

**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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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. In this study, we used the novel
28 parametric framework for visual illusions to generate 10 different classic illusions
29 (Delboeuf, Ebbinghaus, Rod and Frame, Vertical-Horizontal, Zöllner, White, Müller-Lyer,
30 Ponzo, Poggendorff, Contrast) varying in strength, embedded in a perceptual
31 discrimination task. We tested the objective effect of the illusions on errors and reaction
32 times, and extracted participant-level performance scores ($n=250$). Our results provide
33 evidence in favour of a general factor (labelled Factor i) underlying the sensitivity to
34 different illusions. Moreover, we report a positive relationship between illusion sensitivity
35 and personality traits such as Agreeableness, Honesty-Humility, and negative relationships
36 with Psychoticism, Antagonism, Disinhibition, and Negative Affect.

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

38 Word count: 3628

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40 **Favour of a General Factor of Visual Illusion Sensitivity and Personality**
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42 **Introduction**

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

51 Notably, the presence of a common mechanism underlying the effects of different
52 illusions has been contested (Cretenoud et al., 2019; Cretenoud et al., 2020; Hamburger,
53 2016); and the nature of the underlying processes - whether related to low-level features of
54 the visual processing system (Cretenoud et al., 2019; Gori et al., 2016) or to top-down
55 influences of prior beliefs (Caporuscio et al., 2022; Teufel et al., 2018) are strongly debated.
56 The existence of dispositional correlates of illusion sensitivity is another area of
57 controversy, with some studies reporting higher illusion resistance in patients with
58 schizophrenia and autism (Giaouri & Alevriadou, 2011; Keane et al., 2014; Notredame et
59 al., 2014; Park et al., 2022; Pessoa et al., 2008), and in individuals with stronger aggression
60 and narcissism traits (Konrath et al., 2009; Zhang et al., 2017).

61 One key challenge hindering the further development of illusion research is the
62 relative difficulty of adapting visual illusions to an experimental setting, which typically
63 requires the controlled modulation of the specific variables of interest. To address this
64 issue, we first developed a parametric framework to manipulate visual illusions that we

65 implemented and made accessible in the open-source software *Pyllusion* (Makowski et al.,
 66 2021). This software allows us to generate different types of classic visual illusions with a
 67 continuous and independent modulation of two parameters: *illusion strength* and *task*
 68 *difficulty* (Figure 1).

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.

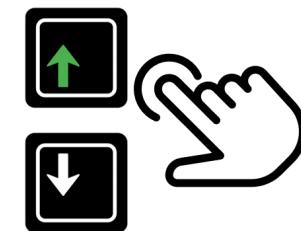


In this illusion, the **task difficulty** corresponds to the difference between the lengths of the red target segments, and the **illusion strength** corresponds to the angle of the arrows.

Example of Stimuli



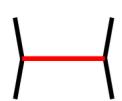
- ✓ Task difficulty: **easy**
(top line is 2 times longer)
- ✓ Illusion Strength: **strong**
(angle is sharp)
- ← Illusion Direction (left): **incongruent**
(the illusion makes the task harder)
- Illusion Direction (right): **congruent**
(the illusion makes the task easier)



- ✓ 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 *Pyllusion* (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.

69 Indeed, many visual illusions can be seen as being composed of *targets* (e.g.,

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

80 This opens the door for an experimental task in which participants make perceptual
81 judgments about the targets (e.g., which segment is the longest) under different conditions
82 of objective difficulty and illusion strength. Moreover, the illusion effect can be either
83 “incongruent” (making the task more difficult by biasing the perception in the opposite
84 way) or “congruent” (making the task easier). Although visual illusions are inherently tied
85 to subjective perception, this framework allows a reversal of the traditional paradigm to
86 potentially quantify the “objective” effect of illusions by measuring its behavioral effect
87 (error rate and reaction times) on the performance in a perceptual task.

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

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

100 **Methods**

101 **Stimuli**

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

115 **Procedure**

116 After a brief demographic survey and a practice series of illusions, the first series of
117 10 illusion blocks was presented in a randomized order, with a further randomization of the
118 stimuli order within each block. Following this first series of blocks, two personality
119 questionnaires were administered, the *IPIP6* (24 items, Sibley et al., 2011) - measuring 6
120 “normal” personality traits (Extraversion, Openness, Conscientiousness, Agreeableness,

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

132 Participants

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

139 We excluded 6 participants upon inspection of the average error rate (when close to
140 50%, suggesting random answers), and reaction time distribution (when implausibly fast).
141 For the remaining participants, we discarded blocks with more than 50% of errors (2.16%
142 of trials), possibly indicating that instructions were misunderstood (e.g., participants
143 focused on the shorter line instead of the longer one), and 0.76% trials with extreme
144 response times (< 125 ms or > 4 SD above mean). Additionally, due to a technical issue,
145 no personality data was recorded for the first eight participants.

¹⁴⁶ The final sample included 250 participants (Mean age = 26.5, SD = 7.6, range: [18,
¹⁴⁷ 69]; Sex: 48% females, 52% males).

¹⁴⁸ **Data Analysis**

¹⁴⁹ The first part of the analysis focused on modelling the effect of illusion strength and
¹⁵⁰ task difficulty on errors and reaction time (RT) within each illusion. We started by fitting
¹⁵¹ General Additive Models (GAMs), which can parsimoniously accommodate possible
¹⁵² non-linear effects and interactions. Errors were analyzed using Bayesian logistic mixed
¹⁵³ models, and RTs of correct responses were analyzed using an ex-Gaussian family with the
¹⁵⁴ same fixed effects entered for the location μ (mean), scale σ (spread) and tail-dominance τ
¹⁵⁵ of the RT distribution (Balota & Yap, 2011; Matzke & Wagenmakers, 2009).

¹⁵⁶ Using GAMs as the “ground-truth” models, we attempted at approximating them
¹⁵⁷ using general linear mixed models, which can be used to estimate the effects'
¹⁵⁸ participant-level variability (via random slopes). Following a comparison of models with a
¹⁵⁹ combination of transformations (raw, log, square root or cubic root) on the main predictors
¹⁶⁰ (task *difficulty* and illusion *strength*), we fitted the best model (based on their indices of
¹⁶¹ fit), and compared their output visually (**Figure 2**).

¹⁶² The inter-individual variability in the effect of illusion strength and its interaction
¹⁶³ with task difficulty was extracted from the models and used as participant-level scores. We
¹⁶⁴ then explored the relationship of these indices across different illusions using exploratory
¹⁶⁵ factor analysis (EFA) and structural equation modelling (SEM), and tested the existence of
¹⁶⁶ a general of illusion sensitivity (Factor *i*).

¹⁶⁷ Finally, for each of the individual illusion sensitivity scores (10 illusion-specific factors
¹⁶⁸ and the general Factor *i*), we tested the effect of contextual variables (screen size, screen
¹⁶⁹ refresh rate), demographic variables (sex, education, age), and personality traits.

170 The analysis was carried out using *R* 4.2 (R Core Team, 2022), *brms* (Bürkner,
171 2017), the *tidyverse* (Wickham et al., 2019), and the *easystats* collection of packages
172 (Lüdecke et al., 2021, 2019; Makowski et al., 2020; Makowski, Ben-Shachar, & Lüdecke,
173 2019). As the full results are available as supplementary materials, we will focus here on
174 the significant results (based on the Bayes Factor *BF* or the Probability of Direction *pd*,
175 see Makowski, Ben-Shachar, Chen, et al., 2019).

176 Results

177 Effects of Illusion Strength and Task Difficulty

178 The best model specifications were $\log(\text{diff}) * \text{strength}$ for Delboeuf;
179 $\sqrt{\text{diff}} * \text{strength}$ for Ebbinghaus; $\log(\text{diff}) * \log(\text{strength})$ for Rod and Frame;
180 $\sqrt{\text{diff}} * \sqrt{\text{strength}}$ for Vertical-Horizontal; $\text{cbrt}(\text{diff}) * \text{strength}$ for Zöllner;
181 $\text{diff} * \sqrt{\text{strength}}$ and $\log(\text{diff}) * \text{strength}$ respectively for errors and RT in White;
182 $\sqrt{\text{diff}} * \sqrt{\text{strength}}$ and $\sqrt{\text{diff}} * \text{strength}$ respectively for errors and RT in
183 Müller-Lyer; $\text{cbrt}(\text{diff}) * \text{strength}$ for Ponzo; $\text{cbrt}(\text{diff}) * \sqrt{\text{strength}}$ and
184 $\text{cbrt}(\text{diff}) * \text{strength}$ respectively for errors and RT in Poggendorff; and
185 $\sqrt{\text{diff}} * \sqrt{\text{strength}}$ for Contrast. For all of these models, the effects of illusion
186 strength, task difficulty and their interaction were significant.

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

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

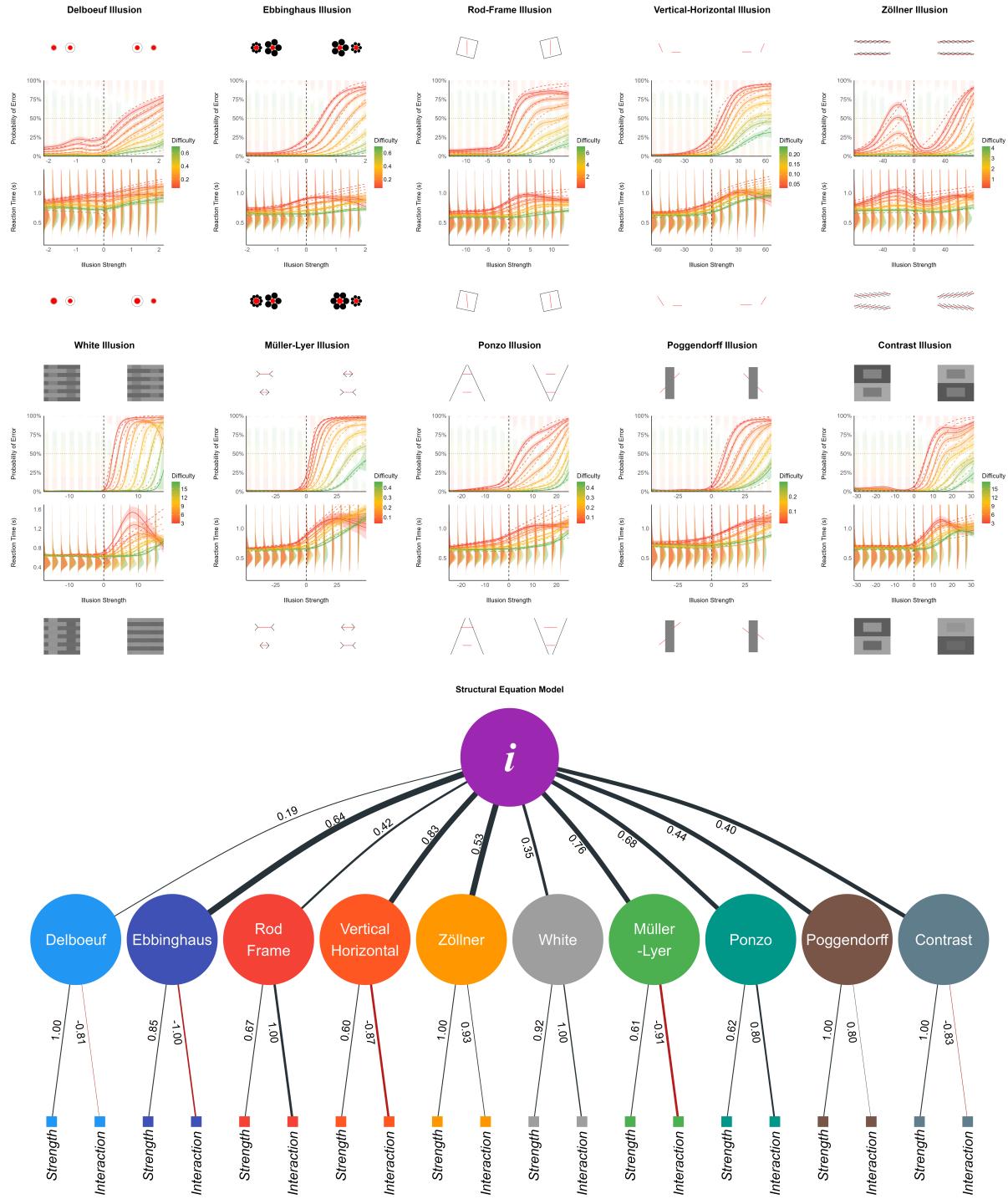


Figure 2. Top: the effect of illusion strength and task difficulty on the error rate and reaction time (RT) for each individual illusion. The solid line represents the General Additive Model (GAM), and the dashed line corresponds to its approximation via linear models. Descriptive data is shown with 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*).

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

199 Factor Structure

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

214 Finally, we tested this data-driven model (*m0*) against four other structural models
215 using structural equation modelling (SEM): one in which the two parameters of each of the
216 10 illusions (illusion strength and interaction with task difficulty) loaded on separate
217 factors, which then all loaded on a common factor (*m1*); one in which the parameters were
218 grouped by illusion type (lines, circles, contrast and angle) before loading on a common
219 factor (*m2*); one in which all the parameters related to strength, and all the parameters
220 related to the interaction loaded onto two respective factors, which then loaded on a

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

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

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

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

250 **Correlations with Inter-individual Characteristics**

251 The Bayesian correlation analysis (with narrow priors centered around a null effect)
252 between the illusion scores and contextual variables (screen size and refresh rate) provided
253 weak evidence in favor of an absence of effect, with the exception of the two contrast-based
254 illusions (**Figure 3**). Anecdotal ($BF_{10} = 2.05$) and moderate evidence ($BF_{10} = 4.11$) was
255 found for a negative correlation between screen size and the sensitivity to the White and
256 the Contrast illusion, respectively. To test whether this result could be an artifact related
257 to the highly skewed screen size distribution (caused by very few participants with extreme
258 screen sizes), we re-ran a robust correlation (with rank-transformed values), which provided
259 even stronger evidence in favor of the effect existence ($BF_{10} = 28.19$, $BF_{10} = 4.31$ for
260 White and Contrast, respectively).

261 The Bayesian t-tests on the effect of sex suggested anecdotal to moderate evidence in
262 favour of the null effect for all scores, with the exception of the sensitivity to the Zöllner
263 illusion, which was higher in males as compared to females ($\Delta = -0.37$, 95% CI [-0.62,
264 -0.13], $BF_{10} = 12.74$). We fitted Bayesian linear models with the education level entered as
265 a monotonic predictor (appropriate for ordinal variables, Bürkner & Charpentier, 2020),
266 which yielded no significant effects. For age, we fitted two types of models for each score,
267 one general additive models (GAM) and a 2nd order polynomial model. These consistently
268 suggested a significant positive linear relationship between age and Factor i ($pd = 100\%$),
269 as well as the sensitivity to Müller-Lyer ($pd = 100\%$), Vertical-Horizontal ($pd = 100\%$),
270 Zöllner ($pd = 100\%$) and Ebbinghaus ($pd = 99\%$) illusions.

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

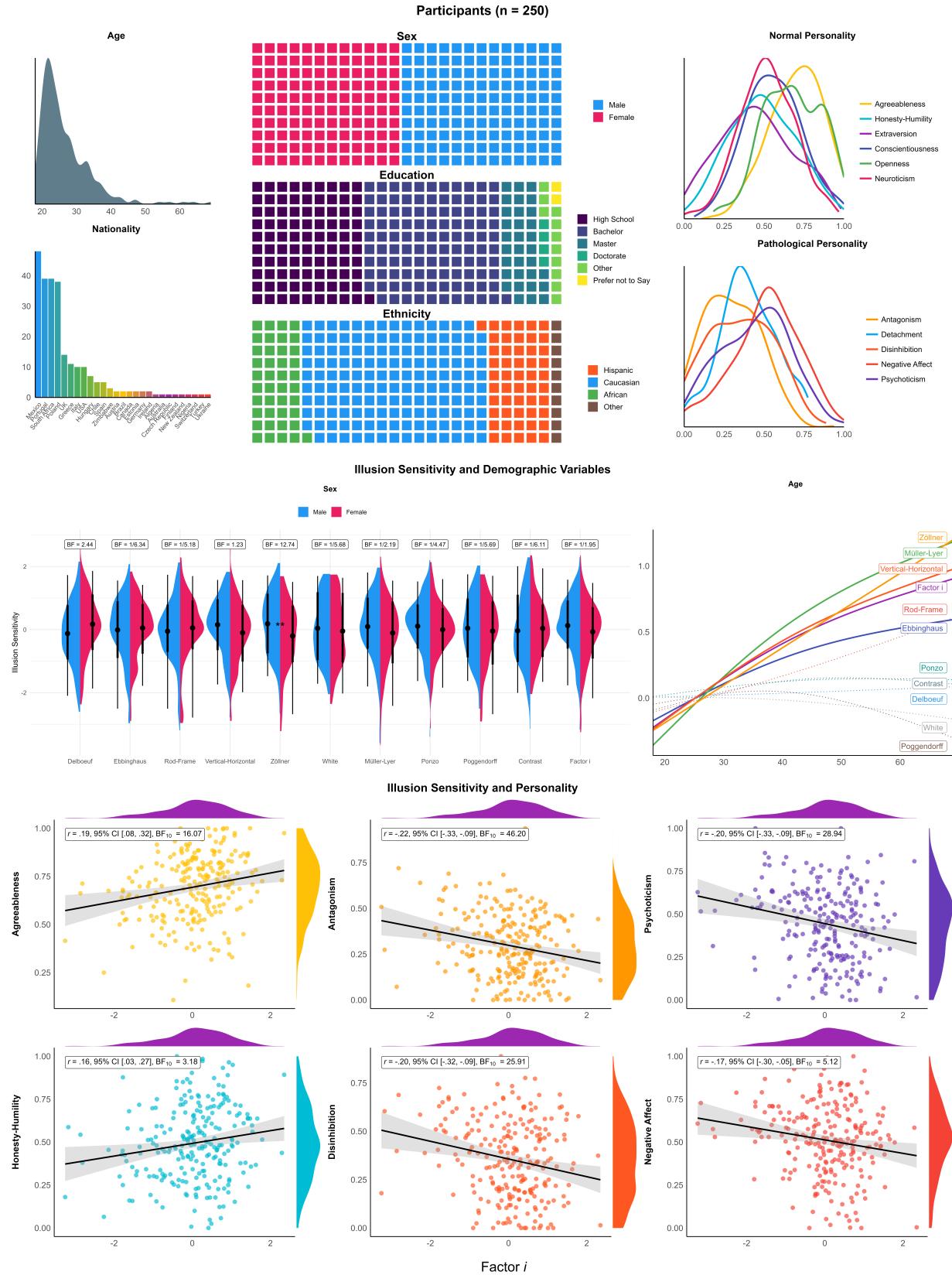


Figure 3. The upper plots show the distribution of demographic and dispositional variables. The middle plots shows the illusion sensitivity scores as a function of sex and age (solid lines indicate significant relationships). Bottom plots show the correlation between the general factor of illusion sensitivity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

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

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

Discussion

The parametric illusion generation framework developed in Makowski et al. (2021) proposes to conceptualize illusions as composed of targets and distractors that can be manipulated independently and continuously. In the present study, we have shown that such gradual modulation of illusion strength is effectively possible across 10 different types of classic visual illusions. Increasing the illusion strength led to an increase in error likelihood, as well as the average and spread of RTs (but only up to a point, after which participants become faster at responding with the wrong answer). Using mixed models, we were able to statistically quantify the effect of illusions for each illusion and each

298 participant separately. This important methodological step opens the door for new
299 illusions-based paradigms and tasks to study the effect of illusions under different
300 conditions and to measure illusion sensitivity using objective behavioral outcomes - such as
301 accuracy or speed - instead of subjective meta-cognitive reports. This new and
302 complementary approach will hopefully help address some of the longstanding literature
303 gaps, as well as cement illusions as valuable stimuli for the study of cognition.

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

319 However, although the illusions did differ in terms of the perceptual task
320 (contrast-based, size-estimation, angle-perception), the possibility of our general factor
321 being driven by inter-individual perceptual skills variability (or other cognitive skills)
322 cannot be discarded. Future studies should investigate the relationship of illusion
323 sensitivity with perceptual abilities (e.g., using similar tasks, but without illusions), and

324 assess the psychometric properties - such as stability (e.g., test-retest reliability) and
325 validity - of similar illusion-based paradigms.

326 Finally, we found the sensitivity to illusions to be positively associated with
327 “positive” personality traits, such as agreeableness and honesty-humility, and negatively
328 associated with maladaptive traits such as antagonism, psychoticism, disinhibition, and
329 negative affect. Although the existing evidence investigating links between illusion
330 sensitivity and personality traits is scarce, these results are consistent with past findings
331 relating pathological egocentric beliefs (often associated with psychoticism, Fox, 2006) to
332 reduced context integration, manifesting in a tendency to separate objects from their
333 surroundings when processing visual stimuli (Fox, 2006; Konrath et al., 2009; Ohmann &
334 Burgmer, 2016). As such, the association between maladaptive traits and lower illusion
335 sensitivity could be linked to a self-centered, decontextualized and disorganized information
336 processing style. Conversely, the relationship between illusion sensitivity and adaptive
337 personality traits is in line with the decreased field dependence (the tendency to rely on
338 external cues in ambiguous contexts) associated with traits negatively correlated with
339 agreeableness and honesty-humility, such as hostility, aggression and narcissism (Konrath
340 et al., 2009; Pessoa et al., 2008; Zhang et al., 2017).

341 Importantly, these findings highlight the relevance of illusions beyond the field of
342 visual perception, pointing towards an association with high-level domain-general
343 mechanisms. In particular, the evidence in favor of a relationship between maladaptive
344 personality traits and illusion sensitivity is in line with clinical observations, in which a
345 greater resistance to illusions have been reported among patients with schizophrenia
346 (Grzeczkowski et al., 2018; Notredame et al., 2014; Pessoa et al., 2008), especially in
347 association with schizotypal traits such as cognitive disorganization (Cretenoud et al., 2019;
348 Lányi et al., 2022). While the search for the exact mechanism(s) underlying these links is
349 an important goal of future research, our findings unlock the potential of illusion-based

350 tasks as sensitive tools to capture specific inter-individual neuro-cognitive differences.

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

355 **Acknowledgments**

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

358

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