

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

Dominique Makowski¹

¹ School of Social Sciences, Nanyang Technological University, Singapore

Author Note

Correspondence concerning this article should be addressed to Dominique Makowski,
HSS 04-18, 48 Nanyang Avenue, Singapore (dom.makowski@gmail.com).

Correspondence concerning this article should be addressed to Dominique Makowski,
HSS 04-18, 48 Nanyang Avenue, Singapore. E-mail: dom.makowski@gmail.com

11

Abstract

12 Abstract abstract. We invite researchers to re-analyze our open-access data to provide
13 complimentary evidence (or absence thereof) on the effect and structure of illusion
14 sensitivity.

15 *Keywords:* visual illusions, illusion game, pyllusion, illusion effect, personality

16 Word count: 1156

17 **The Illusion Game: A Novel Experimental Paradigm provides Evidence in**
18 **Favour of a General Factor of Visual Illusion Sensitivity and Pathological**
19 **Personality Correlates**

20 **Introduction**

21 Visual illusions are fascinating stimuli capturing a key feature of our neurocognitive
22 systems. They eloquently show that our brains did not evolve to be perfect perceptual
23 devices providing veridical accounts of physical reality, but to integrate prior knowledge
24 and contextual information - blended together in our subjective conscious experience
25 (Carbon, 2014). Despite the historical and intensive interest within the fields of visual
26 perception (Day, 1972; Eagleman, 2001; Gomez-Villa et al., 2022), consciousness science
27 Lamme (2020), and psychiatry (Gori et al., 2016; Notredame et al., 2014; Razeghi et al.,
28 2022; Teufel et al., 2015), several important issues remain open.

29 Notably, the presence of a common mechanism underlying the effect of different
30 illusions has been contested (Cretenoud et al., 2020, 2019a; Hamburger, 2016; Teufel et al.,
31 2018b); and the nature of the underlying processes - whether related to low-level features
32 of the visual processing system (Cretenoud et al., 2019b; Gori et al., 2016) or to top-down
33 influences of prior beliefs (Caporuscio et al., 2022; Teufel et al., 2018a) are strongly
34 debated. The existence of dispositional correlates of illusion sensitivity - for example,
35 higher illusion resistance has been reported in schizophrenia and autism (Giaouri &
36 Alevriadou, 2011; Keane et al., 2014; Notredame et al., 2014; Park et al., 2022) or **Insert**
37 **some demographic / personality feature [REF]** - is another area of controversy.

38 One key challenge hindering the further development of illusion research is the
39 relative difficulty in adapting visual illusions to an experimental setting, which typically
40 requires the controlled modulation of the specific variables of interest. To address this
41 issue, we first developed a parametric framework to manipulate visual illusions, which we
42 implemented and made accessible in the open-source software *Pyillusion* (Makowski et al.,

43 2021a). This software allows us to generate different types of classic visual illusions (e.g.,
 44 Müller-Lyer, Ponzo, Delboeuf, Ebbinghaus) with a continuous and independent modulation
 45 of two parameters, *illusion strength* and *task difficulty* (see **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**
(upper 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**
(upper 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.

46 Indeed, many visual illusions can be seen as being composed of *targets* (e.g.,
 47 same-length lines), of which perception is biased by the *context* (e.g., in the Müller-Lyer
 48 illusion, the same-length line segments appear to have different lengths when they end with
 49 inwards or outwards pointing arrows). Past illusion studies traditionally employed
 50 paradigms focusing on participants' subjective experience, by asking them to what extent
 51 they perceive two identical targets as different (*REF*), or having them adjust the targets to
 52 a reference stimulus relying only on their perception (Grzeczkowski et al., 2018; Mylniec &
 53 Bednarek, 2016a). Alternatively, *Pyllusions* allows to create illusions in which the targets
 54 are objectively different (e.g., one segment is truly more or less longer than the other), and

55 in which the illusion varies in strength (the biasing angle of the arrows is more or less
56 acute).

57 This opens the door for an experimental task in which participants have to make
58 perceptual judgments about the targets (e.g., which segment in the longest) under different
59 conditions of objective difficulty and illusion strength. Moreover, the illusion effect can be
60 either “incongruent” (making the task even harder by biasing the perception in the
61 opposite way) or “congruent” (making the task easier). Although visual illusions are
62 inherently tied to subjective perception, this framework allows a reversal of the traditional
63 paradigm to potentially quantify the “objective” effect of illusions by measuring its
64 behavioral effect (error rate and reaction times) on the performance in a perceptual task.

65 In the present set of preregistered studies, we will first test this novel paradigm by
66 investigating if the effect of illusion and task difficulty can be manipulated continuously,
67 and separated statistically. Then, we will further utilize the paradigm to assess whether 10
68 different classic illusions (Delboeuf, Ebbinghaus, Rod and Frame, Vertical-Horizontal,
69 Zöllner, White, Müller-Lyer, Ponzo, Poggendorff, Contrast) share a common latent factor.
70 Finally, we will investigate how the inter-individual sensitivity to illusions relates to
71 dispositional variables, such as demographic characteristics and personality.

72 In line with total open-science standards, all the material (stimuli generation code,
73 experiment code, raw data, analysis script with complementary figures and analyses,
74 preregistration, etc.) is available at
75 <https://github.com/RealityBending/IllusionGameValidation>.

76 Study 1

77 Aim

78 Study 1 can be seen as a pilot experiment aiming at gathering some preliminary data
79 to assess if the stimuli generated by *Pyllusion* behaves as expected for each of the 10

80 illusion types (i.e., whether an increase of task difficulty and illusion strength leads to an
81 increase of errors); and develop an intuition about the magnitude of effects, to refine for
82 the next study the stimuli parameters to a more sensible range (i.e., not overly easy and
83 not impossibly hard).

84 **Procedure**

85 We generated 56 stimuli for each of the 10 illusion types. These stimuli resulted from
86 the combination of 8 linearly-spread levels levels of task difficulty (e.g., [1, 2, 3, 4, 5, 6, 7],
87 where 1 corresponds to the higher difficulty - i.e., the smallest objective difference between
88 targets) and 7 levels of illusion strength (3 values of strength on the congruent side, 3 on
89 the incongruent side, and 0; e.g., [-3, -2, -1, 0, 1, 2, 3], where negative values correspond to
90 congruent illusion strengths).

91 The 10 illusion blocks were randomly presented, and the order of the 56 stimuli
92 within the blocks was also randomized. After the first series of 10 blocks, another series
93 was done (with new randomized order of blocks and trials). In total, each participant saw
94 56 different trials per 10 illusion type, repeated 2 times (total = 1120 trials), to which they
95 had to respond “as fast as possible without making errors” (i.e., an explicit double
96 constraint to mitigate the inter-individual variability in the speed-accuracy trade off). The
97 task was implemented using *jsPsych* (De Leeuw, 2015). The instructions for each illusion
98 type are available in the experiment code.

99 **Participants**

100 Fifty-two participants were recruited via *Prolific* (www.prolificacademic.co.uk), a
101 crowd-sourcing platform providing high data quality (Peer et al., 2022). The only inclusion
102 criterion was a fluent proficiency in English to ensure that the task instructions would be
103 well-understood. Participants were incentivised with a reward of about £7.5 for completing
104 the task, which took about 50 minutes to finish.

We removed 6 participants upon inspection of the average error rage (when close to 50%, suggesting random answers), and when the reaction time distribution was implausibly fast. For the remaining participants, we discarded blocks where the error rate was higher than 50% (possibly indicating that instructions got misunderstood; e.g., participants were selecting the shorter line instead of the longer one). Finally, we removed 692 (1.37%) trials based on an implausibly short or long response time (< 150 ms or > 3000 ms).

The final sample included 46 participants (Mean age = 26.7, SD = 7.7, range: [19, 60]; Sex: 39.1% females, 56.5% males).

113 Data Analysis

The analysis of study 1 focused on the probability of errors as the main outcome variable. For each illusion, we started by visualizing the average effect of task difficulty and illusion strength to gain some intuition on the underlying generative model. Next, we tested the performance of various logistic models differing in their specifications, such as: with or without a transformation of the task difficulty (log, square root or cubic root), with or without a 2nd order polynomial term for the illusion strength, and with or without the illusion side (up *vs.* down or left *vs.* right) as an additional predictor. We then fitted the best performing model under a Bayesian framework, and compared its visualization with that of a General Additive Model (GAM), which has an increased ability of mapping underlying potentially non-linear relationships (at the expense of model simplicity).

The analysis was carried out using *R 4.2* (R Core Team, 2022), *brms* (Bürkner, 2017), the *tidyverse* (Wickham et al., 2019), and the *easystats* collection of packages (Lüdecke et al., 2021, 2019; Makowski et al., 2020, 2019).

127 Results

The statistical models suggested that the effect of task difficulty had a cubic relationship with error rate for the Delboeuf and Ebbinghaus illusions (both composed of

130 circular shapes), square relationship for the Rod and Frame and Vertical-Horizontal
131 illusions, cubic relationship for the Zöllner and Poggendorff illusions, exponential
132 relationship for the White illusion, cubic relationship for the Müller-Lyer and Ponzo
133 illusions (both based on line lengths), and linear relationship for the Contrast illusion. All
134 models suggested a significant effect of illusion strength and task difficulty. See details and
135 figures in the analysis script.

136 **Discussion**

137 This study provided a clearer understanding of the magnitude of the parametric
138 effects at stake and the type of interaction between them. Furthermore, it allowed us to
139 better understand and test the stimuli generated by *Pyllusion*, as well as uncover technical
140 bugs and issues (for instance, the specification direction of the illusion strength was
141 reversed for a few illusions), which were fixed by a new software release. Crucially, this
142 study allowed us to refine the range of task difficulty and illusion strength values in order
143 to maximize information gain.

144 In most illusions, the task difficulty exhibited monotonic power-law scaled effects,
145 which is in line with the psychophysics literature on perceptual decisions (Bogacz et al.,
146 2006; Ditzinger, 2010; Shekhar & Rahnev, 2021). One notable result was the illusion effect
147 pattern for the Zöllner illusion, which suggested a non-linear relationship. By generating a
148 wider range of illusion strength values, the next study will attempt at clarifying this point.

149 **Study 2**

150 **Aim**

151 The aim of study 2 was two-fold. In the first part, we carefully modeled the error rate
152 and the reaction time of each illusion type in order to validate our novel paradigm and
153 show that the effect of illusions can be manipulated continuously. In the second part, we
154 derived the participant-level scores from the models (i.e., the effect of illusion strength for

155 each individual) and analyzed their latent factors structure.

156 **Procedure**

157 The paradigm of study 2 was similar to that of study 1, with the following changes.

158 The illusory stimuli were re-generated within a refined space of parameters based on the
159 results of study 1. Moreover, taking into account the findings of study 1, we used
160 non-linearly spaced difficulty levels, depending on the best underlying model (i.e., with an
161 exponential, square or cubic spacing depending on the relationship). For instance, a linear
162 space of [0.1, 0.4, 0.7, 1.0] can be transformed to an exponential space of [0.1, 0.34, 0.64,
163 1.0].

164 Additionally, instead of repeating each stimulus two times, we generated illusions
165 using more levels of difficulty and illusion strength. As such, for each illusion type, we
166 generated a total of 134 stimuli that were split into two groups (67 stimuli per illusion
167 block). Furthermore, instead of a simple break screen, we added two personality
168 questionnaires between the two series of 10 illusion blocks (see study 3).

169 **Participants**

170 Using the same recruitment procedure as in study 1, we recruited 256 participants,
171 within which 6 were identified as outliers and excluded, leaving a final sample of 250
172 participants (Mean age = 26.5, SD = 7.6, range: [18, 69]; Sex: 48% females, 52% males).
173 Please see study 3 for the full demographic breakdown. We discarded blocks with more
174 than 50% of errors (2.16% of trials) and 0.76% trials with extreme response times (< 125
175 ms or > 4 SD above mean).

176 **Data Analysis**

177 The first part of the analysis focused on modelling the effect of illusion strength and
178 task difficulty on errors and reaction time (RT), within each illusion. In order to achieve

that, we started by fitting General Additive Models (GAMs), which can accommodate possible non-linear effects and interactions. Errors were analyzed using Bayesian logistic mixed models, and RTs of correct responses were analyzed using an ex-Gaussian family with the same fixed effects entered for the location μ (mean), scale σ (spread) and tail-dominance τ of the RT distribution (Balota & Yap, 2011; Matzke & Wagenmakers, 2009).

Using the GAMs as a “ground-truth”, we attempted at approximating them using general linear models, which have the advantage of estimating the participant-level variability of the effects (via random slopes). Following a comparison of models with a combination of transformations (raw, log, square root or cubic root) on the main predictors (task *difficulty* and illusion *strength*), we selected and fitted the best model (best on their indices of fit), and compared their output visually (see **Figure 2**).

We then extracted the inter-individual variability in the effect of illusion strength and its interaction with task difficulty, and used it as participant-level scores. Finally, We explored the relationship of these indices across different illusions using exploratory factor analysis (EFA) and structural equation modelling (SEM).

Results

The best models 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; $\sqrt{\text{diff}} * \sqrt{\text{strength}}$ for Contrast. In all of these models, the effects of illusion strength, task difficulty and their interaction were

204 significant.

205 For errors, most of the models closely matched their GAMs counterpart (see **Figure**
206 **2**), with the exception of Delboeuf (for which the GAM suggested a non-monotonic effect
207 of illusion strength with a local minimum at 0) and Zöllner, in which theoretically
208 congruent illusion effects were related to increased error rate.

209 For RTs, the GAMs suggested a consistent non-linear relationship between RT and
210 illusion strength: as the illusion strength increase beyond a certain threshold, the
211 participants respond faster. While this is not surprising (strong illusions are likely so
212 effective in biasing perception that it is “easier”, i.e., faster, to make the wrong decision),
213 the linear models were not designed to capture this - likely quadratic - pattern and hence
214 are not good representatives of the underlying dynamics. As such, we decided not to use
215 add them for the individual scores analysis.

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

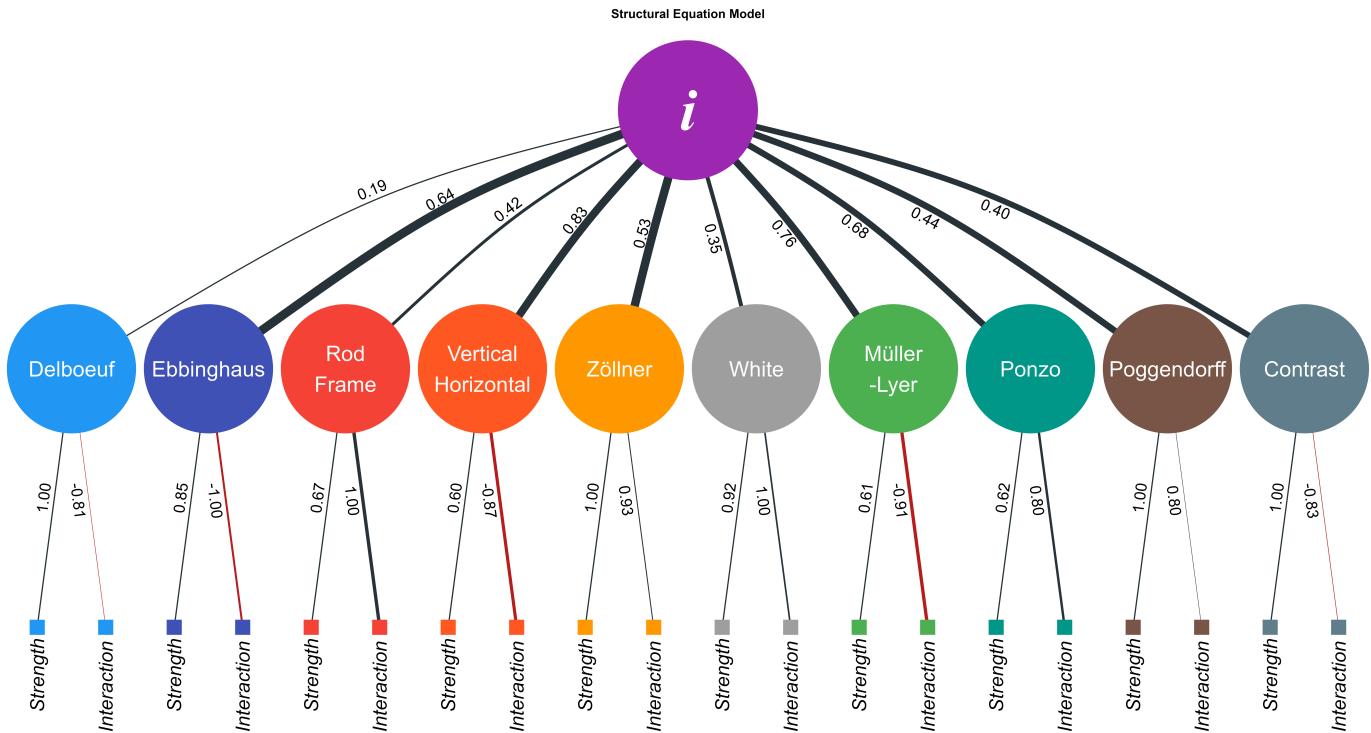
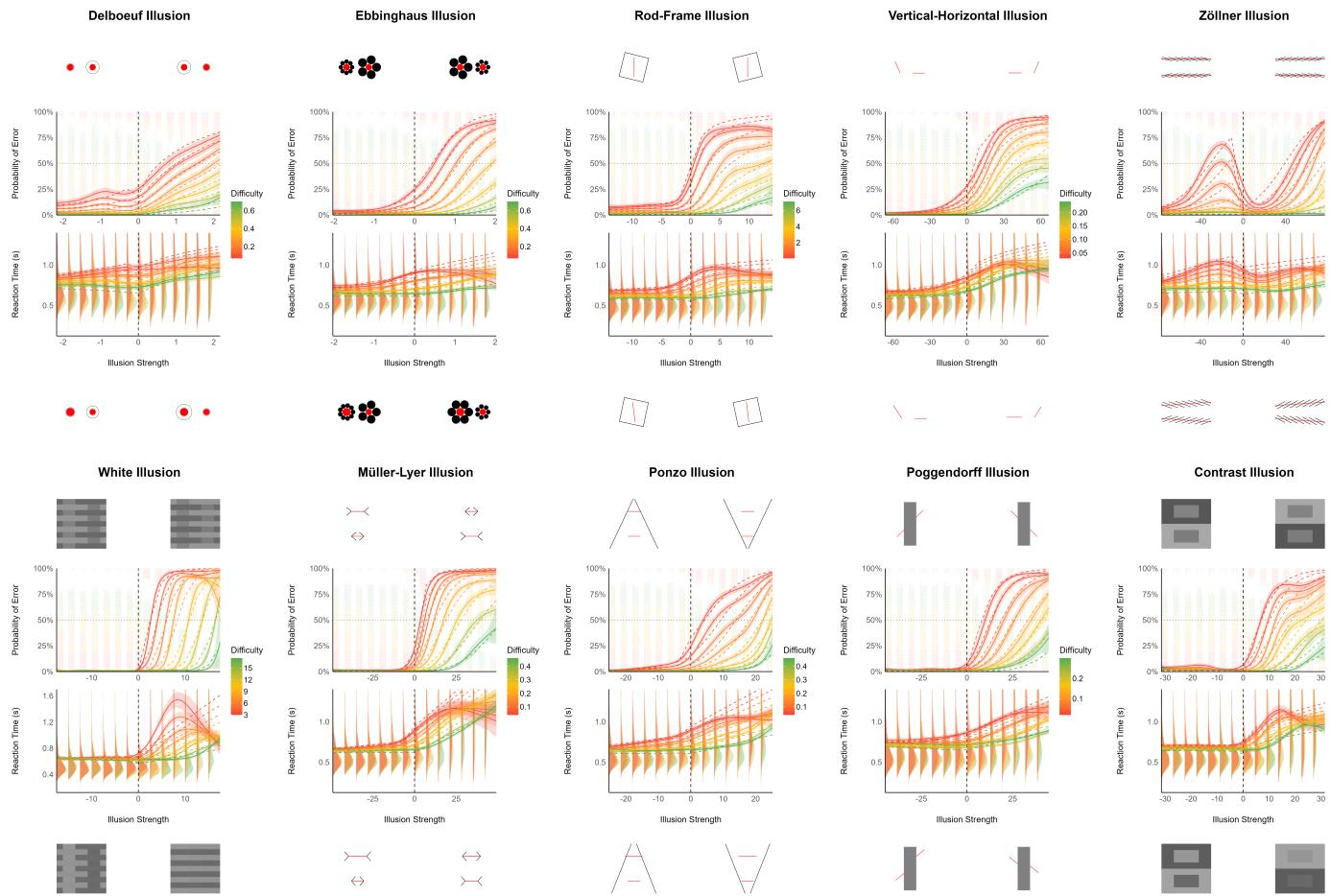


Figure 2. CAPTION.

Finally, we tested this data-driven model ($m0$) against four other structural models using structural equation modelling (SEM): one in which the two parameters of each of the 10 illusions (illusion strength and interaction with task difficulty) loaded on separate factors, which then all loaded on a common factor ($m1$); one which the parameters were grouped by illusion type (lines, circles, contrast and angle) before loading on a common factor ($m2$); one in which all the parameters related to strength, and all the parameters 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 were ranging 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, and positively 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, its score for the 10 illusion-specific factors and for the general Factor i .

We have to keep in mind 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);

255 2) we only used the models on error rate, which could be biased by the speed-accuracy
256 decision criterion used by participants; 3) the structural equation model used to compute
257 the scores also incorporated multiple levels of abstractions. Thus, in order to validate the
258 individual scores, we computed the correlation between them and simple empirical scores,
259 such as the average error rate and the mean RT in the task. This analysis revealed strong
260 and significant correlations between each illusion-specific factor and the average amount of
261 errors in its respective task. Moreover, each individual score was strongly associated with
262 the average RT across multiple illusion types. This suggests that the individual scores
263 obtained from the structural equation model do capture the sensitivity of each participant
264 to visual illusions, manifesting in both the amount of errors and high reaction times.

265 Discussion

266 This study confirmed that it was possible to manipulate continuously the effect of
267 illusion strength for 10 classical illusions. Increasing the illusion strength increased the
268 likelihood of errors, as well as the average and spread of RTs (but only up to a point, after
269 which participants become faster at responding with the wrong answer). Future studies are
270 needed to explore reaction times and try to identify the most appropriate models, and / or
271 use models that integrate errors and reaction time (e.g., drift diffusion models).

272 The effect on errors was monotonic for most illusions, but Delboeuf and Zöllner. For
273 both of them, mildly congruent illusion strengths (which theoretically were supposed to be
274 associated with less errors than incongruent effects) were related to a slight and strong
275 increase of errors, respectively. For Delboeuf, we believe that it was an artifact caused by
276 illusion generation algorithm: the outline of the target circles was always created as slightly
277 bigger, which made the difference between them more obvious at an illusion strength of 0.
278 This was fixed in latest release of *Pyllusion* (v1.2), which now generate outlines of the same
279 size as the target circle. For Zöllner, however, we did not find a good explanation of the
280 pattern. **TODO: is there some explanation that we can find in the literature?**

281 Finally, this study provided evidence for both the existence of illusion-specific factors,
282 as well as for a common latent factor (labelled Factor *i*) that explained about half of the
283 total variance. These participant-level scores were related to the error rate and average
284 reaction time, and can thus be interpreted as indices of illusion sensitivity.

285 **Study 3**

286 **Aim**

287 **Procedure**

288 This study was based on the data collected in study 2. However, the variables of
289 interest here were taken from the questionnaires that were inserted in between the two
290 series of illusion blocks. We used the *IPIP6* (24 items; (Sibley et al., 2011)) to measure 6
291 personality traits (namely, extraversion, openness, conscientiousness, agreeableness,
292 neuroticism and honesty-humility). On the other hand, the PID-5 (25 items; (Hopwood et
293 al., 2012)) was used to measure the degree to which participants inhibit psychopathological
294 personality traits (disinhibition, antagonism, detachment, negative affect and
295 psychotism). The participants were the same as in study 2. However, due to a technical
296 issue, no data on the personality questions are available for the first eight participants.

297 **General Discussion**

298 Using the parametric illusion generation framework we developed, Pyllusion
299 (Makowski et al., 2021b), we have hence shown that illusions can be manipulated
300 continuously across several different visual illusions. This opens the door for new
301 illusions-based paradigms and tasks, therefore making it possible for future researchers to
302 directly manipulate specific features and parameters of the illusion that are of interest. The
303 validation of this novel framework also affords future illusion scientists a standardized
304 measure of illusion susceptibility, instead of relying on conventional methods that depend
305 upon participants' subjective perceptions. In our paradigm, in which we apply this

306 approach to a reaction-time task, we were able to measure inter-individual scores of
307 objective illusion sensitivity.

308 Most notably, there is currently no universally agreed upon neurocognitive
309 mechanism that explains individuals' susceptibility to visual illusions (Mylniec &
310 Bednarek, 2016b). For instance, while some researchers have tried to explain our sensitivity
311 to illusory effects as a result of deficits in the low-level visual processing system (Cretenoud
312 et al., 2019b; Gori et al., 2016), others have provided a compelling case using a top-down
313 approach, suggesting that such visual phenomena occur as a result of a conflict between
314 our visual input and our prior beliefs(Caporuscio et al., 2022; Teufel et al., 2018a).

315 Furthermore, results from studies that have been conducted to elucidate the
316 mechanism underlying our susceptibility towards visual illusions remain relatively mixed.
317 Whereas higher resistance towards such illusions have been reported for individuals with
318 pathologically strong prior beliefs (such as schizophrenics) and atypical sensory perception
319 (for example, those with autism spectrum disorder [ASD]) (Giaouri & Alevriadou, 2011;
320 Keane et al., 2014; Notredame et al., 2014; Park et al., 2022), other studies have found no
321 significant differences between such individuals and healthy controls (Kaliuzhna et al.,
322 2019; Spencer & Ghorashi, 2014; Tibber et al., 2013; Yang et al., 2012) or only a weak
323 correlation between the magnitude of visual illusions and such individuals' susceptibility to
324 these illusory effects (Grzeczkowski et al., 2018; Manning et al., 2017).

325 Future Directions

326 We strongly invite researchers to explore and re-analyze our dataset with other
327 approaches and methods to push the understanding of visual illusions and illusion
328 sensitivity further. The task, data and analysis script are available in open-access at
329 <https://github.com/RealityBending/IllusionGameValidation>.

330

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333

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