of the stimuli presented, such as intensity, size, duration, etc., but is also influenced by internal neural processes involved in the perception of such stimuli and in the cognition that regulates behaviour in response.

It is known that in tasks that involve a subject having to select which group of dots is more numerous between two groups a certain perceptual bias can make the subject perceive either more or less dots depending on the previous stimuli having less or more dots correspondingly (Burr & Ross, 2008); this has been known as the numerosity bias/adaptation and is based on the presumption that humans, including infants, and some primates have the capacity to perceive the numerosity of a stimulus as a semantic property that can be sensed independently of verbal counting (Sawamura et al., 2002; Whalen et al., 1999; Xu et al., 2005; Xu & Spelke, 2000). This phenomenon has been seen to take place not only visually, but also through audition and touch (Togoli & Arrighi, 2021), however we will focus on the visual modality of this phenomenon in this work.

This adaptation through vision appears to be dependent on the difference of dots between the current and the previous stimulus and not on the duration of the last stimulus (Aagten-Murphy & Burr, 2016), although according to Dakin et al. (2011) stimulus density also plays a role. This phenomenon has been observed to be reduced in children with autism (Turi et al., 2015) and, surprisingly, it does take place in people with dyscalculia, though the difference threshold between groups of dots needed to take place is higher (Anobile et al., 2018)

Even though this bias has been demonstrated to take place beyond any doubt, its interpretation remains a polemic subject; there is an ongoing debate about it and the basis of numerosity perception as a whole, some argue that it is not the number of stimuli that is perceived in low-level visual processing but rather density (Ibid), while Yousif et al. (2008) argue in a yet to be published paper that this adaptation occurs not based on the number of dots of the previous stimulus but on the location of each of these dots and that this phenomenon ought to be named item adaptation, and Castaldi et al. (2016) found that numerosity adaptation acts directly on intra-parietal sulcus rather than in low visual areas. However, the precise mechanisms behind this bias are beyond the scope of the present work.

Despite knowledge about these and other biases, in the traditional view errors committed despite clear evidence of the presented stimuli were named “lapses” and were considered as random cognitive mistakes. This phenomenon has been seen in many species; in mice they can conform a tenth of all trials (Aguillon-Rodriguez et al., 2021; Odoemene et al., 2018; Pinto et al., 2018).

This interpretation has given rise to the classic lapse model in which the subject can be in one of two different states; either engaged (forming the classic psychometric function) or lapse (producing a flat function in which the evidence is not considered to form a decision).

The “lapse” interpretation has been numerously debated and alternative interpretations have been proposed. However, Ashwood et al. (2022) proposed to used Hidden Markov Models in combination with the traditional Generalized Linear Model (together GLMHMM) based on the psychometric curve formed in signal detection tasks to generate different models based on a selected number of hidden states, each of which can be given a different interpretation.

In the aforementioned paper, GLMHMMs based on a different number of hidden states were built and assessed using two mice and a human data set; in all cases GLMHMMs with more than one state proved to explain the data better than the single state and the two states lapse model. Even the two states GLMHMM prove to be better for, contrary to the classic lapse model, it did not assume that errors follow an independent random Bernoulli distribution and that they cannot occur in blocks.

For the first mice data set, which was obtained from Aguillon-Rodriguez et al. (2021), it was found that the three states model conformed by an engaged, a bias-left, and a bias-right state was the best at explaining the data without risking overfitting. While for the other mice data base, which was retrieved from Odoemene et al. (2018), a four state model composed by an engaged, bias-right, bias-left, and a win-stay state showed a marginally better log-likelihood than the three states model while also taking interpretability and simplicity into account. The fact that models with a different number of states proved to be the best for each mice data set might result from a difference in the experimental protocols used in each experiment.

Lastly and most importantly for our research, for the human data set obtained from Urai et al. (2017), which was composed by the results in a motion discrimination task, the model conformed by two states (one biased toward responding more and the other less perceived movement) was the one that best explained the observations.

Even though Ashwood et al. (2022) demonstrated that the modelling with GLMHMMs was better at explaining three different data sets, it remains to be seen whether this applies to other samples obtained through different perceptual decision-making protocols. The characterization of this states in humans can share light about the factors that influence the prominence and transitions between states, which can in turn give us useful insight to design better protocols and to study the neural mechanisms involved in perceptual and cognitive processes.

The objectives of the present work are: (i) to see if the human results seen in Ashwood et al. (2022) can be replicated in a general manner and also taking the numerosity and serial bias into account with the data base provided in Rouault et al. (2018) (ii) to assess which number of states provides the best model, (iii) to find possible interpretations for these states, and (iv) explain which could be the neural mechanisms behind each state.

The completion of these objectives may help to better understand the mechanisms behind perceptual decision-making and support this novel way of modelling such mechanisms.

Even though in the paper were we got our data base from (Rouault et al., 2018) psychiatric symptoms did not predict changes in accuracy, it has been seen multiple times that different pathologies can affect performance in perceptual decision-making (Foryś et al., 2017; Jassim et al., 2022; Reckless et al., 2015). Because of this, developing better methods for modelling perceptual decision-making is important because it can share light into both perceptual and cognitive processes involved in this complex set of phenomena and how the differ in health and illness, so having a better understanding and way of understanding these processes can be helpful to develop new treatments and diagnostic protocols as has been done in the past (Dully et al., 2018).

Serial bials (discutir si agregar y analizar esto con Dani).

No sé si poner algo aquí sobre la posible base neuronal de los distintos estados o es mejor dejarlo únicamente para la discusión.

## 2.- Materials and Methods

As mentioned above, for the present work we used the human data set from the experiment one of Rouault et al. (2018) which consisted of 498 volunteers (mean age= 35.71; SD= 11.37; 237 women).

According to the supplementary information of this article, for each of the 210 trials, subjects saw a fixation cross for one second, then two black squares containing different quantities of white dots set in a random position were observed by the participants for 300 ms. One of the two squares had half of all possible positions filled with dots (313 out of 625), while the other had from one to 70 more dots (mean dot difference= 35.5; SD= 20.20) . After the observation time, the dots disappeared, while the black squares remained until the subject pressed a button of the keyboard.

Then, subjects had to choose the position (right/left) of the square that contained the highest number of dots; the position of this was pseudo-randomised across all trials within five difficulty bins. The selected square was highlighted for 500 ms; subject received no feedback.

## 3.- Results

más significativos reforzados con tablas, gráficos, fotografías, etc.

y tratamiento de los datos.

## 4.- Discussion

de los resultados y la relación con los objetivos y/o hipótesis

planteados.

## 5.- Conclusions

## 6.- Bibliography

Lista de publicaciones en orden alfabético según el primer autor. Si el

autor se cita más de una vez, irá en primer lugar el trabajo más antiguo. Si un autor

figura en varios trabajos como primer firmante, en el listado irá primero el trabajo

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## 7.- Appendix