Testing the Relationship between Phenomenological Control related to Illusion Sensitivity

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Abstract

Visual illusions highlight how easily our conscious experience can be altered with respect to perceptual reality. Despite sharing in-principle mechanisms with phenomenological control, i.e., the ability to alter our perceptual experience to match task demands or expectations, research tying the two remains scarce. This study aims to replicate and expand Lush et al. (2022) reporting an absence of correlation between phenomenological control (measured using the Phenomenological Control Scale) and illusion sensitivity to different illusion types. *[N participants were recruited in an online study. Results will be added in the final version of the manuscript].*

Keywords: illusion sensitivity, visual illusions, phenomenological control, suggestibility, hypnotizability

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Visual Illusions are an interesting type of stimuli highlighting the ease with which our phenomenological conscious experience can become dissociated from physical reality. Their robust and reliable effect makes them useful stimuli to explore how perception is constructed and shaped, and several theoretical models have been put forth to explain how they work. **In particular, illusions have been reframed using a predictive coding account of perception (e.g., Notredame et al., 2014; Nour & Nour, 2015)** in which the brain optimally combines, using some flavour of Bayesian inference, perceptual inputs with prior knowledge to make sense of ambiguous environments (Friston, 2010).

Such computational model(s) propose to conceptualize illusions as stimuli providing weak or conflicting sensory evidence (Gershman et al., 2012; Sundareswara & Schrater, 2008) that bias perception toward prior knowledge. In other words, the weight of priors, in the form of perceptual knowledge about the world (e.g., internalized rules of perspective) is amplified when the sensory input is confusing. For instance, in the Müller-Lyer illusion, we "compute" the two (actually identical) lines as being of different lengths because the line flanked with converging fins is misinterpreted as being further away (Notredame et al., 2014). In this context, measuring sensitivity to illusion can be operationalized as indexing the parameters of the Bayesian inference process (e.g., prior precision).

These accounts also provide a compelling framework to explain existing findings reporting interindividual variability in the sensitivity to illusions. Indeed, several studies suggest a potential link with psychopathology, in particular schizophrenia (Costa et al., 2023) and autism (Gori et al., 2016), in which the reported lower sensitivity to illusions has been attributed to a diminished influence of top-down processes such as prior knowledge (Mitchell et al., 2010) and a greater emphasis on (i.e., precision of) sensory information (Palmer et al., 2017). Evidence beyond psychopathology also suggests variability in the general population, potentially correlated with personality traits such as agreeableness and honest-humility (Makowski et al., 2023), as well as cognitive abilities (Shoshina & Shelepin, 2014).

However, the exact nature of this interindividual variability and its potential origin remains unclear. The somewhat mixed evidence in the literature regarding its generalizability and strength could be related to the variety of the paradigms used and the type of processes being mobilised (Makowski et al., 2021). Indeed, traditional methods frequently focus on participant's experience by prompting them to assess the difference between two identical targets, estimate the target's physical properties, or adjust the targets to match a reference stimulus (Todorović, 2020). Relying on metacognitive judgments about one's subjective experiences adds an additional layer to the measure that might not be desired when attempting to measure illusion **sensitivity**. Moreover, paradigms often face challenges in diversifying the illusory effects (i.e., using multiple stimuli to experimentally manipulate the strength of the illusion) and the illusion types (i.e., using various illusions, such as Müller-Lyer, Ebbinghaus, Delboeuf which might rely on a different admixture of mechanisms), hindering the potential of obtaining a comprehensive, valid, and reliable measure of illusion sensitivity.

The "Illusion Game" paradigm (Makowski et al., 2023) has been recently developed to measure illusion sensitivity to various illusion types through its behavioural impact (on response time and error rate) in a perceptual decision task (where participants have to respond as fast as possible; e.g., "which of the left or right circles is bigger"). The stimuli for different classical illusions are created using the *Pyllusion* software (Makowski et al., 2021), which allows researchers to modulate the strength of the illusion as a continuous dimension, independently from the difficulty of the perceptual task. This paradigm, inspired by psychophysics, lends itself to the computational modelling of illusion sensitivity through its **interference effect —an effect that disrupts an individual's ability to accurately discriminate between perceptual stimuli. This approach aims to bypass some of the metacognitive processes involved in other paradigms, offering a more direct and objective measure of how illusions influence perceptual judgment.**

Interestingly, the fact that inter-individual variability in illusion sensitivity seems to persist in this task suggests that it is not solely explained by **metacognitive ability differences**, and gives rise to the following question: is the variability in illusion sensitivity related to low-level perceptual processes (e.g., baseline precision of perceptual priors), or rather to the ability to actively control and "resist" the illusion in order to achieve the task at hand (higher-level modulation of the perceptual inference parameters). If the latter is true, then illusion sensitivity measured in contexts with strong task-demand characteristics, e.g., in paradigms where participants' performance is explicitly or implicitly assessed (i.e., where there is an incentive to downplay the illusion effect) might correlate with one's ability to alter one's subjective experience following suggestions - a mechanism referred to as "phenomenological control".

The idea that we are endowed with the potential to unconsciously alter our subjective experience and distort reality - even momentarily - to meet the goals at hand is not novel. While this phenomenon has been historically often studied under the label of "hypnotisability" - the tendency to alter our conscious experience to match external demands (Lush et al., 2021), the term "phenomenological control" (PC) has been recently introduced to disconnect this concept from the potentially negative associations with hypnosis and the misconception that a hypnotic context is necessary for responding to imaginative suggestions (Dienes et al., 2022).

To encourage the empirical exploration of our ability and tendency to alter our phenomenological experience and further accelerate investigations away from the hypnotic context, Lush et al. (2021) adapted the Sussex-Waterloo Scale of Hypnotisability (SWASH, Lush et al., 2018) by removing all its references to hypnosis, to measure trait phenomenological control. **This newly developed phenomenological control scale (PCS) consists of 10 imaginative suggestions followed by subjective ratings for each suggestion and has demonstrated validity in online experiments (Lush et al., 2022).**

Interestingly, Lush et al. (2022) did test for a relationship between PC and illusion sensitivity using the Müller-Lyer illusion (in which the arrangement of the arrowheads flanking two lines makes them appear as having different lengths), and reported evidence in favour of an absence of correlation between the two measures. This finding was interpreted as indicative of the cognitive impenetrability of illusions, implying that the effect is driven by low-level processes and therefore not influenced by top-down mechanisms such as PC. **Note that both prior-knowledge**

and phenomenological control are considered top-down processes, but the cognitive impenetrability hypothesis suggests that the processes at stake for the illusions happen at a lower- encapsulated- level (in the form of *perceptual* priors).

The goal of this study is thus to replicate the results from Lush et al. (2022) pointing to an absence of a relationship between phenomenological control and illusion sensitivity, by generalising them to a different illusion paradigm that encompasses other illusion types. **Additionally, we will explore the relationship between psychoticism, as a proxy for schizophrenia, and illusion sensitivity to assess the potential impact of lower-level effects—such as weak priors observed in individuals with schizophrenia (Costa et al., 2023)—on sensitivity to illusions. These analyses may offer evidence clarifying whether inter-individual variability in illusion sensitivity is driven by lower-level perceptual mechanisms or higher-level cognitive processes (Table 1).**

Table 1

Study Design Table

Question	
Hypothesis	In line with Lush et al. (2022), we h
Sampling Plan	
Analysis Plan	Bayesian correlations will be conducte
Rationale for Deciding the Sensitivity of the Test	For the PC–VI sensiti
Interpretation Given Different Outcomes	If there is no evidence for a PC–V
Theory That Could Be Shown Wrong by the Outcomes	The cognitive impenetrability of visual illusions, which posits t

Methods

Participants

We aim to recruit around 500 (in line with the sample sizes used in Lush et al., 2021; Lush et al., 2022) adult English native speakers with a desktop device using Prolific (www.prolific.co). Participants will be first presented with an explanatory statement and the consent form, and can proceed by pressing a button to confirm they have read and understood the information. This study has been approved by the ethics board of the School of Psychology of the University of Sussex (ER/ASF25/5).

Procedure

The experiment's setup follows of the born-open principle (De Leeuw, 2023). The online experiment, implemented entirely using JsPsych (De Leeuw, 2015), has its code stored on GitHub and will leverage the power of the platform to host the experiment for free. Participant's raw data files (containing identifiers) **are** automatically stored in a private OSF repository. The preprocessing and analysis scripts, as well as the anonymized data, will be available directly on GitHub, ensuring the transparency and reproducibility of all the analysis steps.

Participants will be presented with a consent form followed by demographic questions (gender, education level, age, and ethnicity). **Although these variables are not directly analyzed in the current study, they will be used to provide a detailed and thorough description of the sample and maximizing data reusability. Participants will then be administered the PCS and the Illusion Game task (IG) in a counterbalanced order.**

Phenomenological Control Scale (PCS)

Participants will be asked to put on their headphones and await further auditory instructions. The PCS procedure starts with a recorded introduction explaining that a series of tests will be applied to evaluate how experiences can be created through imagination. This will be followed by 10 suggestions in a fixed order (see Lush et al., 2021), such as "now extend your arms ahead of you, with palms facing each other, hands about a foot apart" and "as you sit comfortably in your chair with your eyes closed, a picture of two balls will be displayed on the computer screen". **Once the 10 suggestions are completed, participants will be asked to rate their subjective experiences and response to each suggestion on a 6-points Likert scale (from 0-5).** Phenomenological control will be indexed by averaging the scores from the 10 scales.

Illusion Game

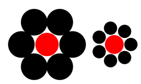
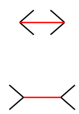
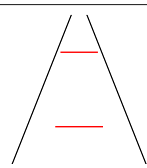
The task is an adaptation of the one used in Makowski et al. (2023) to make it shorter, in which participants must make perceptual judgments (e.g., "which red line is the longer") as quickly and accurately as possible. It includes 3 illusion types, namely Ebbinghaus, Müller-Lyer, and Vertical-Horizontal (see Figure 1). **In the original Illusion Game, 10 visual illusions were presented in two sets, following a practice trial, and separated by two short questionnaires. Participants completed a total of 1,340 trials, with the experiment lasting approximately 55 minutes. In the current procedure, only three illusions are used, selected based on the original study's findings that these illusions most strongly contribute to illusion sensitivity.**

The procedure encompasses 2 sets of 80 trials for each illusion type, **preceded by a practice trial for each illusion**. Each set will include, in a random order, the 3 blocks of illusion types, in which trials are separated by a fixation cross, temporally (uniformly sampled duration of 500 - 1000s) and spatially jittered (around the centre of the screen in a radius of a 1 cm) to attenuate its potential usefulness as a reference point. After each illusion type block, an arbitrary score is presented (computed as a scaled Inverse Efficiency Score) as a gamification mechanism to increase motivation to perform to the best of one's abilities. To mitigate for the potential variability in the speed/accuracy trade-off, the instructions emphasize with equal weight to be fast and to avoid errors.

For each illusion type, two continuous dimensions are orthogonally manipulated namely task difficulty and illusion strength, so that each trial corresponds to a unique combination, **providing an objectively correct answer for each trial. The use of these manipulations allows concise, standardised reporting of illusion parameters and ensures our stimuli are fully reproducible (see Makowski et al., 2021).**

Figure 1

The study involved three visual illusions, in which participants were instructed to respond as quickly as possible without making errors. Each illusion included two manipulated parameters: strength (e.g., the angle of the outward- or inward-pointing arrow-like fins in the Müller-Lyer illusion) and difficulty (e.g., the difference in line lengths in the Müller-Lyer illusion).

Illusion	Example	Task	Description
Ebbinghaus		Which red circle is bigger?	Two circles surrounded by other circles. The circle surrounded by smaller circles appears larger than the one with the larger surrounding circles.
Müller-Lyer		Which red line is longer?	Two parallel segments that end with inwards/outwards pointing arrow-like fins. The segment with inward-pointing fins is typically perceived to be longer.
Vertical-Horizontal		Which red line is longer?	Two lines segments, one horizontal and one angled. The angled line is usually perceived as longer.

Task difficulty corresponds to the difficulty of the perceptual decision (e.g., if the task is to select the longest red line, task difficulty corresponds to how the lines are objectively different). Illusion strength corresponds to the degree to which the illusion elements (e.g., the black arrow lines in Müller-Lyer) are interfering with the aforementioned task. Note that the illusion effect can be either "incongruent", **making the task more difficult by biasing perceptual decisions toward the incorrect response** or "congruent", **making the task easier by biasing decisions toward the correct response (e.g., in the Müller-Lyer illusion, if the outwards-facing arrowheads are placed on the longer line, identifying which line is the longest becomes easier)**. Participants respond with a key arrow (left vs. right; or up vs. down), and their reaction time (RT) and accuracy are recorded.

Visual illusion sensitivity will be measured as the average error rate in the incongruent condition, and separately for the 3 illusion types. Although the error rate is arguably a crude score, which does not take into account the effect of varying illusion strength, the interaction with task difficulty and the possible adjustments in response strategy (speed-accuracy trade off), it is also the most simple and easy to reproduce, hence its usage as our primary outcome for the current **registered report**. **As a secondary exploratory outcome, the Inverse Efficiency Score (IES, Townsend & Ashby, 2014) will also be computed. This metric incorporates both speed and accuracy by dividing the mean reaction time of correct responses by the proportion of correct responses, separately for each illusion.**

The two sets of 3 illusion blocks will be separated by 2 short questionnaires acting as a break, namely the IPIP-6 (Sibley et al., 2011), measuring 6 personality traits with 24 analogue scales items, and the PID-5 (Krueger et al., 2011), measuring 5 maladaptive personality traits with 25 Likert scales items. These questionnaires are included as a way of providing a break between the two cognitively taxing blocks and maintain paradigmatic consistency with previous studies (Makowski et al., 2023). **Additionally, the psychoticism subscale of the PID-5 will be used to examine the correlation between maladaptive traits and illusion sensitivity, evaluating the existence of the link proposed in previous studies (Costa et al., 2023).**

Data Analysis

The phenomenological control scale will include several attention checks to identify problematic participants. The task consists of various auditory and visual exercises; at the outset, participants hear a voice say "hello" and are asked to select the corresponding phrase from multiple options (e.g., "Hello," "Goodbye," "How are you," "Thank you"). Selecting an incorrect response indicates inattention to auditory stimuli. In a subsequent exercise, participants are instructed: "Open your eyes. You will see only two balls on the screen… just two balls". However, three differently coloured balls are displayed. If a participant selects the response "no balls were shown," it suggests they failed to attend to both the auditory instruction and the visual stimuli. In another task, participants are instructed to press the spacebar six times. Pressing it fewer than five times within the allotted time indicates a failure to follow the auditory instructions. Participants who fail any

one of these will be excluded from further analysis. Finally, the reliability of the PCS will be assessed by computing Cronbach's alpha of its items (Cronbach, 1951).

Outliers in the Illusion Game will be identified based on participants' performance. **Specifically, any participant exhibiting an error rate greater than 45% for any illusion type will be considered to be responding at chance level (i.e., randomly) and flagged accordingly**. **If this level of performance occurs in the first block, the entire participant will be excluded from analysis, as it suggests a failure to properly engage with the task. However, if the elevated error rate is observed only in the second block, this will be interpreted as a loss of engagement or motivation (e.g., boredom due to task repetition). In such cases, only the second block will be discarded, allowing for estimation of illusion sensitivity based on the valid data from the first block, albeit with reduced precision. To mitigate the risk of confounding effects driven by extreme speed or accuracy strategies, participants whose RTs are significantly slower than the group average (RT > 4 SD above the mean, based on Makowski et al., 2023) will be excluded from the analysis.** After removing problematic participants and trials, the outcome measures (PC and VI sensitivity scores) will be computed.

To assess whether the illusions functioned as expected, stimuli will be categorized into three groups: Strong Illusion Strength & Incongruent, Mild Illusion Strength & Incongruent, and Congruent. The two outcome measures—error rate and IES—will be computed separately for each illusion and each illusion strength group. To evaluate differences between these conditions, two Bayesian t-tests will be conducted: one comparing the Congruent and Mild conditions, and the other comparing the Mild and Strong conditions. Significant differences in either IES or error rate across these comparisons will be taken as evidence that the illusions operated as intended.

Next, to determine whether the Mild and Strong Illusion Strength groups can be collapsed for further analysis, Bayesian correlations will be computed between them for each illusion and outcome measure. If these correlations are sufficiently high (r > .50, Cohen, 2013), the groups will be collapsed and outcomes recomputed across all relevant trials (i.e.,

by averaging across these groups). If not, the groups will be analysed separately. This step is necessary because reaction time may not have a linear relationship with illusion strength (Makowski et al., 2023), and collapsing the data without this check may obscure meaningful differences. Finally, reliability analyses will be conducted on all resulting indices, with Cronbach's alpha used to evaluate internal consistency across the three illusion types.

Bayesian correlations are then computed between PCS and illusion sensitivity scores - with the resulting IES and error rate indices. Following Lush et al. (2022), we expect to collect evidence against ($BF10 <= 1/3$) a relationship between PCS and VI sensitivity. **Additionally, Bayesian correlations will be computed between maladaptive trait facets and illusion sensitivity scores. Based on prior research (Makowski et al., 2023), we expect to find evidence ($BF10 \geq 3$) supporting a relationship between the psychoticism facet of the PID-5 and illusion sensitivity.**

All Bayesian analyses will be conducted using the BayesFactor package (Morey & Rouder, 2024). **For correlations, a medium shifted beta prior will be applied (r-scale parameter set to 1/3), as recommended by Morey and Rouder (2018), providing a balanced approach to estimating effect sizes, without placing undue weight on larger effect sizes or artificially inflating evidence for the null hypothesis. For t-tests, the ttestBF function will be used with a medium Cauchy prior on the standardised effect size (r-scale = $\sqrt{2/3}$), corresponding to the default for independent samples.**

Data analysis will be carried out using R, using *tidyverse* (Wickham et al., 2019) and *easystats* (Lüdecke et al., 2020, 2022; Makowski et al., 2019, 2022; Patil et al., 2022). The analysis script and additional information are available at **https://osf.io/da3u6/?view_only=247d4efa1afe456aa07662732946d4e6** [Note this link will be replaced with the GitHub page of the current project upon completion of the review process to ensure continued anonymisation].

Results

This section will be completed after data is collected.

Discussion

This section will be completed after data is collected.

Data Availability

All the study materials, experiment, data, and analysis is available on GitHub. [For the review process the pcs materials, the illusion game, and the analyses scripts can be accessed here: **https://osf.io/da3u6/?view_only=247d4efa1afe456aa07662732946d4e6**. Note this link will be replaced with the GitHub page of the current project upon completion of the review process to ensure continued anonymisation].

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