

**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. 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: 3873

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

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

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

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

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

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

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

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

116 Following open-science standards, all the material (stimuli generation code,

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.

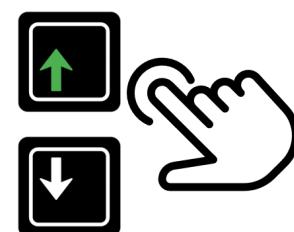


In this illusion, the **task difficulty** corresponds to the difference between the lengths of the red target segments, and the **illusion strength** corresponds to the angle of the arrows.

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.

117 experiment code, raw data, analysis script with complementary figures and analyses,
118 preregistration, etc.) is available as **Supplementary Materials** at
119 <https://github.com/RealityBending/IllusionGameValidation>.

120 **Methods**

121 **Stimuli**

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

135 **Procedure**

136 After a brief demographic survey and a practice series of illusions, the first series of
137 10 illusion blocks was presented in a randomized order, with a further randomization of the
138 stimuli order within each block. Following this first series of blocks, two personality
139 questionnaires were administered, the *IPIP6* (24 items, Sibley et al., 2011) - measuring 6
140 “normal” personality traits (Extraversion, Openness, Conscientiousness, Agreeableness,
141 Neuroticism and Honesty-Humility), and the *PID-5* (25 items, Hopwood et al., 2012) -

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

Participants

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

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

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 reaction 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 μ (mean), scale σ (spread) and tail-dominance τ
¹⁷⁵ of the RT distribution (Balota & Yap, 2011; Matzke & Wagenmakers, 2009).

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 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
¹⁸⁹ refresh rate), demographic variables (sex, education, age), and personality traits.

¹⁹⁰ The analysis was carried out using *R* 4.2 (R Core Team, 2022), *brms* (Bürkner,

¹⁹¹ 2017), the *tidyverse* (Wickham et al., 2019), and the *easystats* collection of packages
¹⁹² (Lüdecke et al., 2021, 2019; Makowski et al., 2020; Makowski, Ben-Shachar, & Lüdecke,
¹⁹³ 2019). As the full results are available as supplementary materials, we will focus here on
¹⁹⁴ the significant results (based on the Bayes Factor *BF* or the Probability of Direction *pd*,
¹⁹⁵ see Makowski, Ben-Shachar, Chen, et al., 2019).

¹⁹⁶ **Results**

¹⁹⁷ **Effects of Illusion Strength and Task Difficulty**

¹⁹⁸ The best model specifications were $\log(\text{diff}) * \text{strength}$ for Delboeuf;
¹⁹⁹ $\sqrt{\text{diff}} * \text{strength}$ for Ebbinghaus; $\log(\text{diff}) * \log(\text{strength})$ for Rod and Frame;
²⁰⁰ $\sqrt{\text{diff}} * \sqrt{\text{strength}}$ for Vertical-Horizontal; $\text{cbrt}(\text{diff}) * \text{strength}$ for Zöllner;
²⁰¹ $\text{diff} * \sqrt{\text{strength}}$ and $\log(\text{diff}) * \text{strength}$ respectively for errors and RT in White;
²⁰² $\sqrt{\text{diff}} * \sqrt{\text{strength}}$ and $\sqrt{\text{diff}} * \text{strength}$ respectively for errors and RT in
²⁰³ Müller-Lyer; $\text{cbrt}(\text{diff}) * \text{strength}$ for Ponzo; $\text{cbrt}(\text{diff}) * \sqrt{\text{strength}}$ and
²⁰⁴ $\text{cbrt}(\text{diff}) * \text{strength}$ respectively for errors and RT in Poggendorff; and
²⁰⁵ $\sqrt{\text{diff}} * \sqrt{\text{strength}}$ for Contrast. For all of these models, the effects of illusion
²⁰⁶ strength, task difficulty and their interaction were significant.

²⁰⁷ For error rates, most of the models closely matched their GAMs counterpart, with
²⁰⁸ the exception of Delboeuf (for which the GAM suggested a non-monotonic effect of illusion
²⁰⁹ strength with a local minimum at 0) and Zöllner (for which theoretically congruent illusion
²¹⁰ effects were related to increased error rate). A specific discussion regarding these 2 illusions
²¹¹ is available in the Supplementary Materials (Part 1 - Discussion).

²¹² For RTs, the GAMs suggested a consistent non-linear relationship between RT and
²¹³ illusion strength: as the illusion strength increases beyond a certain threshold, the
²¹⁴ participants responded faster. While this is not surprising (strong illusions are likely so
²¹⁵ effective in biasing perception that it is “easier”, i.e., faster, to make the wrong decision),

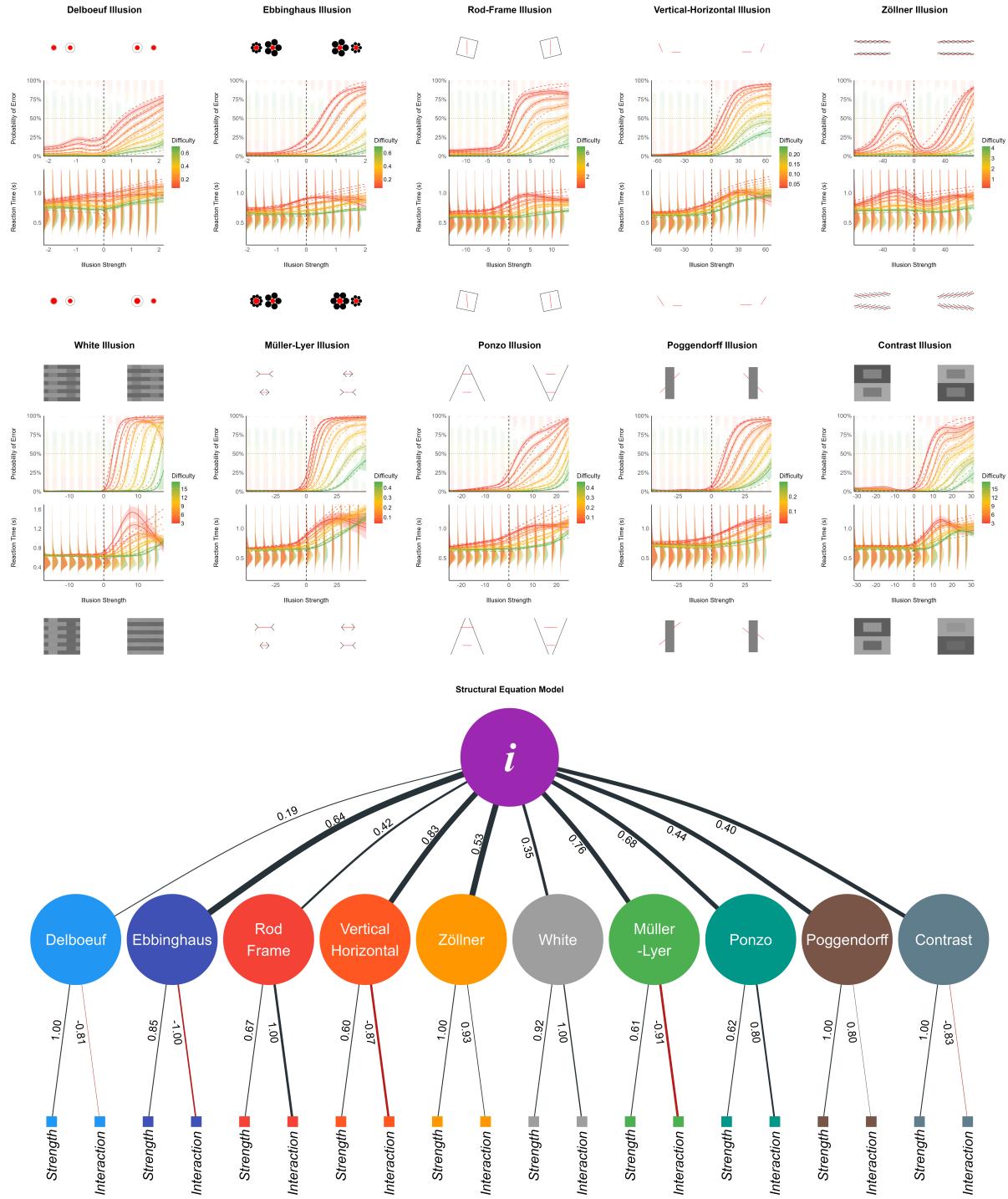


Figure 2. Top: the effect of illusion strength and task difficulty on the error rate and reaction time (RT) for each individual illusion. The solid line represents the General Additive Model (GAM), and the dashed line corresponds to its approximation via linear models. Descriptive data is shown with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

216 the linear models were not designed to capture this - likely quadratic - pattern and hence
217 are not good representatives of the underlying dynamics. As such, we decided not to use
218 them for the individual scores analysis.

219 **Factor Structure**

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

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

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

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

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

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

270 **Correlations with Inter-individual Characteristics**

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

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

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

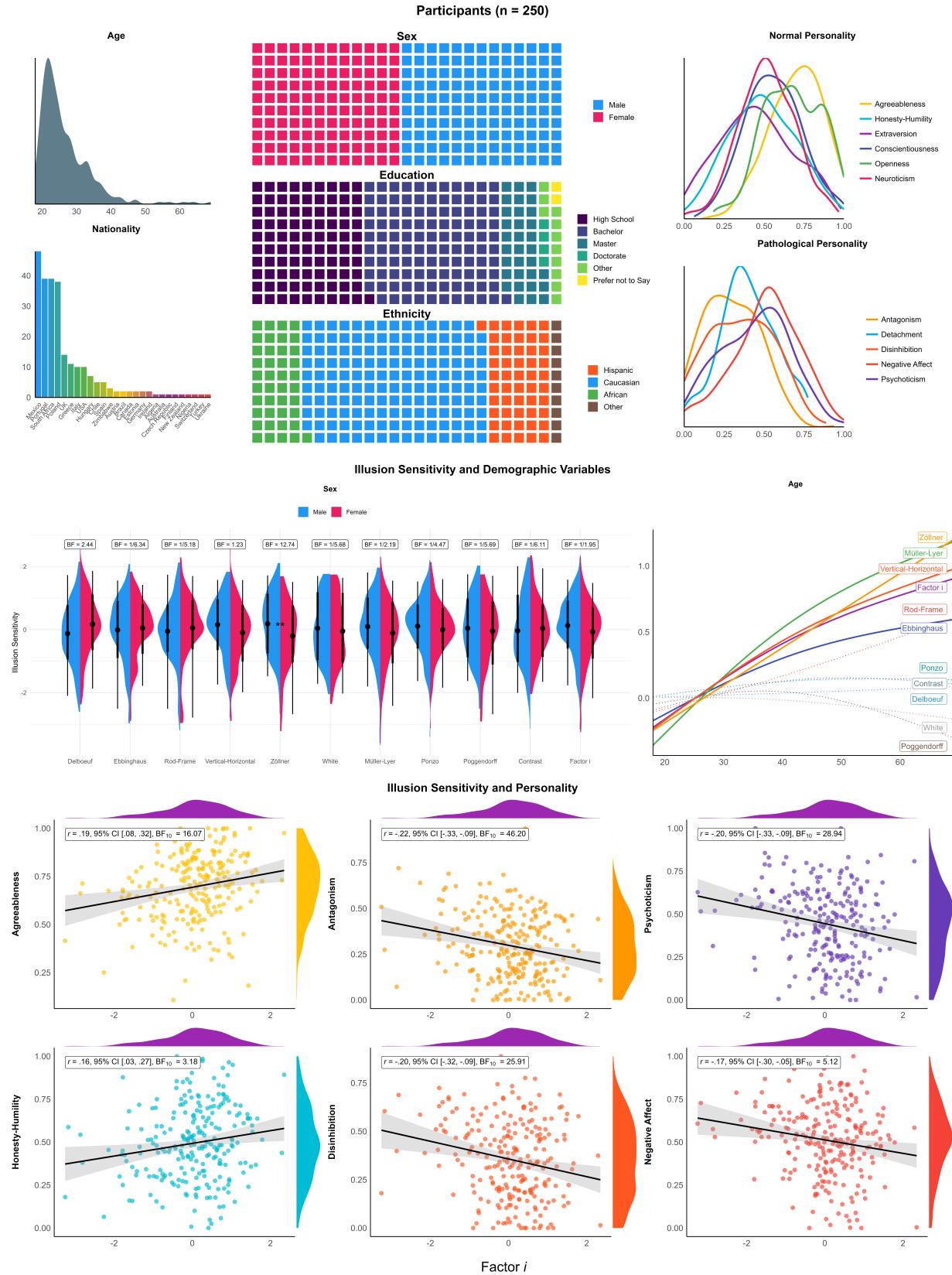


Figure 3. The upper plots show the distribution of demographic and dispositional variables. The middle plots shows the illusion sensitivity scores as a function of sex and age (solid lines indicate significant relationships). Bottom plots show the correlation between the general factor of illusion sensitivity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

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

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

309 Discussion

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

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

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

339 However, although the illusions did differ in terms of the perceptual task
340 (contrast-based, size-estimation, angle-perception), the possibility of our general factor
341 being driven by inter-individual perceptual skills variability (or other cognitive skills)
342 cannot be discarded. Future studies should investigate the relationship of illusion
343 sensitivity with perceptual abilities (e.g., using similar tasks, but without illusions), and
344 assess the psychometric properties - such as stability (e.g., test-retest reliability) and

345 validity - of similar illusion-based paradigms.

346 Finally, we found the sensitivity to illusions to be positively associated with
347 “positive” personality traits, such as agreeableness and honesty-humility, and negatively
348 associated with maladaptive traits such as antagonism, psychoticism, disinhibition, and
349 negative affect. Although the existing evidence investigating links between illusion
350 sensitivity and personality traits is scarce, these results are consistent with past findings
351 relating pathological egocentric beliefs (often associated with psychoticism, Fox, 2006) to
352 reduced context integration, manifesting in a tendency to separate objects from their
353 surroundings when processing visual stimuli (Fox, 2006; Konrath et al., 2009; Ohmann &
354 Burgmer, 2016). As such, the association between maladaptive traits and lower illusion
355 sensitivity could be linked to a self-centered, decontextualized and disorganized information
356 processing style. Conversely, the relationship between illusion sensitivity and adaptive
357 personality traits is in line with the decreased field dependence (the tendency to rely on
358 external cues in ambiguous contexts) associated with traits negatively correlated with
359 agreeableness and honesty-humility, such as hostility, aggression and narcissism (Konrath
360 et al., 2009; Pessoa et al., 2008; Zhang et al., 2017).

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

371 In conclusion, we strongly invite researchers to explore and re-analyze our dataset

372 with other approaches and methods to push the understanding of visual illusions and

373 illusion sensitivity further. The task, data and analysis script are available in open-access

374 at **<https://github.com/RealityBending/IllusionGameValidation>**.

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378

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