

<sup>1</sup> **The Illusion Game: A Novel Experimental Paradigm Provides Evidence for a  
2 General Factor of Visual Illusion Sensitivity and Personality Correlates**

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## Abstract

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

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

38 Word count: 4070

39 The Illusion Game: A Novel Experimental Paradigm Provides Evidence for a  
40 General Factor of Visual Illusion Sensitivity and Personality Correlates

**Significance Statement.** A novel paradigm to study the objective effect of visual illusions yielded evidence in favor of a common factor to visual illusions (Factor *i*) and a relationship between illusion resistance and maladaptive personality traits, such as antagonism, psychoticism and disinhibition.

## Introduction

Visual illusions are fascinating stimuli capturing a key feature of our neurocognitive systems. They eloquently show that our brains did not evolve to be perfect perceptual devices providing veridical accounts of physical reality, but integrate prior knowledge and contextual information - blended together in our subjective conscious experience<sup>1</sup>. Despite the long-standing interest within the fields of visual perception<sup>2-4</sup>, consciousness science<sup>5,6</sup>, and psychiatry<sup>7-10</sup>, several important issues remain open.

52 One area of contention concerns the presence of a common mechanism underlying the  
53 effect of different illusions<sup>11,12</sup>. While early research has suggested a common factor of  
54 illusion sensitivity indexed by overall vision proficiency<sup>13,14</sup>, recent empirical studies  
55 observed at most weak correlations between inter-individual resistance to distinct  
56 illusions<sup>15,16</sup>. The existence of dispositional correlates of illusion sensitivity has also been  
57 controversial, with evidence suggesting a lower illusion sensitivity in patients with  
58 schizophrenia and autism<sup>7-9,16,17</sup>, as well as individuals with stronger aggression and  
59 narcissism traits<sup>18,19</sup>.

Although the nature of the processes underlying illusion perception - whether related to low-level features of the visual processing system<sup>8,20</sup> or to top-down influences<sup>5,21</sup> - remains debated, a growing body of literature proposes to conceptualize illusions under the Bayesian brain hypothesis<sup>22</sup>. In this context, illusions are conceptualized as ambiguous

64 percepts (noisy sensory evidence) giving ample weight to prior knowledge to minimize  
65 prediction error and provide a coherent perceptual experience. The predictive coding  
66 account further provides an explanation regarding the observations from clinical  
67 populations. Certain dispositional traits or characteristics (e.g., psychoticism) are seen as  
68 driven by alterations in the system's metacognitive components<sup>23</sup>, resulting in an  
69 underweighting of priors during perceptual inferences, and manifesting as a decreased  
70 sensitivity to illusions<sup>24</sup>.

71 Despite strong theoretical foundations and hypotheses, the empirical evidence  
72 remains scarce, clouded by methodological hurdles. For instance, one key challenge can be  
73 found in the difficulty of adapting visual illusions to an experimental setting, which  
74 typically requires the controlled modulation of the specific variables of interest. Instead,  
75 existing studies typically use only one or a small subset of illusion types, with few  
76 contrasting conditions, restricting the findings' generalizability<sup>12,20,25</sup>. Moreover,  
77 conventional paradigms often focus on the participants' subjective experience, by asking  
78 them the extent to which they perceive two identical targets as different<sup>26</sup>, having them  
79 estimate the targets' physical properties<sup>27</sup>, or having them adjust the targets to  
80 perceptually match a reference stimulus<sup>16,28</sup>. This reliance on meta-cognitive judgements  
81 about one's subjective experience likely distorts the measurand, limiting the ability to  
82 reliably obtain more direct and objective measures of illusion sensitivity<sup>29</sup>.

83 To address these issues, we first developed a parametric framework to manipulate  
84 visual illusions that we implemented and made accessible in the open-source software  
85 *Pyillusion*<sup>30</sup>. This software allows us to generate different types of classic visual illusions  
86 with a continuous and independent modulation of two parameters: *illusion strength* and  
87 *task difficulty* (**Figure 1**). Indeed, many visual illusions can be seen as being composed of  
88 *targets* (e.g., same-length lines), of which perception is biased by the *context* (e.g., in the  
89 Müller-Lyer illusion, the same-length line segments appear to have different lengths if they

90 end with inwards vs. outwards pointing arrows). Past illusion studies traditionally  
91 employed paradigms focusing on participants' subjective experience, by asking them the  
92 extent to which they perceive two identical targets as different<sup>26</sup>, or having them adjust the  
93 targets to match a reference stimulus relying only on their perception<sup>16,28</sup>. Alternatively,  
94 *Pyllusion* allows the creation of illusions in which the targets are objectively different (e.g.,  
95 one segment is truly more or less longer than the other), and in which the illusion varies in  
96 strength (the biasing angle of the arrows is more or less acute).

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

106 The aim of the present preregistered (<https://osf.io/5d6xp>) study is three-fold. First,  
107 we will test this novel paradigm by investigating if the effect of illusion strength and task  
108 difficulty can be manipulated continuously for 10 different classic illusions (Delboeuf,  
109 Ebbinghaus, Rod and Frame, Vertical-Horizontal, Zöllner, White, Müller-Lyer, Ponzo,  
110 Poggendorff, Contrast). Next, we will investigate the factor structure of illusion-specific  
111 performance scores and test the existence of a common latent factor of illusion sensitivity.  
112 Finally, we will explore how illusion sensitivity relates to demographic characteristics,  
113 contextual variables, and 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.

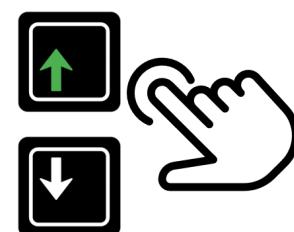


In this illusion, the **task difficulty** corresponds to the difference between the lengths of the red target segments, and the **illusion strength** corresponds to the angle of the arrows.

### 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.

114

## Methods

115 **Ethics Statement**

116 This study was approved by the NTU Institutional Review Board (NTU  
117 IRB-2022-187) and all procedures performed were in accordance with the ethical standards  
118 of the institutional board and with the 1964 Helsinki Declaration. All participants  
119 provided their informed consent prior to participation and were incentivized after  
120 completing the study.

121 **Stimuli**

122 A pilot study ( $n = 46$ ), of which a full description is available at  
123 <https://github.com/RealityBending/IllusionGameValidation>, was first conducted  
124 to determine a sensitive range of stimuli parameters. Then, for each of the 10 illusion  
125 types, we generated a total of 134 stimuli. These stimuli resulted from the combination of  
126 15 equally-spaced levels of illusion *strength* (7 negative, i.e., congruent effects; 7 positive,  
127 i.e., incongruent effects; and 0) overlapped with 16 non-linearly spaced task *difficulty* levels  
128 (i.e., with an exponential, square or cubic spacing depending on the pilot results). For  
129 instance, a linear space of [0.1, 0.4, 0.7, 1.0] can be transformed to an exponential space of  
130 [0.1, 0.34, 0.64, 1.0], where 0.1 corresponds to the highest difficulty - i.e., the smallest  
131 objective difference between targets). For each illusion type, the stimuli were split into two  
132 series (56 and 72 stimuli per series) with alternating parameter values to maintain their  
133 homogeneity. Additionally, 6 stimuli per illusion type were generated for a practice series  
134 using parameters with more extreme variations (i.e., containing very easy trials to help  
135 cement the task instructions).

136 **Procedure**

137 After a brief demographic survey and a practice series of illusions, the first series of  
138 10 illusion blocks was presented in a randomized order, with a further randomization of the

139 stimuli order within each block. Following this first series of blocks, two personality  
140 questionnaires were administered, the *IPIP6*<sup>24 items, 31</sup> - measuring 6 “normal” personality  
141 traits (Extraversion, Openness, Conscientiousness, Agreeableness, Neuroticism and  
142 Honesty-Humility), and the *PID-5*<sup>25 items, 32</sup> - measuring 5 “pathological” personality traits  
143 (Disinhibition, Antagonism, Detachment, Negative Affect and Psychoticism). Next, the  
144 second series of 10 illusion blocks was presented (with new randomized orders of blocks and  
145 trials). In total, each participant underwent 1340 trials of which they had to respond “as  
146 fast as possible without making errors” (i.e., an explicit double constraint to mitigate the  
147 inter-individual variability in the speed-accuracy trade off) by pressing the correct arrow  
148 key (left/right, or up/down depending on the illusion type). For instance, in the  
149 Müller-Lyer block, participants had to answer which one of the upper or bottom target line  
150 was the longest. The task was implemented using *jsPsych*<sup>33</sup>, and the set of instructions for  
151 each illusion type is available in the experiment code.

## 152 Participants

153 Participants were recruited via *Prolific*, a crowd-sourcing platform recognized for  
154 providing high quality data<sup>34</sup>. The only inclusion criterion was a fluent proficiency in  
155 English to ensure that the task instructions would be well-understood. Participants were  
156 incentivised with a reward of about £7.50 for completing the task, which took about 50  
157 minutes to finish. Demographic variables (age, gender, and ethnicity) were self-reported on  
158 a voluntary basis.

159 We excluded 6 participants upon inspection of the average error rate (when close to  
160 50%, suggesting random answers), and reaction time distribution (when implausibly fast).  
161 For the remaining participants, we discarded blocks with more than 50% of errors (2.16%  
162 of trials), possibly indicating that instructions were misunderstood (e.g., participants  
163 focused on the shorter line instead of the longer one), and 0.76% trials with extreme  
164 response times (< 125 ms or > 4 SD above mean). Additionally, due to a technical issue,

165 no personality data was recorded for the first eight participants.

166 The final sample included 250 participants (Mean age = 26.5, SD = 7.6, range: [18 -  
167 69]; Sex: 48% females, 52% males).

168 **Data Analysis**

169 The first part of the analysis focused on modelling the effect of illusion strength and  
170 task difficulty on errors and response time (RT) within each illusion. We started by fitting  
171 General Additive Models (GAMs), which can parsimoniously accommodate possible  
172 non-linear effects and interactions. Errors were analyzed using Bayesian logistic mixed  
173 models, and RTs of correct responses were analyzed using an ex-Gaussian family with the  
174 same fixed effects entered for the location  $\mu$  (mean), scale  $\sigma$  (spread) and tail-dominance  $\tau$   
175 of the RT distribution<sup>35,36</sup>.

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

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

187 Finally, for each of the individual illusion sensitivity scores (10 illusion-specific factors  
188 and the general Factor  $i$ ), we tested the effect of contextual variables (screen size, screen

refresh rate), demographic variables (sex, education, age), and personality traits.

The analysis was carried out using *R* 4.2<sup>37</sup>, *brms*<sup>38</sup>, the *tidyverse*<sup>39</sup>, and the *easystats* collection of packages<sup>40–43</sup>. As all the full results have been made available (see **Data Availability**), we will focus here on the significant results based on the Bayes Factor *BF* or the Probability of Direction *pd*, see 44.

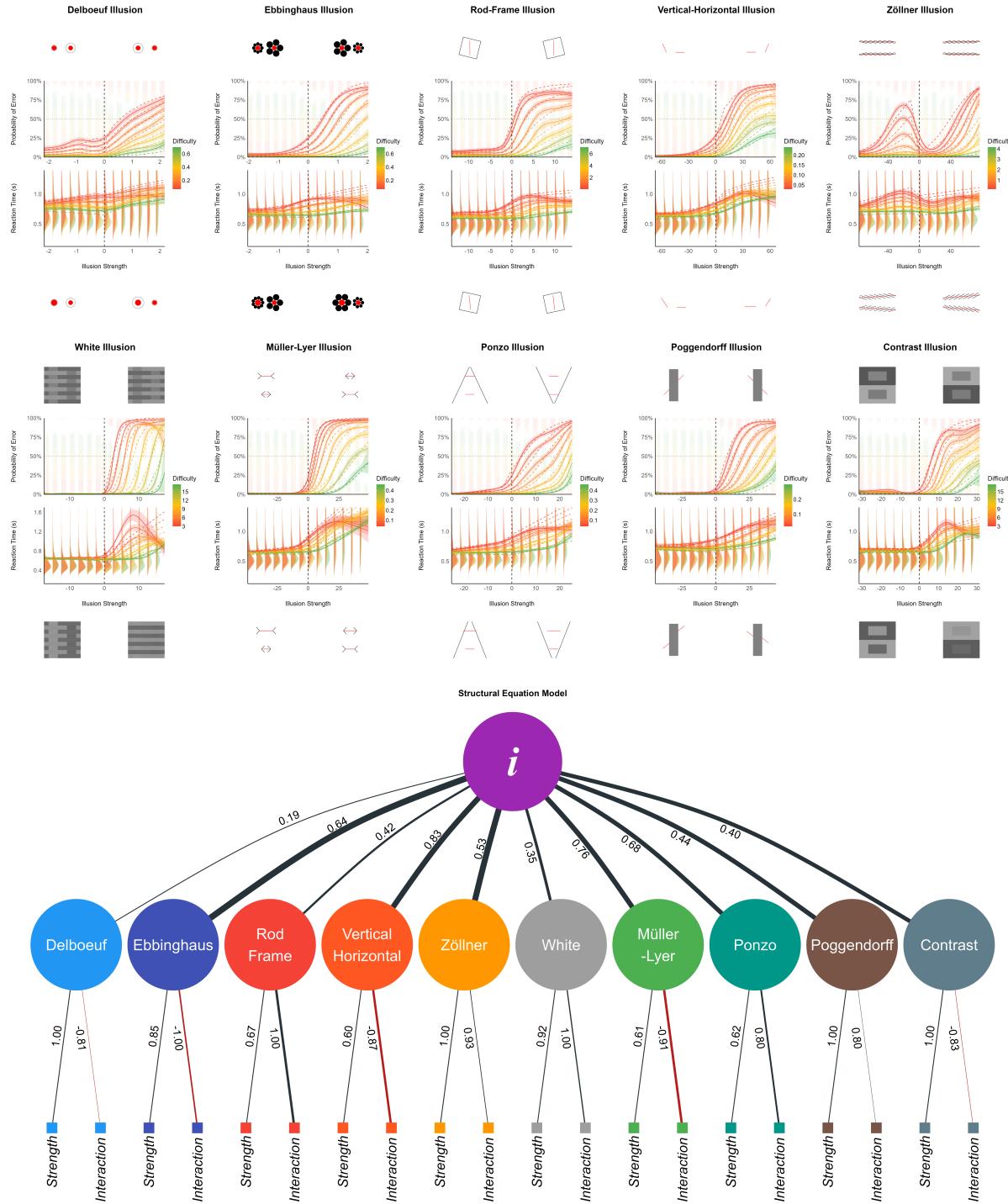
## 194 Results

### 195 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 study documentation (part 1) at <https://github.com/RealityBending/IllusionGameValidation>.

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*).

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

## 218 Factor Structure

219 Though imperfect, we believe that the random-slope models capture inter-individual  
220 differences with more accuracy (and also provide more conservative estimates due to  
221 shrinkage) than basic empirical scores, such as the total number of errors, or the average  
222 RT. Thus, for each illusion and within each participant, we extracted the effect of illusion  
223 strength and its interaction with task difficulty when the illusion effect was incongruent.  
224 These twenty participant-level scores were subjected to exploratory factor analysis (EFA).  
225 The Method Agreement Procedure<sup>45</sup> suggested the presence of 7 latent factors. An oblique  
226 (*oblimin* rotation) factor solution explaining 66.69% of variance suggested separate  
227 dimensions for the effect of Zöllner, White, Poggendorff, Contrast, Ebbinghaus, Delboeuf,  
228 and a common factor for the parameters related to Müller-Lyer, Vertical-Horizontal, Ponzo  
229 and Rod and Frame. We submitted these factors to a second-level analysis and extracted  
230 two orthogonal (*varimax* rotation) factors. The first factor was loaded by all the previous  
231 dimensions with the exception of Delboeuf, which formed its own separate factor.

232 Finally, we tested this data-driven model ( $m0$ ) against four other structural models  
233 using structural equation modelling (SEM): one in which the two parameters of each of the  
234 10 illusions (illusion strength and interaction with task difficulty) loaded on separate  
235 factors, which then all loaded on a common factor ( $m1$ ); one in which the parameters were  
236 grouped by illusion type (lines, circles, contrast and angle) before loading on a common  
237 factor ( $m2$ ); one in which all the parameters related to strength, and all the parameters  
238 related to the interaction loaded onto two respective factors, which then loaded on a  
239 common factor ( $m3$ ); and one in which there was no intermediate level: all 20 parameters

240 loaded directly on a common factor (*m4*).

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

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

266 obtained from the structural equation model do capture the sensitivity of each participant  
267 to visual illusions, manifesting in both the number of errors and long reaction times.

268 **Correlations with Inter-individual Characteristics**

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

279 The Bayesian t-tests on the effect of sex suggested anecdotal to moderate evidence in  
280 favour of the null effect for all scores, with the exception of the sensitivity to the Zöllner  
281 illusion, which was higher in males as compared to females ( $\Delta = -0.37$ , 95% CI [-0.62,  
282 -0.13],  $BF_{10} = 12.74$ ). We fitted Bayesian linear models with the education level entered as  
283 a monotonic predictor<sup>appropriate for ordinal variables,</sup><sup>46</sup> which yielded no significant effects. For  
284 age, we fitted two types of models for each score, one general additive models (GAM) and  
285 a 2nd order polynomial model. These consistently suggested a significant positive linear  
286 relationship between age and Factor  $i$  ( $pd = 100\%$ ), as well as the sensitivity to  
287 Müller-Lyer ( $pd = 100\%$ ), Vertical-Horizontal ( $pd = 100\%$ ), Zöllner ( $pd = 100\%$ ) and  
288 Ebbinghaus ( $pd = 99\%$ ) illusions (**Figure 3**).

289 Regarding “normal” personality traits, Bayesian correlations suggested substantial  
290 evidence in favor of a positive relationship between *Honesty-Humility* and Zöllner

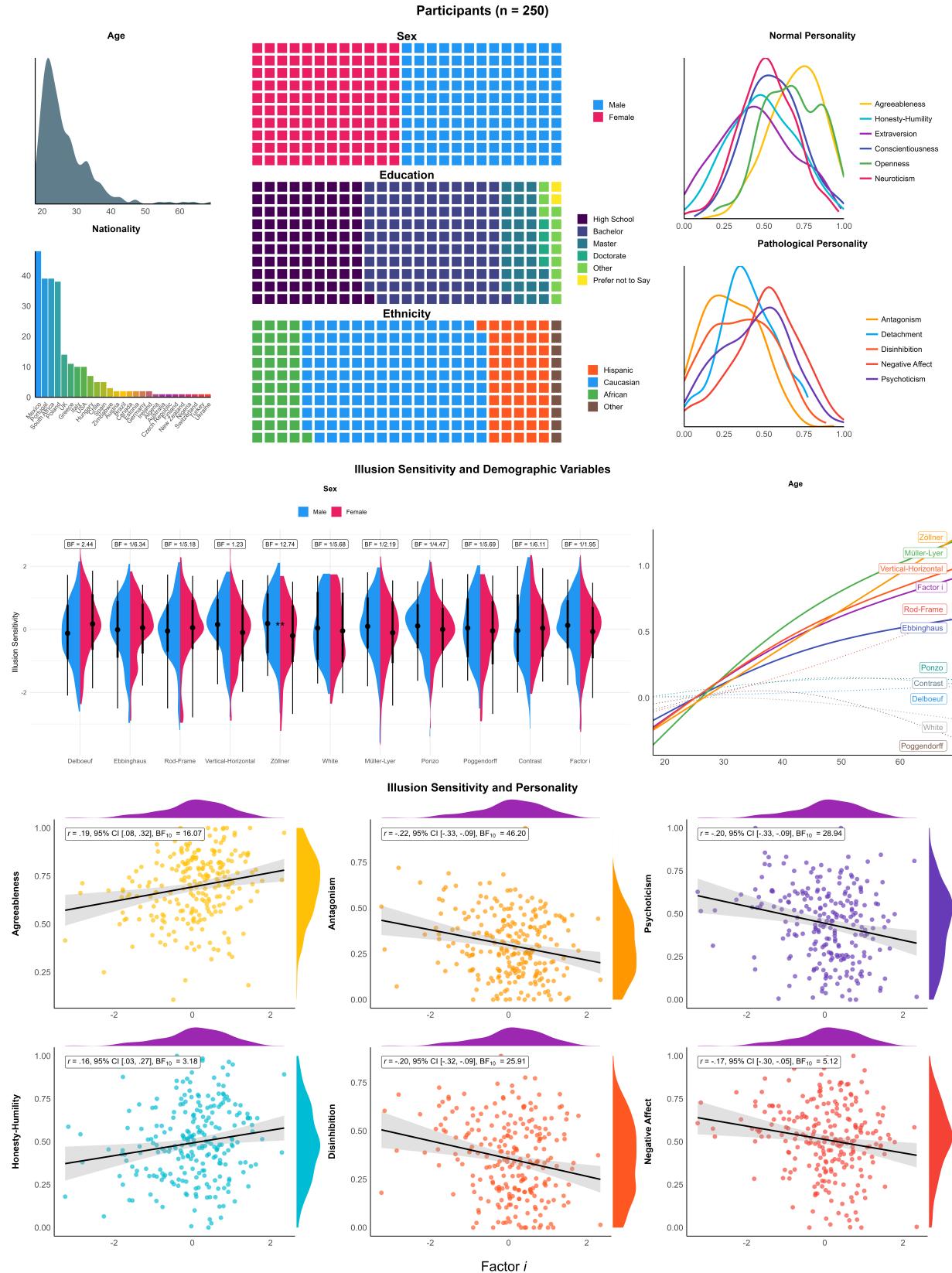
291 ( $BF_{10} > 100$ ), Vertical-Horizontal ( $BF_{10} = 9.78$ ) and the Factor *i* ( $BF_{10} = 4.00$ ); as well as  
292 between *Agreeableness* and Vertical-Horizontal ( $BF_{10} = 25.06$ ), Ponzo ( $BF_{10} = 4.88$ ) and  
293 the Factor *i* ( $BF_{10} = 19.65$ ).

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

306

## Discussion

307 This study tested a novel illusion sensitivity task paradigm based on the parametric  
308 illusion generation framework<sup>30</sup>. Using the carefully generated stimuli in a perceptual  
309 decision task, we have shown that a gradual modulation of illusion strength is effectively  
310 possible across 10 different types of classic visual illusions. Increasing the illusion strength  
311 led to an increase in error likelihood, as well as the average and spread of RTs (but only up  
312 to a point, after which participants become faster at responding with the wrong answer).  
313 Using mixed models, we were able to statistically quantify the effect of illusions for each  
314 illusion and each participant separately. This important methodological step opens the  
315 door for new illusions-based paradigms and tasks to study the effect of illusions under  
316 different conditions and to measure illusion sensitivity using objective behavioral outcomes



**Figure 3.** The upper plots show the distribution of demographic and dispositional variables. The middle plots show 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.

317 - such as accuracy or speed - instead of subjective meta-cognitive reports. This new and  
318 complementary approach will hopefully help address some of the longstanding literature  
319 gaps, as well as cement illusions as valuable stimuli for the study of cognition.

320 Our findings suggest that the sensitivity to 10 different types of visual illusions share  
321 a common part of variance, supporting the existence of a general factor of illusion  
322 sensitivity (Factor *i*). This result comes in a field of mixed findings. In fact, contrary to  
323 early studies on visual illusions, more recent research have generally not found any  
324 significant evidence for a common stable factor across illusions within  
325 individuals<sup>12,15,16,20,47</sup>. Instead, past findings suggest illusory effects are highly specific to  
326 the perceptual features of the illusions at stake<sup>15,20</sup>. It should be noted, however, that most  
327 of these studies were low-powered and/or relied on conventional paradigms, such as the  
328 adjustment procedure to measure the participants' subjective perception. We believe that  
329 our study presents several methodological improvements, including statistical power (high  
330 number of trials per participant), homogeneous stimuli (with minimal and highly controlled  
331 features) and tasks (decision-making reaction-time task), and a more reliable  
332 participant-level score extraction method (based on random-factors models), which in our  
333 opinion contributed to the emergence of the common factor.

334 Finally, we found illusion sensitivity to be positively associated with "positive"  
335 personality traits, such as agreeableness and honesty-humility, and negatively associated  
336 with maladaptive traits such as antagonism, psychotism, disinhibition, and negative  
337 affect. Although the existing evidence investigating links between illusion sensitivity and  
338 personality traits is scarce, these results are consistent with past findings relating  
339 pathological egocentric beliefs<sup>often associated with psychotism,</sup><sup>48</sup> to reduced context integration,  
340 manifesting in a tendency to separate objects from their surroundings when processing  
341 visual stimuli<sup>19,48,49</sup>. As such, the association between maladaptive traits and lower illusion  
342 sensitivity could be linked to a self-centered, decontextualized and disorganized information

343 processing style. Conversely, the relationship between illusion sensitivity and adaptive  
344 personality traits is in line with the decreased field dependence (the tendency to rely on  
345 external cues in ambiguous contexts) associated with traits negatively correlated with  
346 agreeableness and honesty-humility, such as hostility, aggression and narcissism<sup>18,19,50</sup>.

347 Importantly, these findings highlight the relevance of illusions beyond the field of  
348 visual perception, pointing towards an association with high-level domain-general  
349 mechanisms. In particular, the evidence in favor of a relationship between maladaptive  
350 personality traits and illusion sensitivity is in line with clinical observations, in which a  
351 greater resistance to illusions have been reported among patients with schizophrenia<sup>7,16,50</sup>,  
352 especially in association with schizotypal traits such as cognitive disorganization<sup>20,26</sup>.  
353 While the search for the exact mechanism(s) underlying these links is an important goal of  
354 future research, our findings unlock the potential of illusion-based tasks as sensitive tools to  
355 capture specific inter-individual neuro-cognitive differences.

356 Future research is needed to address several limitations. One key question concerns  
357 the relationship of illusion sensitivity with perceptual abilities (e.g., using similar tasks, but  
358 without illusions). Although the illusions used in the present study did differ in terms of  
359 the perceptual task (contrast-based, size-estimation, angle-perception), the possibility of  
360 our general factor being driven by inter-individual perceptual skills variability (or other  
361 cognitive skills) cannot be discarded. Moreover, using only the error rate models to extract  
362 individual-level scores might fail in capturing the whole range of behavioral dynamics.  
363 Future work should attempt at integrating the reaction times data (e.g., by jointly  
364 analyzing them using drift diffusion models), and assess the psychometric properties - such  
365 as stability (e.g., test-retest reliability) and validity - of similar illusion-based paradigms.  
366 Finally, while the personality measures used in this study highlight illusion sensitivity as an  
367 interesting measure rather than a mere perceptual artifact, further studies should test its  
368 relationship with more specific dispositional characteristics (e.g., autistic or schizotypal

369 traits), cognitive styles and abilities, to help understand the potential underlying  
370 mechanisms of these associations.

371 **Data Availability**

372 The datasets generated and/or analysed during the current study are available in the  
373 GitHub repository <https://github.com/RealityBending/IllusionGameValidation>

374 **Funding**

375 This work was supported by the Presidential Postdoctoral Fellowship Grant  
376 (NTU-PPF-2020-10014) from Nanyang Technological University (awarded to DM).

377 **Acknowledgments**

378 We would like to thank Zen J. Lau, Tam Pham, and W. Paul Boyce for their  
379 contribution to *Pyllusion*, as well as Prof Dólos for the inspiration.

380

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