

**The Illusion Game: A Novel Experimental Paradigm Provides Evidence in  
Favour of a General Factor of Visual Illusion Sensitivity and Personality  
Correlates**

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24

## Abstract

25 Visual illusions highlight how the brain uses contextual and prior information to inform our  
26 perception of reality. Unfortunately, illusion research has been hampered by the difficulty  
27 of adapting these stimuli to experimental settings, leaving open the questions pertaining to  
28 a potential unique factor underlying the sensitivity to different types of illusions. In this  
29 study, we used a novel parametric framework for visual illusions to generate 10 different  
30 classic illusions (Delboeuf, Ebbinghaus, Rod and Frame, Vertical-Horizontal, Zöllner,  
31 White, Müller-Lyer, Ponzo, Poggendorff, Contrast) varying in strength, embedded in a  
32 perceptual discrimination task. We tested the objective effect of the illusions on errors and  
33 reaction times, and extracted participant-level performance scores ( $n=250$ ). Our results  
34 provide evidence in favour of a general factor (labelled Factor  $i$ ) underlying the sensitivity  
35 to different illusions. Moreover, we report a positive relationship between illusion  
36 sensitivity and personality traits such as Agreeableness, Honesty-Humility, and negative  
37 relationships with Psychoticism, Antagonism, Disinhibition, and Negative Affect.

38 *Keywords:* visual illusions, illusion game, Pyllusion, personality, general factor

39 Word count: 3977

40      **The Illusion Game: A Novel Experimental Paradigm Provides Evidence in**  
41      **Favour of a General Factor of Visual Illusion Sensitivity and Personality**  
42      **Correlates**

43      **Introduction**

44      Visual illusions are fascinating stimuli capturing a key feature of our neurocognitive  
45      systems. They eloquently show that our brains did not evolve to be perfect perceptual  
46      devices providing veridical accounts of physical reality, but integrate prior knowledge and  
47      contextual information - blended together in our subjective conscious experience (Carbon,  
48      2014). Despite the long-standing interest within the fields of visual perception (Day, 1972;  
49      Eagleman, 2001; Gomez-Villa et al., 2022), consciousness science (Caporuscio et al., 2022;  
50      Lamme, 2020), and psychiatry (Gori et al., 2016; Notredame et al., 2014; Razeghi et al.,  
51      2022; Teufel et al., 2015), several important issues remain open.

52      One area of contention concerns the presence of a common mechanism underlying the  
53      effect of different illusions (Cretenoud et al., 2020; Hamburger, 2016). While early research  
54      has suggested a common factor of illusion sensitivity indexed by overall vision proficiency  
55      (Halpern et al., 1999; Thurstone, 1944), recent empirical studies observed at most weak  
56      correlations between resistance to distinct illusions (Grzeczkowski et al., 2017, 2018). The  
57      existence of dispositional correlates of illusion sensitivity has also been controversial, with  
58      evidence suggesting a lower illusion sensitivity in patients with schizophrenia and autism  
59      (Gori et al., 2016; Grzeczkowski et al., 2018; Notredame et al., 2014; Park et al., 2022;  
60      Razeghi et al., 2022), as well as individuals with stronger aggression and narcissism traits  
61      (Konrath et al., 2009; Zhang et al., 2017).

62      Although the nature of the processes underlying illusion perception - whether related  
63      to low-level features of the visual processing system (Cretenoud et al., 2019; Gori et al.,  
64      2016) or to top-down influences (Caporuscio et al., 2022; Teufel et al., 2018) - remains  
65      debated, a growing body of literature proposes to conceptualize illusions under the

66 Bayesian brain hypothesis (Friston, 2010), as ambiguous percepts (noisy sensory evidence)  
67 giving ample weight to prior knowledge to minimize prediction error and provide a  
68 coherent perceptual experience. In this framework, certain dispositional traits or  
69 characteristics (e.g., psychotism) are seen as driven by alterations in the system's  
70 metacognitive components (Adams et al., 2013), resulting in an underweighting of priors  
71 during perceptual inferences, and manifesting as a decreased sensitivity to illusions (Koethe  
72 et al., 2009).

73 Despite strong theoretical foundations and hypotheses, the empirical evidence  
74 remains scarce, clouded by methodological hurdles. For instance, one key challenge can be  
75 found in the difficulty of adapting visual illusions to an experimental setting, which  
76 typically requires the controlled modulation of the specific variables of interest. Instead,  
77 existing studies typically use only one or a small subset of illusion types, with few  
78 contrasting conditions, restricting the findings' generalizability (Bressan & Kramer, 2021;  
79 Cretenoud et al., 2019; Cretenoud et al., 2020). Moreover, conventional paradigms often  
80 focus on the participants' subjective experience, by asking them the extent to which they  
81 perceive two identical targets as different (Lányi et al., 2022), or having them adjust the  
82 targets to perceptually match a reference stimulus (Grzeczkowski et al., 2018; Mylniec &  
83 Bednarek, 2016). This reliance on meta-cognitive judgements about one's subjective  
84 experience likely distorts the measurand, limiting the ability to reliably obtain more direct  
85 and objective measures of illusion sensitivity (Skottun & Skoyles, 2014).

86 To address these issues, we first developed a parametric framework to manipulate  
87 visual illusions that we implemented and made accessible in the open-source software  
88 *Pyillusion* (Makowski et al., 2021). This software allows us to generate different types of  
89 classic visual illusions with a continuous and independent modulation of two parameters:  
90 *illusion strength* and *task difficulty* (**Figure 1**). Indeed, many visual illusions can be seen  
91 as being composed of *targets* (e.g., same-length lines), of which perception is biased by the

92 context (e.g., in the Müller-Lyer illusion, the same-length line segments appear to have  
93 different lengths if they end with inwards vs. outwards pointing arrows). Past illusion  
94 studies traditionally employed paradigms focusing on participants' subjective experience,  
95 by asking them the extent to which they perceive two identical targets as different (Lányi  
96 et al., 2022), or having them adjust the targets to match a reference stimulus relying only  
97 on their perception (Grzeczkowski et al., 2018; Mylniec & Bednarek, 2016). Alternatively,  
98 *Pyllusion* allows the creation of illusions in which the targets are objectively different (e.g.,  
99 one segment is truly more or less longer than the other), and in which the illusion varies in  
100 strength (the biasing angle of the arrows is more or less acute).

101 This systematic calibration of the stimuli enables the creation of experimental tasks  
102 in which participants make perceptual judgments about the targets (e.g., which segment is  
103 the longest) under different conditions of objective difficulty and illusion strength.  
104 Moreover, the illusion effect can be specified as either “incongruent” (making the task more  
105 difficult by biasing the perception in the opposite way) or “congruent” (making the task  
106 easier). Although visual illusions are inherently tied to subjective perception, this  
107 framework allows a reversal of the traditional paradigm to potentially quantify the  
108 “objective” effect of illusions by measuring its behavioral effect (error rate and reaction  
109 times) on the performance in a perceptual task.

110 The aim of the present preregistered study is three-fold. First, we will test this novel  
111 paradigm by investigating if the effect of illusion strength and task difficulty can be  
112 manipulated continuously for 10 different classic illusions (Delboeuf, Ebbinghaus, Rod and  
113 Frame, Vertical-Horizontal, Zöllner, White, Müller-Lyer, Ponzo, Poggendorff, Contrast).  
114 Next, we will investigate the factor structure of illusion-specific performance scores and test  
115 the existence of a common latent factor of illusion sensitivity. Finally, we will explore how  
116 illusion sensitivity relates to demographic characteristics, contextual variables, and  
117 personality traits.

## Parametric Framework for Visual Illusions

### Example with the Müller-Lyer Illusion



The Müller-Lyer Illusion is traditionally presented as two segments (the **red targets**), which perception is biased by the **context** (the arrows). Here, the lower segment appears longer despite being of the same length.

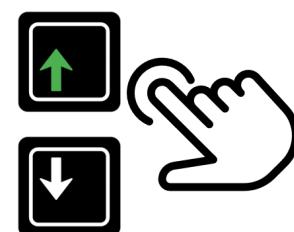


In this illusion, the **task difficulty** corresponds to the difference between the lengths of the red target segments, and the **illusion strength** corresponds to the angle of the arrows.

### Example of Stimuli



- ✓ Task difficulty: **easy**  
(top line is 2 times longer)
- ✓ Illusion Strength: **strong**  
(angle is sharp)
- ← Illusion Direction (left): **incongruent**  
(the illusion makes the task harder)
- Illusion Direction (right): **congruent**  
(the illusion makes the task easier)



- ✓ Task difficulty: **hard**  
(top line is only 1.1 times longer)
- ✓ Illusion Strength: **weak**  
(angle is flat)
- ← Illusion Direction (left): **incongruent**  
(the illusion makes the task harder)
- Illusion Direction (right): **congruent**  
(the illusion makes the task easier)



**Task:** For these stimuli, the correct response is always the « up » arrow, indicating the longer red segment. We measured the reaction time and the errors (in this case, the « down » arrow).

Stimuli created with the open-source software PyMusion (Makowski et al., 2021)

*Figure 1.* The parametric framework for visual illusions (Makowski et al., 2021) applied to the Müller-Lyer illusion (above). Below are examples of stimuli showcasing the manipulation of two parameters, task difficulty and illusion strength.

Following open-science standards, all the material (stimuli generation code, experiment code, raw data, analysis script with complementary figures and analyses, preregistration, etc.) is available as **Supplementary Materials** at <https://github.com/RealityBending/IllusionGameValidation>.

## Methods

### Stimuli

A pilot study ( $n = 46$ ), of which full description is available in the Supplementary Materials, was first conducted to determine a sensitive range of stimuli parameters. Then, for each of the 10 illusion types, we generated a total of 134 stimuli. These stimuli resulted from the combination of 15 equally-spaced levels of illusion *strength* (7 negative, i.e., congruent effects; 7 positive, i.e., incongruent effects; and 0) overlapped with 16 non-linearly spaced task *difficulty* levels (i.e., with an exponential, square or cubic spacing depending on the pilot results). For instance, a linear space of [0.1, 0.4, 0.7, 1.0] can be transformed to an exponential space of [0.1, 0.34, 0.64, 1.0], where 0.1 corresponds to the highest difficulty - i.e., the smallest objective difference between targets). For each illusion type, the stimuli were split into two series (56 and 72 stimuli per series) with alternating parameter values to maintain their homogeneity. Additionally, 6 stimuli per illusion type were generated for a practice series using parameters with more extreme variations (i.e., containing very easy trials to help cement the task instructions).

### Procedure

After a brief demographic survey and a practice series of illusions, the first series of 10 illusion blocks was presented in a randomized order, with a further randomization of the stimuli order within each block. Following this first series of blocks, two personality questionnaires were administered, the *IPIP6* (24 items, Sibley et al., 2011) - measuring 6 “normal” personality traits (Extraversion, Openness, Conscientiousness, Agreeableness,

143 Neuroticism and Honesty-Humility), and the *PID-5* (25 items, Hopwood et al., 2012) -  
144 measuring 5 “pathological” personality traits (Disinhibition, Antagonism, Detachment,  
145 Negative Affect and Psychoticism). Next, the second series of 10 illusion blocks was  
146 presented (with new randomized orders of blocks and trials). In total, each participant  
147 underwent 1340 trials of which they had to respond “as fast as possible without making  
148 errors” (i.e., an explicit double constraint to mitigate the inter-individual variability in the  
149 speed-accuracy trade off) by pressing the correct arrow key (left/right, or up/down  
150 depending on the illusion type). For instance, in the Müller-Lyer block, participants had to  
151 answer which one of the upper or bottom target line was the longest. The task was  
152 implemented using *jsPsych* (De Leeuw, 2015), and the set of instructions for each illusion  
153 type is available in the experiment code.

## 154 Participants

155 Participants were recruited via *Prolific*, a crowd-sourcing platform recognized for  
156 providing high quality data (Peer et al., 2022). The only inclusion criterion was a fluent  
157 proficiency in English to ensure that the task instructions would be well-understood.  
158 Participants were incentivised with a reward of about £7.5 for completing the task, which  
159 took about 50 minutes to finish. Demographic variables (age, gender, and ethnicity) were  
160 self-reported on a voluntary basis.

161 We excluded 6 participants upon inspection of the average error rate (when close to  
162 50%, suggesting random answers), and reaction time distribution (when implausibly fast).  
163 For the remaining participants, we discarded blocks with more than 50% of errors (2.16%  
164 of trials), possibly indicating that instructions were misunderstood (e.g., participants  
165 focused on the shorter line instead of the longer one), and 0.76% trials with extreme  
166 response times (< 125 ms or > 4 SD above mean). Additionally, due to a technical issue,  
167 no personality data was recorded for the first eight participants.

168        The final sample included 250 participants (Mean age = 26.5, SD = 7.6, range: [18,  
169        69]; Sex: 48% females, 52% males).

170        **Data Analysis**

171        The first part of the analysis focused on modelling the effect of illusion strength and  
172        task difficulty on errors and reaction time (RT) within each illusion. We started by fitting  
173        General Additive Models (GAMs), which can parsimoniously accommodate possible  
174        non-linear effects and interactions. Errors were analyzed using Bayesian logistic mixed  
175        models, and RTs of correct responses were analyzed using an ex-Gaussian family with the  
176        same fixed effects entered for the location  $\mu$  (mean), scale  $\sigma$  (spread) and tail-dominance  $\tau$   
177        of the RT distribution (Balota & Yap, 2011; Matzke & Wagenmakers, 2009).

178        Using GAMs as the “ground-truth” models, we attempted at approximating them  
179        using general linear mixed models, which can be used to estimate the effects'  
180        participant-level variability (via random slopes). Following a comparison of models with a  
181        combination of transformations (raw, log, square root or cubic root) on the main predictors  
182        (task *difficulty* and illusion *strength*), we fitted the best model (based on their indices of  
183        fit), and compared their output visually (**Figure 2**).

184        The inter-individual variability in the effect of illusion strength and its interaction  
185        with task difficulty was extracted from the models and used as participant-level scores. We  
186        then explored the relationship of these indices across different illusions using exploratory  
187        factor analysis (EFA) and structural equation modelling (SEM), and tested the existence of  
188        a general factor of illusion sensitivity (Factor *i*).

189        Finally, for each of the individual illusion sensitivity scores (10 illusion-specific factors  
190        and the general Factor *i*), we tested the effect of contextual variables (screen size, screen  
191        refresh rate), demographic variables (sex, education, age), and personality traits.

The analysis was carried out using *R* 4.2 (R Core Team, 2022), *brms* (Bürkner, 2017), the *tidyverse* (Wickham et al., 2019), and the *easystats* collection of packages (Lüdecke et al., 2021, 2019; Makowski et al., 2020; Makowski, Ben-Shachar, & Lüdecke, 2019). As the full results are available as supplementary materials, we will focus here on the significant results (based on the Bayes Factor *BF* or the Probability of Direction *pd*, see Makowski, Ben-Shachar, Chen, et al., 2019).

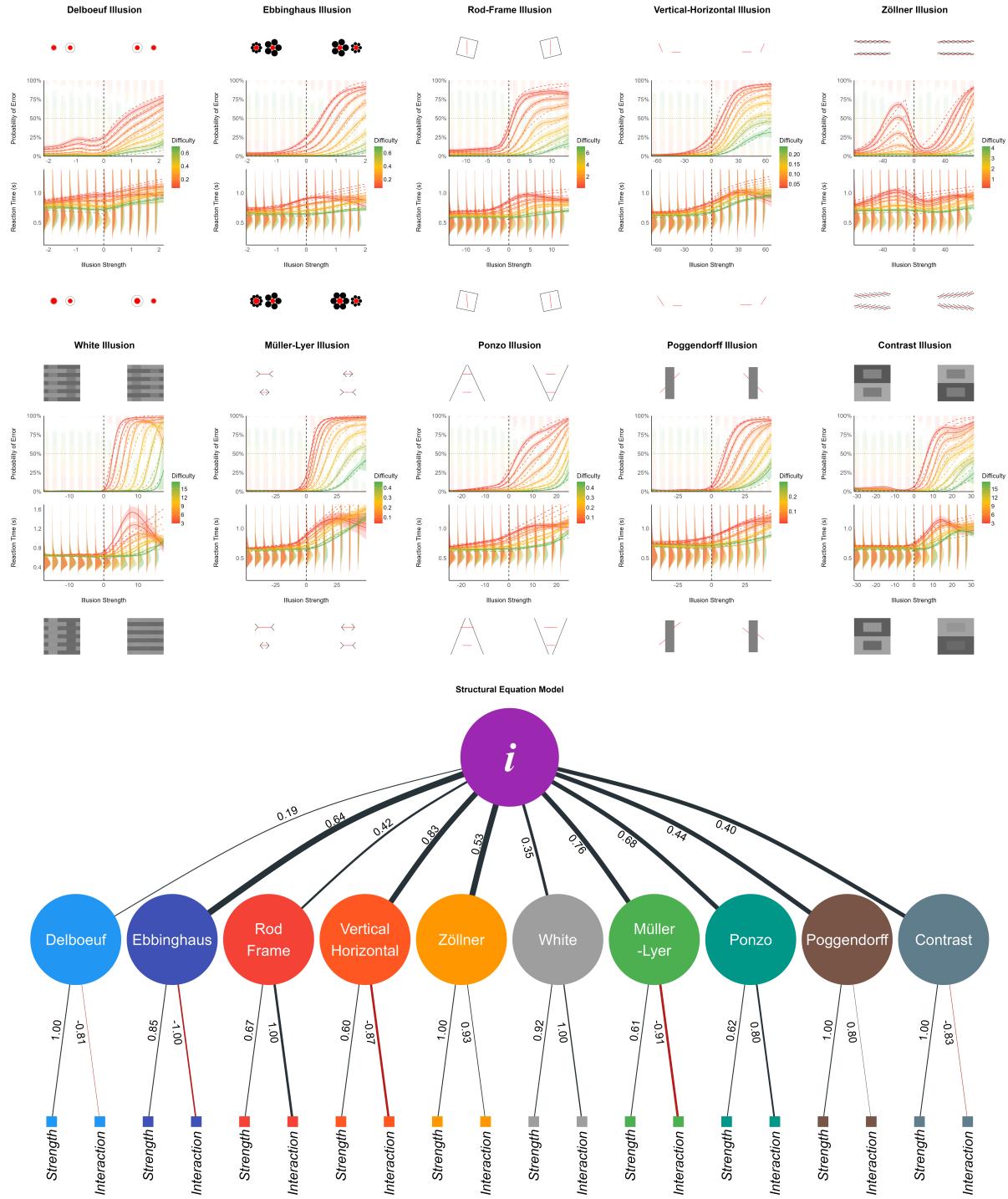
## Results

### Effects of Illusion Strength and Task Difficulty

The best model specifications were  $\log(\text{diff}) * \text{strength}$  for Delboeuf;  $\sqrt{\text{diff}} * \text{strength}$  for Ebbinghaus;  $\log(\text{diff}) * \log(\text{strength})$  for Rod and Frame;  $\sqrt{\text{diff}} * \sqrt{\text{strength}}$  for Vertical-Horizontal;  $\text{cbrt}(\text{diff}) * \text{strength}$  for Zöllner;  $\text{diff} * \sqrt{\text{strength}}$  and  $\log(\text{diff}) * \text{strength}$  respectively for errors and RT in White;  $\sqrt{\text{diff}} * \sqrt{\text{strength}}$  and  $\sqrt{\text{diff}} * \text{strength}$  respectively for errors and RT in Müller-Lyer;  $\text{cbrt}(\text{diff}) * \text{strength}$  for Ponzo;  $\text{cbrt}(\text{diff}) * \sqrt{\text{strength}}$  and  $\text{cbrt}(\text{diff}) * \text{strength}$  respectively for errors and RT in Poggendorff; and  $\sqrt{\text{diff}} * \sqrt{\text{strength}}$  for Contrast. For all of these models, the effects of illusion strength, task difficulty and their interaction were significant.

For error rates, most of the models closely matched their GAMs counterpart, with the exception of Delboeuf (for which the GAM suggested a non-monotonic effect of illusion strength with a local minimum at 0) and Zöllner (for which theoretically congruent illusion effects were related to increased error rate). A specific discussion regarding these 2 illusions is available in the Supplementary Materials (Part 1 - Discussion).

For RTs, the GAMs suggested a consistent non-linear relationship between RT and illusion strength: as the illusion strength increases beyond a certain threshold, the participants responded faster. While this is not surprising (strong illusions are likely so



**Figure 2.** Top: the effect of illusion strength and task difficulty on the error rate and reaction time (RT) for each individual illusion. The solid line represents the General Additive Model (GAM), and the dashed line corresponds to its approximation via linear models. Descriptive data is shown with stacked dots (for which errors start from the top) and distributions for RTs. Negative values for illusion strength correspond to congruent (i.e., facilitating) illusion effects. Task difficulty (the objective difference between the targets of perceptual decision) levels are shown as colors, with lower values corresponding to harder trials. The results for each illusion are surrounded by 4 extreme examples of stimuli, corresponding to the hardest difficulty (on top) and the strongest illusion (on the right for incongruent illusions). Bottom: We extracted the effect slope of the illusion strength and its interaction with task difficulty for each participant. We fitted a Structural Equation Model (SEM) suggesting that these manifest variables group to first-level illusion-specific latent factors, which then load on a general factor of illusion sensitivity (Factor *i*).

217 effective in biasing perception that it is “easier”, i.e., faster, to make the wrong decision),  
218 the linear models were not designed to capture this - likely quadratic - pattern and hence  
219 are not good representatives of the underlying dynamics. As such, we decided not to use  
220 them for the individual scores analysis.

## 221 Factor Structure

222 Though imperfect, we believe that the random-slope models capture inter-individual  
223 differences with more accuracy (and also provide more conservative estimates due to  
224 shrinkage) than basic empirical scores, such as the total number of errors, or the average  
225 RT. Thus, for each illusion and within each participant, we extracted the effect of illusion  
226 strength and its interaction with task difficulty when the illusion effect was incongruent.  
227 These twenty participant-level scores were subjected to exploratory factor analysis (EFA).  
228 The Method Agreement Procedure (Lüdecke et al., 2020) suggested the presence of 7 latent  
229 factors. An oblique (*oblimin* rotation) factor solution explaining 66.69% of variance  
230 suggested separate dimensions for the effect of Zöllner, White, Poggendorff, Contrast,  
231 Ebbinghaus, Delboeuf, and a common factor for the parameters related to Müller-Lyer,  
232 Vertical-Horizontal, Ponzo and Rod and Frame. We submitted these factors to a  
233 second-level analysis and extracted two orthogonal (*varimax* rotation) factors. The first  
234 factor was loaded by all the previous dimensions with the exception of Delboeuf, which  
235 formed its own separate factor.

236 Finally, we tested this data-driven model (*m0*) against four other structural models  
237 using structural equation modelling (SEM): one in which the two parameters of each of the  
238 10 illusions (illusion strength and interaction with task difficulty) loaded on separate  
239 factors, which then all loaded on a common factor (*m1*); one in which the parameters were  
240 grouped by illusion type (lines, circles, contrast and angle) before loading on a common  
241 factor (*m2*); one in which all the parameters related to strength, and all the parameters  
242 related to the interaction loaded onto two respective factors, which then loaded on a

<sup>243</sup> common factor ( $m3$ ); and one in which there was no intermediate level: all 20 parameters  
<sup>244</sup> loaded directly on a common factor ( $m4$ ).

<sup>245</sup> The model  $m1$ , in which the parameters loaded on a first level of 10 illusion-specific  
<sup>246</sup> factors, which then all loaded on a common factor, significantly outperformed the other  
<sup>247</sup> models. Its indices of fit ranged from acceptable to satisfactory (CFI = .92; SRMR = .08;  
<sup>248</sup> NNFI = .91; PNFI = .74; RMSEA = .08), and all the specified effects were significant.  
<sup>249</sup> The illusion-specific latent factors were loaded positively by the sensitivity to illusion  
<sup>250</sup> strength, as well as by the interaction effect with task difficulty (with the exception of  
<sup>251</sup> Delboeuf, Ebbinghaus, Vertical-Horizontal, Müller-Lyer and Contrast, for which the  
<sup>252</sup> loading was negative). The general factor of illusion sensitivity, labelled Factor  $i$  (i- for  
<sup>253</sup> illusion), explained 48.02% of the total variance of the initial dataset, and was strongly  
<sup>254</sup> related to Vertical-Horizontal ( $\beta_{std.} = 0.83$ ), Müller-Lyer ( $\beta_{std.} = 0.76$ ), Ponzo  
<sup>255</sup> ( $\beta_{std.} = 0.65$ ), Ebbinghaus ( $\beta_{std.} = 0.64$ ); moderately to Zöllner ( $\beta_{std.} = 0.53$ ), Poggendorff  
<sup>256</sup> ( $\beta_{std.} = 0.44$ ), Rod and Frame ( $\beta_{std.} = 0.42$ ), Contrast ( $\beta_{std.} = 0.40$ ) and White  
<sup>257</sup> ( $\beta_{std.} = 0.35$ ); and weakly to Delboeuf ( $\beta_{std.} = 0.19$ ). We then computed, for each  
<sup>258</sup> participant, the score for the 10 illusion-specific factors and for the general Factor  $i$ .

<sup>259</sup> It is important to note that these individual scores are the result of several layers of  
<sup>260</sup> simplification: 1) the individual coefficient is that of simpler models that sometimes do not  
<sup>261</sup> perfectly capture the underlying dynamics (especially in the case of Delboeuf and Zöllner);  
<sup>262</sup> 2) we only used the models on error rate, which could be biased by the speed-accuracy  
<sup>263</sup> decision criterion used by participants; 3) the structural equation model used to compute  
<sup>264</sup> the scores also incorporated multiple levels of abstractions. Thus, in order to validate the  
<sup>265</sup> individual scores, we computed the correlation between them and simple empirical scores,  
<sup>266</sup> such as the average error rate and the mean RT in the task. This analysis revealed strong  
<sup>267</sup> and significant correlations between each illusion-specific factor and the average amount of  
<sup>268</sup> errors in its corresponding task. Moreover, each individual score was strongly associated

269 with the average RT across multiple illusion types. This suggests that the individual scores  
270 obtained from the structural equation model do capture the sensitivity of each participant  
271 to visual illusions, manifesting in both the number of errors and long reaction times.

## 272 Correlations with Inter-individual Characteristics

273 The Bayesian correlation analysis (with narrow priors centered around a null effect)  
274 between the illusion scores and contextual variables (screen size and refresh rate) provided  
275 weak evidence in favor of an absence of effect, with the exception of the two contrast-based  
276 illusions. Anecdotal ( $BF_{10} = 2.05$ ) and moderate evidence ( $BF_{10} = 4.11$ ) was found for a  
277 negative correlation between screen size and the sensitivity to the White and the Contrast  
278 illusion, respectively. To test whether this result could be an artifact related to the highly  
279 skewed screen size distribution (caused by very few participants with extreme screen sizes),  
280 we re-ran a robust correlation (with rank-transformed values), which provided even  
281 stronger evidence in favor of the effect existence ( $BF_{10} = 28.19$ ,  $BF_{10} = 4.31$  for White and  
282 Contrast, respectively).

283 The Bayesian t-tests on the effect of sex suggested anecdotal to moderate evidence in  
284 favour of the null effect for all scores, with the exception of the sensitivity to the Zöllner  
285 illusion, which was higher in males as compared to females ( $\Delta = -0.37$ , 95% CI [-0.62,  
286 -0.13],  $BF_{10} = 12.74$ ). We fitted Bayesian linear models with the education level entered as  
287 a monotonic predictor (appropriate for ordinal variables, Bürkner & Charpentier, 2020),  
288 which yielded no significant effects. For age, we fitted two types of models for each score,  
289 one general additive models (GAM) and a 2nd order polynomial model. These consistently  
290 suggested a significant positive linear relationship between age and Factor  $i$  ( $pd = 100\%$ ),  
291 as well as the sensitivity to Müller-Lyer ( $pd = 100\%$ ), Vertical-Horizontal ( $pd = 100\%$ ),  
292 Zöllner ( $pd = 100\%$ ) and Ebbinghaus ( $pd = 99\%$ ) illusions (**Figure 3**).

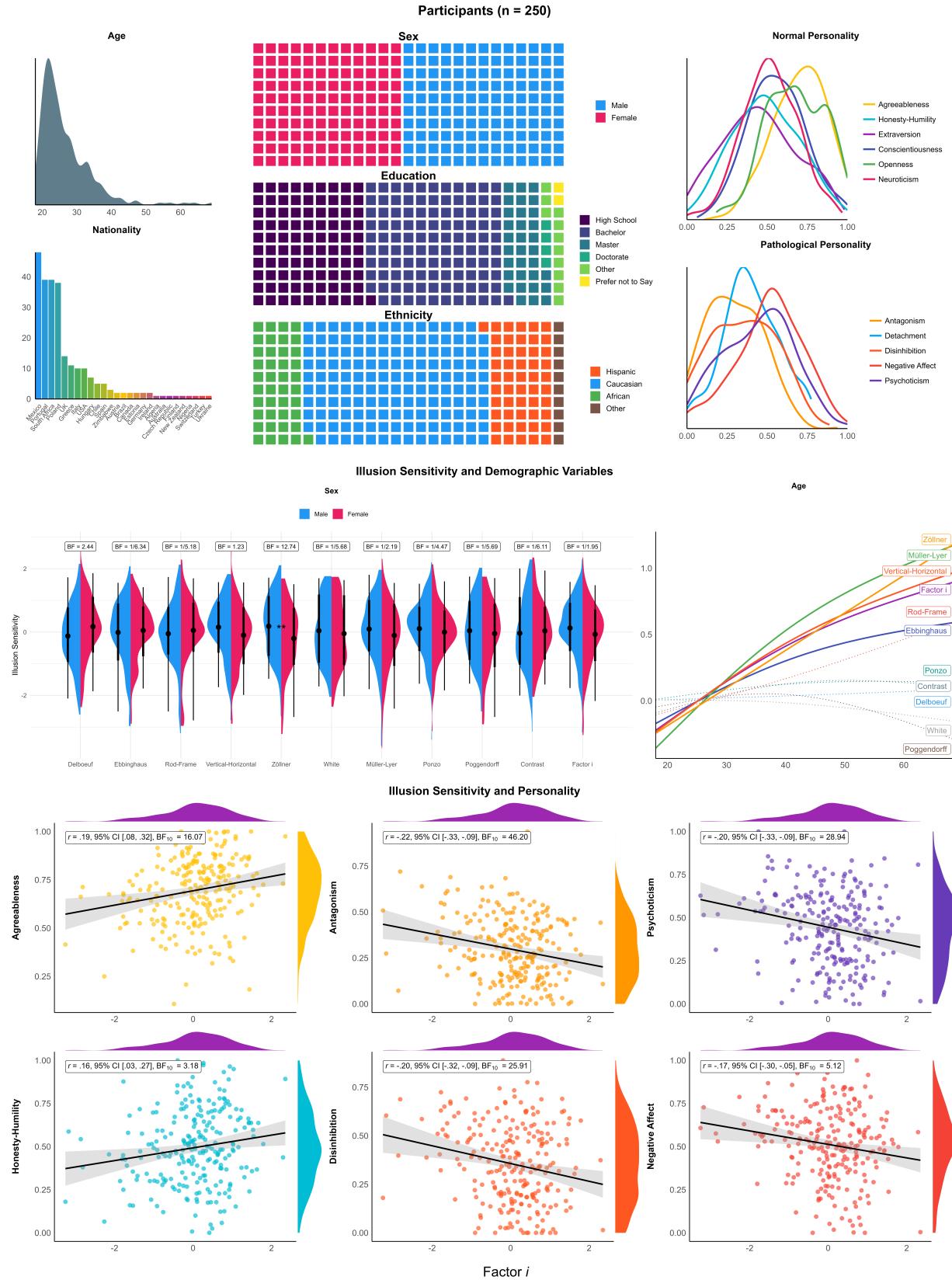
293 Regarding “normal” personality traits, Bayesian correlations suggested substantial

294 evidence in favor of a positive relationship between *Honesty-Humility* and Zöllner  
295 ( $BF_{10} > 100$ ), Vertical-Horizontal ( $BF_{10} = 9.78$ ) and the Factor *i* ( $BF_{10} = 4.00$ ); as well as  
296 between *Agreeableness* and Vertical-Horizontal ( $BF_{10} = 25.06$ ), Ponzo ( $BF_{10} = 4.88$ ) and  
297 the Factor *i* ( $BF_{10} = 19.65$ ).

298 Regarding “pathological” personality traits, the results yielded strong evidence in  
299 favor of a negative relationship between illusion scores and multiple traits. *Antagonism* was  
300 associated with the sensitivity to Vertical-Horizontal ( $BF_{10} > 100$ ), Müller-Lyer  
301 ( $BF_{10} = 21.57$ ), Ponzo ( $BF_{10} = 17.97$ ) illusions, and the Factor *i* ( $BF_{10} = 55.45$ );  
302 *Psychoticism* was associated with the sensitivity to Vertical-Horizontal ( $BF_{10} = 66.63$ ) and  
303 Müller-Lyer ( $BF_{10} = 35.59$ ) illusions, and the Factor *i* ( $BF_{10} = 35.02$ ); *Disinhibition* was  
304 associated with the sensitivity to Vertical-Horizontal ( $BF_{10} = 25.38$ ), Zöllner  
305 ( $BF_{10} = 7.59$ ), Müller-Lyer ( $BF_{10} = 5.89$ ) illusions, and the Factor *i* ( $BF_{10} = 31.42$ ); and  
306 *Negative Affect* was associated with Zöllner ( $BF_{10} = 62.04$ ), Vertical-Horizontal  
307 ( $BF_{10} = 12.65$ ), Müller-Lyer ( $BF_{10} = 3.17$ ), and the Factor *i* ( $BF_{10} = 6.39$ ). The last  
308 remaining trait, *Detachment*, did not share any significant relationship with illusion  
309 sensitivity. See Supplementary Materials (Part 2 - Discussion) for a detailed discussion  
310 regarding these associations.

## 311 Discussion

312 This study tested a novel illusion sensitivity task paradigm based on the parametric  
313 illusion generation framework (Makowski et al., 2021). Using the carefully generated  
314 stimuli in a perceptual decision task, we have shown that a gradual modulation of illusion  
315 strength is effectively possible across 10 different types of classic visual illusions. Increasing  
316 the illusion strength led to an increase in error likelihood, as well as the average and spread  
317 of RTs (but only up to a point, after which participants become faster at responding with  
318 the wrong answer). Using mixed models, we were able to statistically quantify the effect of  
319 illusions for each illusion and each participant separately. This important methodological



**Figure 3.** The upper plots show the distribution of demographic and dispositional variables. The middle plots shows the illusion sensitivity scores as a function of sex and age (solid lines indicate significant relationships). Bottom plots show the correlation between the general factor of illusion sensitivity (Factor  $i$ ) and personality traits.

320 step opens the door for new illusions-based paradigms and tasks to study the effect of  
321 illusions under different conditions and to measure illusion sensitivity using objective  
322 behavioral outcomes - such as accuracy or speed - instead of subjective meta-cognitive  
323 reports. This new and complementary approach will hopefully help address some of the  
324 longstanding literature gaps, as well as cement illusions as valuable stimuli for the study of  
325 cognition.

326 Our findings suggest that the sensitivity to 10 different types of visual illusions share a  
327 common part of variance, supporting the existence of a general factor of illusion sensitivity  
328 (Factor *i*). This result comes in a field of mixed findings. In fact, contrary to early studies  
329 on visual illusions, more recent research have generally not found any significant evidence  
330 for a common stable factor across illusions within individuals (Cretenoud et al., 2019;  
331 Cretenoud et al., 2020; Grzeczkowski et al., 2017, 2018; Yang et al., 2012). Instead, past  
332 findings suggest illusory effects are highly specific to the perceptual features of the illusions  
333 at stake (Cretenoud et al., 2019; Grzeczkowski et al., 2017). It should be noted, however,  
334 that most of these studies were low-powered and/or relied on conventional paradigms, such  
335 as the adjustment procedure to measure the participants' subjective perception. We believe  
336 that our study presents several methodological improvements, including statistical power  
337 (high number of trials per participant), homogeneous stimuli (with minimal and highly  
338 controlled features) and tasks (decision-making reaction-time task), and a more reliable  
339 participant-level score extraction method (based on random-factors models), which in our  
340 opinion contributed to the emergence of the common factor.

341 Finally, we found illusion sensitivity to be positively associated with "positive"  
342 personality traits, such as agreeableness and honesty-humility, and negatively associated  
343 with maladaptive traits such as antagonism, psychotism, disinhibition, and negative  
344 affect. Although the existing evidence investigating links between illusion sensitivity and  
345 personality traits is scarce, these results are consistent with past findings relating

346 pathological egocentric beliefs (often associated with psychoticism, Fox, 2006) to reduced  
347 context integration, manifesting in a tendency to separate objects from their surroundings  
348 when processing visual stimuli (Fox, 2006; Konrath et al., 2009; Ohmann & Burgmer,  
349 2016). As such, the association between maladaptive traits and lower illusion sensitivity  
350 could be linked to a self-centered, decontextualized and disorganized information  
351 processing style. Conversely, the relationship between illusion sensitivity and adaptive  
352 personality traits is in line with the decreased field dependence (the tendency to rely on  
353 external cues in ambiguous contexts) associated with traits negatively correlated with  
354 agreeableness and honesty-humility, such as hostility, aggression and narcissism (Konrath  
355 et al., 2009; Pessoa et al., 2008; Zhang et al., 2017).

356 Importantly, these findings highlight the relevance of illusions beyond the field of  
357 visual perception, pointing towards an association with high-level domain-general  
358 mechanisms. In particular, the evidence in favor of a relationship between maladaptive  
359 personality traits and illusion sensitivity is in line with clinical observations, in which a  
360 greater resistance to illusions have been reported among patients with schizophrenia  
361 (Grzeczkowski et al., 2018; Notredame et al., 2014; Pessoa et al., 2008), especially in  
362 association with schizotypal traits such as cognitive disorganization (Cretenoud et al., 2019;  
363 Lányi et al., 2022). While the search for the exact mechanism(s) underlying these links is  
364 an important goal of future research, our findings unlock the potential of illusion-based  
365 tasks as sensitive tools to capture specific inter-individual neuro-cognitive differences.

366 Future research is needed to address several limitations. One key question concerns  
367 the relationship of illusion sensitivity with perceptual abilities (e.g., using similar tasks, but  
368 without illusions). Although the illusions used in the present study did differ in terms of  
369 the perceptual task (contrast-based, size-estimation, angle-perception), the possibility of  
370 our general factor being driven by inter-individual perceptual skills variability (or other  
371 cognitive skills) cannot be discarded. Moreover, using only the error rate models to extract

372 individual-level scores might fail in capturing the whole range of behavioral dynamics.  
373 Future work should attempt at integrating the reaction times data (e.g., by jointly  
374 analyzing them using drift diffusion models), and assess the psychometric properties - such  
375 as stability (e.g., test-retest reliability) and validity - of similar illusion-based paradigms.  
376 Finally, while the personality measures used in this study highlight illusion sensitivity as an  
377 interesting measure rather than a mere perceptual artifact, further studies should test its  
378 relationship with more specific dispositional characteristics (e.g., autistic or schizotypal  
379 traits), cognitive styles and abilities, to help understanding the potential underlying  
380 mechanisms of these associations.

381 In conclusion, we strongly invite researchers to explore and re-analyze our dataset  
382 with other approaches and methods to push the understanding of visual illusions and  
383 illusion sensitivity further. The task, data and analysis script are available in open-access  
384 at <https://github.com/RealityBending/IllusionGameValidation>.

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388

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