Introducing the Choice-Confidence (CHOCO) Model for Bimodal Data from Subjective Ratings: Application to the Effect of Attractiveness on Reality Beliefs about AI-Generated Faces

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We introduce the Choice-Confidence (CHOCO) model as a tool to dissect the cognitive mechanisms underlying decision-making judgments, offering a better fit for data from subjective rating scales for which the two extremes correspond to discrete choices (e.g., “positive” *vs.* “negative”, “true” *vs.* false”, “real” *vs.* “AI-generated”, …), and for which the distance from the center might reflect a gradual process, such as confidence or certainty in that choice. Conceptualized as a mixture of two Beta distributions, CHOCO simultaneously estimates the probability of selecting one category (the right side of the scale over the left side) and the confidence associated with each choice. To demonstrate its usage, we apply this model to two datasets (N=141 and N=189) in which participants judged whether face images were real photographs or AI-generated images, finding that facial attractiveness increased the likelihood of being judged as “real”, particularly for male participants. As AI-generated content becomes increasingly indistinguishable from real stimuli, understanding how individuals form beliefs about the reality of what they perceive is both theoretically and practically urgent. We discuss how these findings relate to the broader effect of facial attractiveness, and suggest future directions for both the cognitive and psychometric application of the CHOCO framework.

Keywords: subjective scales, choice confidence model, reality beliefs, AI-generated faces, attractiveness, simulation monitoring, zero-and-one inflated Beta regression

Introduction

Despite significant advancements in psychological science following the replication crisis (Collaboration, 2015), its progress is still hindered by its sub-optimal (or inappropriate) usage of statistical tools (Blanca et al., 2018; Cumming, 2014; Makowski & Waggoner, 2023). A prevalent issue is the continued reliance on linear models that assume normally distributed (Gaussian) data[1] - as this assumption often does not hold true for many types of psychological outcomes. For instance, reaction times typically exhibit skewed distributions, choices can be represented as binary variables, and count data consist of strictly positive integers. Applying models that presume normality and model the “mean” of the outcome variable can lead to misinterpretation and potentially misleading conclusions when applied indiscriminately. It is thus important that psychologists use models that can best describe (or generate) the data they collect, to exploit them fully and bring more nuance and accuracy to their conclusions.

Among the most commonly collected data in psychology are responses on subjective scales, such as Likert-type items or visual analog scales, which exhibit some fundamental properties: these responses are bounded (and can be rescaled to a 0-1 range) and frequently display clustering at the extremes. Traditional linear models being ill-suited for such data, researchers have turned to using Beta distributions to model these data (instead of Gaussian), suited for continuous data within the (0,1) interval (i.e., excluding extreme responses). To address the frequent occurrence of exact zeros and ones (i.e., extreme values), zero-one inflated beta (ZOIB) models have been developed (Ospina & Ferrari, 2012) to accommodate the excess of boundary values by incorporating additional components that model the probabilities of responses at 0 and 1 as a separate, independent process.

The Beta-Gate Model

The Beta-Gate model is a reparametrized Ordered Beta model (Kubinec, 2023)[2] available in the *cogmod* package in R (https://github.com/DominiqueMakowski/cogmod), in which participants’ answers on bounded scales are conceptualized as latent responses that can fall past a pair of probabilis-

[1]More specifically, that the outcome is distributed according to a Normal distribution which parameters are expressed as a linear function of the predictors.

[2]In the Ordered Beta model, the cutpoints on the log-scale are directly used as parameters, instead of being derived from *pex* and *bex*.

tic "gates" (or cutpoints) that control whether the response is recorded as an extreme (0 or 1) or as a nuanced, continuous value in between (Figure 1). The distance of these gates from the edges of the scale varies based on two interpretable parameters: *pex* (the propensity by which people are likely to answer extreme values), and *bex*, a bias toward the upper extreme (1) versus the lower (0). A person's internal response that lies close to the edge might be "caught" by a gate and recorded as an extreme, while others pass through to express a continuous response (Beta-distributed with μ (*mu*) and ϕ (*phi*) as its mean and precision parameters). The Beta-Gate model is based on the idea that extreme values can emerge not just from a fundamentally different underlying processes - as assumed in ZOIB models - but from a common process governed by thresholds of decisiveness and confidence.

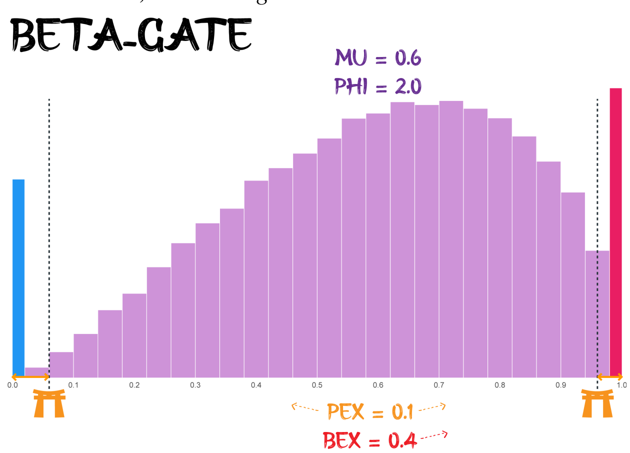
Mathematically, the Beta-Gate distribution defines the observed outcome $x \in [0, 1]$ as a mixture of three components; a point mass at 0, a point mass at 1, and a continuous Beta density over $x \in (0, 1)$, scaled by the remaining probability mass. The probability of these components are:

$$\begin{cases} \text{logistic}\left(\text{logit}(pex \cdot (1 - bex)) - \text{logit}(\mu)\right), & x = 0, \\ 1 - \text{logistic}\left(\text{logit}(1 - pex \cdot bex) - \text{logit}(\mu)\right), & x = 1, \\ 1 - P(x = 0) - P(x = 1), & 0 < x < 1. \end{cases}$$

The continuous part follows a Beta distribution with parameters[3]:

Figure 1

The Beta-Gate Distribution is a reparametrized ordered Beta model (Kubinec, 2023) that is governed by 4 parameters. 'Mu' and 'phi' correspond to the mean and precision of the continuous part of the distribution (between 0 and 1), and 'pex' (propensity of extremes) and 'bex' (balance of extremes) indirectly control the proportion of zeros and ones by specifying the location of the "gates", past which the latent response process is likely to generate extreme values. Specifically, 'pex' defines the total distance of both gates from the extremes (i.e., the sum length of the two orange arrows), and 'bex' determines the proportion of the right gate distance relative to the left (i.e., the length of the right arrow relative to the left one). In this example, the total distance from the extremes is 'pex' = 0.1, with 40% ('bex' = 0.4) of that distance being on the right (and 60% on the left). The left gate is thus located at 0.6, and the right at 1-0.04 = 0.96.



$$Beta(\alpha = \mu \cdot 2\phi, \quad \beta = (1 - \mu) \cdot 2\phi)$$

The Choice-Confidence (CHOCO) Model

Decision-making is often conceptualized as involving distinct processes: the choice itself, and the confidence associated with that choice (Sanders et al., 2016). In experimental paradigms, these can be somewhat disentangled by prompting participants to make a discrete choice selection (e.g., correct *vs.* error), followed by a separate confidence rating, which has led to the development of bespoke approaches to model the underlying data-generation process (e.g., Fleming, 2017; Rausch et al., 2021). However, this artificial separation may not reflect real-world scenarios, where individuals express simultaneously through a single scale both a discrete

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[3]Note that *phi* is scaled in Beta-Gate models relative to the traditional mu/phi Beta particularization so that a phi of 1 corresponds to a uniform distribution - to facilitate setting priors on this parameter

choice and an analog judgment of confidence, certainty, or degree of agreement (note that we will use the term "confidence" hereafter as a general term, without assuming a specific cognitive process). In instances where each side represents a distinct latent category (e.g., True/False, Agree/Disagree, Positive/Negative) - as opposed to a truly unimodal dimension, the absolute distance from the midpoint could be conceptualized as a indicating a continuous degree of "confidence". This integrated response format typically results in bimodal distributions, with peaks corresponding to the mean confidence on either side. Traditional beta regression models, which assume unimodal distributions within the (0,1) interval, are ill-suited for such data. One alternative is to transform the data into two variables a posteriori: binarizing the side to represent choice and calculating the absolute distance from the midpoint to represent confidence. These can then be modeled separately, for instance, using logistic regressions for choice and beta regressions for confidence (see Makowski, Te, et al., 2025 for an example). While this approach can provide additional insights into underlying mechanisms compared to a unique model, it assumes psychological and statistical independence between choice and confidence, which may not hold true in practice.

To model data of subjective scales in which the left and right sides can be conceptualized as two different choices and the magnitude of the response (how much the cursor is set away from the mid-point) as the confidence, we introduce the Choice-Confidence (CHOCO) model (Figure 2). It consists of a three-part mixture on $x \in [0, 1]$:

- An (optional) point-mass at the midpoint *mid* (typically 0.5) of weight p_{mid} for undecided or neutral responses.
- A left-choice component governed by a Beta-Gate density on the rescaled variable x/mid with mean *1 - confleft*, precision *precleft*, and boundary-excess parameter *pex(1 - bex)*.
- A right-choice component governed by a Beta-Gate density on the rescaled variable $(x - mid)/(1 - mid)$ with mean *confright*, precision *precright*, and boundary-excess parameter *pex x bex*.

The overall probability of the right choice (relative to the left choice) is controlled by a main parameter p. The full CHOCO density is:

$$\begin{cases} pmid, & x = mid, \\ (1 - pmid)(1 - p)\,\dfrac{1}{mid} \cdot \text{BetaGate}\left(\dfrac{x}{mid}\right), & 0 < x < mid, \\ (1 - pmid)\,p\,\dfrac{1}{1 - mid} \cdot \text{BetaGate}\left(\dfrac{x - mid}{1 - mid}\right), & mid < x < 1. \end{cases}$$

By coupling choice probability p, midpoint mass p_{mid}, and side-specific Beta-Gate parameters $(conf, prec, pex, bex)$, CHOCO flexibly captures both bimodality and confidence intensity in a single unified model. Despite this theoretical appeal, it is unclear whether this heavily parametrized model can be estimated reliably from data, and whether it can provide more useful insights than simpler alternatives.

Aim of the Present Study

Study 1 aims to evaluate the CHOCO model's ability to better capture subjective scale responses that (potentially) reflect an underlying discrete choice, in comparison to existing models such as the ZOIB and Beta-Gate. Specifically, we will assess whether 1) CHOCO provides improved model fit, 2) yields deeper insights into population-level effects than traditional approaches (sex differences in reality beliefs), and 3) allows for the reliable estimation of interpretable individual-level parameters through random effects. **Study 2** will apply this model to more subtle effects, such as the effect of perceived facial attractiveness on reality judgments, and test the ability to fit alternative data structures (scales with ordinal response options and mid-points). As a case-study illustration, we analyze data from two separate studies in which participants judged whether a face image was AI-generated ("fake") or a real photograph.

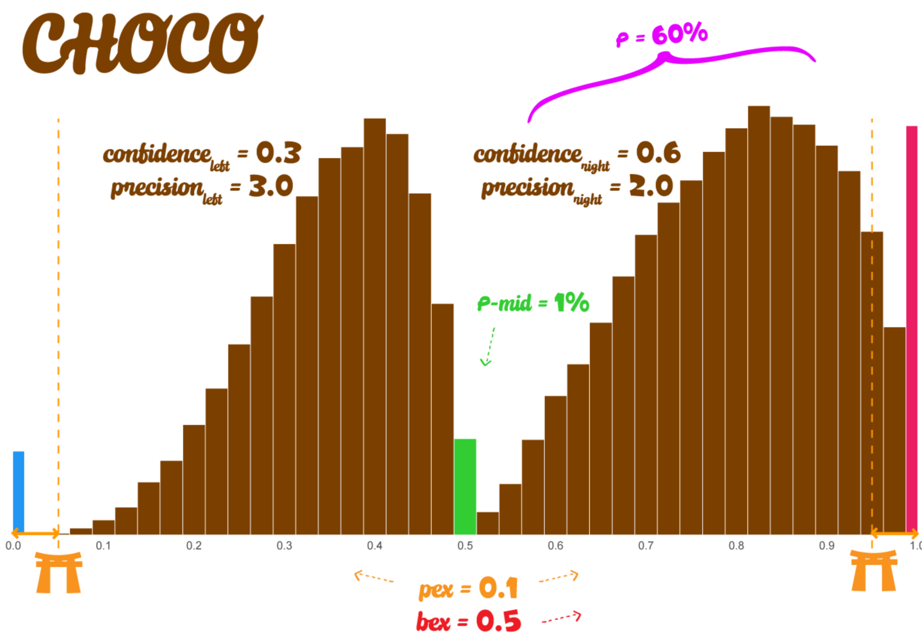
Study 1

The question of "what is real" has become increasingly relevant in the context of recent technological developments, particularly with the rise of artificial intelligence (AI), capable of mass producing highly realistic and relevant content, such as images, videos or text. These synthetic productions are flooding the cyberspace across various domains, such as art, advertising and entertainment, to education and information. The democratization of such technology carries an important potential for misuse, such as in disinformation campaigns and scams (e.g., AI-bots, identity theft), and abuse (e.g., deepfakes, Viola & Voto, 2023), and raises pressing concerns about the value of authenticity and the potential erosion of media trust in our increasingly *post-truth* society (Lewandowsky et al., 2017). Critically, as technology improves, traditional cues for detecting what is fake become less reliable (e.g., visual glitches and artefacts in generated images; formulaic generated text, etc.), leading people to increasingly depend on contextual information and cognitive heuristics to assess authenticity, a process referred to as "simulation monitoring" (Makowski, Sperduti, et al., 2019).

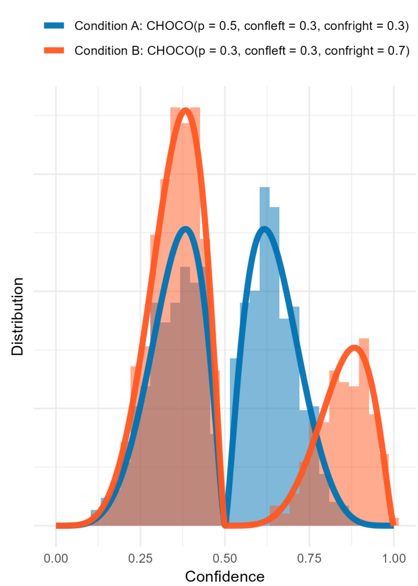
This reliance on alternative epistemological sources is particularly pronounced under conditions of high ambiguity, where the decontextualization of information, especially prevalent in online environments, complicates authenticity assessments. An open question in this domain is the extent to which reality judgments are influenced by the stimuli themselves versus stable individual characteristics like personality,

Figure 2

Top: The CHOCO Model uses a mixture of Beta-Gate distributions to model separately the right and left sides of the scale (e.g., a rating of whether a statement was 'Truth' vs. 'Lie'), as well as their relative proportion. In this example, the participants are more likely overall (p = 60%) to select the right side of the scale ('Lie') than the left ('Truth'). They are also more confident in their choice (confright = 0.6 vs. confleft = 0.3). Extreme values (zeros and ones) are governed by the same mechanism as for Beta-Gate models. Below: An illustrative dataset in which participants, in condition A (blue), respond as often on the left and right side of the scale, with low confidence (the confidence is concentrated towards the centre). In condition B (orange), they answer more often on the left (but also with low confidence), but their responses on the right are more extreme. As shown in the top table, a typical linear model could lead the imprudent researcher to misleadingly conclude that "there is no effect of Condition" (as a linear regression models changes in the mean, which is actually equal for the two conditions). The CHOCO model correctly reveals that condition B is associated with a lower probability but higher confidence of answers on the right side of the scale. Note that the CHOCO model is currently only available through Bayesian modeling, hence we report for consistency pseudo t- and p-values in the table, which correspond respectively to the coefficients divided by their SE, and the values obtained via the pd-to-p conversion (Makowski, Ben-Shachar, et al., 2019).



Usage Example



Linear Model

```
lm(y ~ Condition)
```

Effect	Coefficient	95% CI	t(1998)	p
(Intercept)	0.50	[0.49, 0.51]	75.93	< .001
Condition [B]	0.00	[-0.01, 0.02]	0.44	0.663

CHOCO Model

```
brm(bf(
  y ~ Condition,
  confleft ~ Condition,
  confright ~ Condition),
family = cogmod::choco())
```

Parameter	Effect	Coefficient	95% CI	t	p
p	(Intercept)	0.49	[0.46, 0.53]	30.58	< .001
p	Condition [B]	-0.19	[-0.23, -0.14]	-8.55	< .001
confleft	(Intercept)	0.30	[0.28, 0.31]	44.84	< .001
confleft	Condition [B]	0.01	[-0.01, 0.02]	0.84	0.395
confright	(Intercept)	0.30	[0.29, 0.31]	44.55	< .001
confright	Condition [B]	0.40	[0.37, 0.42]	36.08	< .001

expectations or expertise - or transient psychophysiological states (Makowski, Te, et al., 2025).

Images of faces - socially and perceptually rich stimuli for which AI-generation has been particularly successful - are a paradigmatic example that have been used to investigate reality judgments (Azevedo et al., 2020; Makowski, Te, et al., 2025; Nightingale & Farid, 2022; Tucciarelli et al., 2022). Studies asking participants to judge whether face images are real or artificially generated reveal that such judgments can be shaped by low-level features (e.g., clarity, symmetry), higher-level attributes (e.g., attractiveness, trustworthiness), and interindividual variability. In the present study, we apply the CHOCO model to such data to evaluate its capacity to recover interpretable parameters related to individual-level determinants of reality beliefs.

Methods

Participants

Using the open-access data from Makowski, Te, et al. (2025), we included all heterosexual and bisexual (as these two groups did not seem to differ based on preliminary analyses and were thus grouped to maximize power) male and female participants, for a final sample of 141 participants (Mean age = 28.4, SD = 9.0, range: [19, 66]; Sex: 47.5% females). For each participant, we included only stimuli of the opposite sex (i.e., all 89 female faces for males and 20 male faces for females).

Procedure

In the first phase, participants viewed 109 neutral-expression photographs of faces (random order, display time of 3 s) from the American Multiracial Face Database (AMFD, Chen et al., 2021). After each image, participants rated the face on trustworthiness, familiarity, attractiveness, and beauty using visual analog scales. In the second phase, participants were informed that “about half of the previously seen images were AI-generated” (in actuality, all faces were photographs). The same faces were presented again in a new random order (same display time), followed by ratings of “reality” (whether they believed the image was fake - left anchor - or real - right anchor).

Data Analysis

We fitted 3 models to predict the reality ratings: a ZOIB model, a Beta-Gate model, and the CHOCO model. For all models and each parameter, the full formula was entered: $Real \sim Sex + (1|Participant) + (1|Item)$ (with Sex as the main predictor and participants and items entered as random intercepts). The models were run using *brms* (Bürkner, 2017) R package, and analyzed using the *easystats* collection of packages (Lüdecke et al., 2020; Makowski, Ben-Shachar, et al., 2025; Patil et al., 2022). To maximize comparability across models, we used the default priors (uniform) for all models, and we ran 16 chains of 1400 iterations each on the University of Sussex High-Performance Computing (HPC) cluster.

Model comparisons were performed using the *loo* R package (Vehtari et al., 2017), which computes the Widely Applicable Information Criterion (WAIC) and estimates the Expected Log Predictive Density (ELPD) and penalizes the number of parameters. We assessed model performance by examining ELPD differences and their standard errors (SE), reporting corresponding *p*-values to determine significant differences in predictive accuracy.

For the population-level effects, we will consider “significant” (noteworthy) and report (using the median of the posterior distribution) effects for which the 95% Credible Interval (CI) does not include zero (and when the probability of direction *pd* is > ~97%, Makowski, Ben-Shachar, et al., 2019). For the individual-level parameters (i.e., the random intercepts of each parameter for each participant and each item), we will first analyze their reliability using the Variance-Over-Uncertainty Ratio index (*D-vour*). This index, implemented in the *performance* package (Lüdecke et al., 2021), is inspired by recent work on mixed models reliability (Rouder & Mehrvarz, 2024; Williams et al., 2021), and corresponds to the normalized ratio of observed variability to uncertainty in random effect estimates, defined as:

$$D_{\text{vour}} = \frac{\sigma^2_{\text{between}}}{\sigma^2_{\text{between}} + \mu^2_{\text{within}}}$$

Where $\sigma^2_{between}$ is the between-group variability (computed as the SD of the random effect point-estimates) and μ^2_{within} is the mean squared uncertainty (SE) in random effect estimates (i.e., the average uncertainty). We use as *D-vour* = 0.666 as the threshold for moderately reliable random effect estimates, which corresponds to a 2:1 ratio of between-group variance to uncertainty. Reliable in this context means that the variability between groups (e.g., participants) is greater than the uncertainty in the estimates, suggesting that the parameter can be used to assess inter-individual differences.

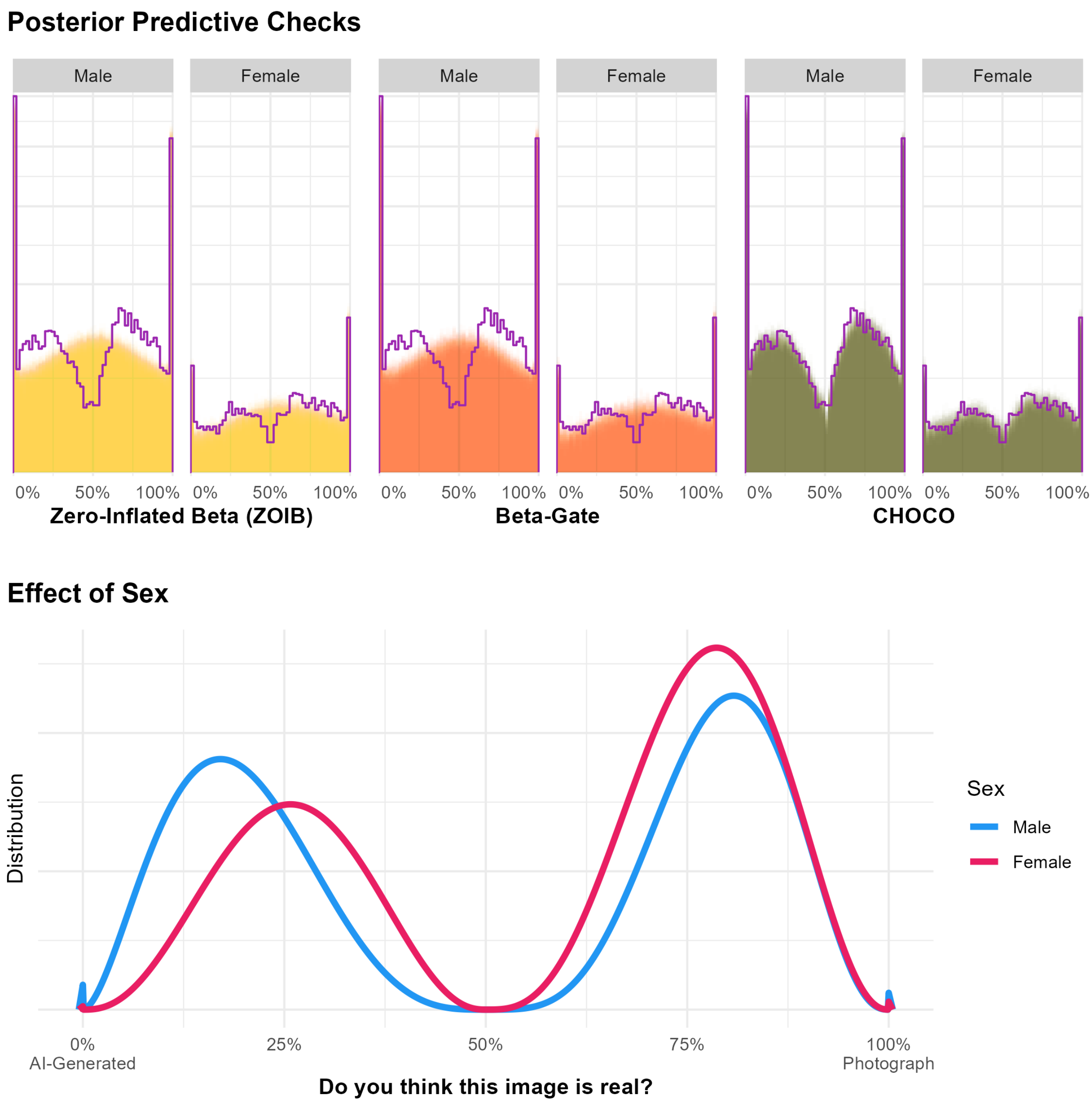
Finally, we will run a correlation analysis of the models' individual-level estimates against “empirical” (indices computed directly on the observed data), including the empirical *p*, the overall *conf*, *pex* and *bex* (respectively calculated as $P(y > 0.5)$; $mean(|y - 0.5|)$; $P(y \in [0, 1])$; and $P(y == 1)/P(y \in [0, 1])$), assessing whether the model's estimate are in-line with easily interpretable indices.

Results

The reproducible code and full result report are available at https://github.com/RealityBending/FictionChoco.

Figure 3

Top: Model comparison revealed that the CHOCO model was a significantly better fit for the data (raw distribution in purple) compared to a ZOIB or Beta-Gate models, capturing its bimodal distribution. Bottom: the CHOCO model can be set to estimate effect on any of its parameters, such as the overall probability of responding on one side as well as the confidence in both choices. We illustrate this by showing the effect of Sex on the distribution of reality beliefs based on a CHOCO model.



Model Comparison

The models did converge without divergent transitions, and the effective sample size was sufficient for all parameters (all $n_{\text{eff}} > 1000$). The difference in predictive accuracy, as indexed by Expected Log Predictive Density (ELPD-WAIC), suggests that the *CHOCO* is the best model ($ELPD = -203.54$), followed by *Beta-Gate* ($\Delta_{ELPD} = -1794.57 \pm 63.12$, $p < .001$) and *ZOIB* ($\Delta_{ELPD} = -1833.59 \pm 63.52$, $p < .001$). See Figure 3 for the posterior predictive checks, showing that only the CHOCO model managed to capture the bimodal distribution of data.

Effect of Sex

The ZOIB model suggested that females had higher mean scores of reality beliefs ($\mu_{\text{Female}} = 0.20,\ 95\%\ CI\ [0.03, 0.37],\ pd = 98.77\%$), less extreme values ($zoi_{\text{Female}} = -1.24,\ 95\%\ CI\ [-2.46, -0.07],\ pd = 98.25\%$) but more ones relative to zeros ($coi_{\text{Female}} = 1.63,\ 95\%\ CI\ [0.70, 2.56],\ pd = 99.97\%$).

The Beta-Gate model similarly suggested that females had higher mean scores of reality beliefs ($\mu_{\text{Female}} = 0.21,\ 95\%\ CI\ [0.02, 0.40],\ pd = 98.52\%$), less extreme values ($pex_{\text{Female}} = -1.34,\ 95\%\ CI\ [-2.56, -0.17],\ pd = 98.75\%$), and a greater tendency to answer one relative to zero ($bex_{\text{Female}} = 1.13,\ 95\%\ CI\ [0.34, 1.91],\ pd = 99.76\%$).

The CHOCO model shows that females had a higher probability p of judging faces as real ($P_{\text{Female}} = 0.45,\ 95\%\ CI\ [0.05, 0.86],\ pd = 98.54\%$), but are not more confident when doing so ($confright_{\text{Female}} = -0.13,\ 95\%\ CI\ [-0.47, 0.21],\ pd = 77.73\%$). However, they were less confident when answering that an image was AI-generated ($confleft_{\text{Female}} = -0.53,\ 95\%\ CI\ [-0.89, -0.17],\ pd = 99.84\%$). There were also less likely to produce extreme answers ($pex_{\text{Female}} = -1.19,\ 95\%\ CI\ [-2.40, 0.01],\ pd = 97.64\%$), but no strong evidence supporting a directional bias was observed ($bex_{\text{Female}} = 0.48,\ 95\%\ CI\ [-0.12, 1.09],\ pd = 94.32\%$).

Across all these models, no effect of Sex on the precision parameter was observed.

Individual-Level Parameters

The ZOIB model estimated reliable variability in the participant's *phi* parameter (D-vour = 0.88) and *zoi* parameter (D-vour = 0.85), as well as in the *mu* parameter related to individual items (D-vour = 0.82). Moderate reliability was also observed for items in the *coi* parameter (D-vour = 0.71) and for participants in the *mu* parameter (D-vour = 0.69). The Beta-Gate model yielded similar results: a high reliability of participant's *phi* parameter (D-vour = 0.88), *pex* parameter (D-vour = 0.85). The *mu* parameter's variability was reliably captured for items (D-vour = 0.85) and moderately for participants (D-vour = 0.72).

The CHOCO model yielded reliable estimates (Figure 4) for all parameters except *bex* for participants (*confright* D-vour = 0.94, *confleft* D-vour = 0.91, *pex* D-vour = 0.79, *p* D-vour = 0.73, *precright* D-vour = 0.77, *precleft* D-vour = 0.67). Item's variability was primarily reflected through the *p* parameter (D-vour = 0.86).

Finally, the empirical average correlated the most strongly with CHOCO's *p* (r = .86), rather than ZOIB's *mu* (r = .77) or Beta-Gate's *mu* (r = .82). The empirical overall confidence was the strongest correlated with CHOCO's *confright* (r = .91), followed by ZOIB's *phi* (r = -.86), Beta-Gate's phi (r = -.83), and other CHOCO's parameters. The empirical proportion of "right" answer *p* correlated the strongest with CHOCO's *p* (r = 0.94), followed by Beta-Gate's *mu* (r = .82) and ZOIB's *mu* (r = .77). The empirical *pex* correlated the strongest with ZOIB's *zoi* (r = .90), and Beta-Gate's *pex* (r = .90), and CHOCO's *pex* (r = .88). Of note that the parameters of Beta-Gate and ZOIB correlate almost perfectly, underlining their empirical similarity despite a different parametrization.

Discussion

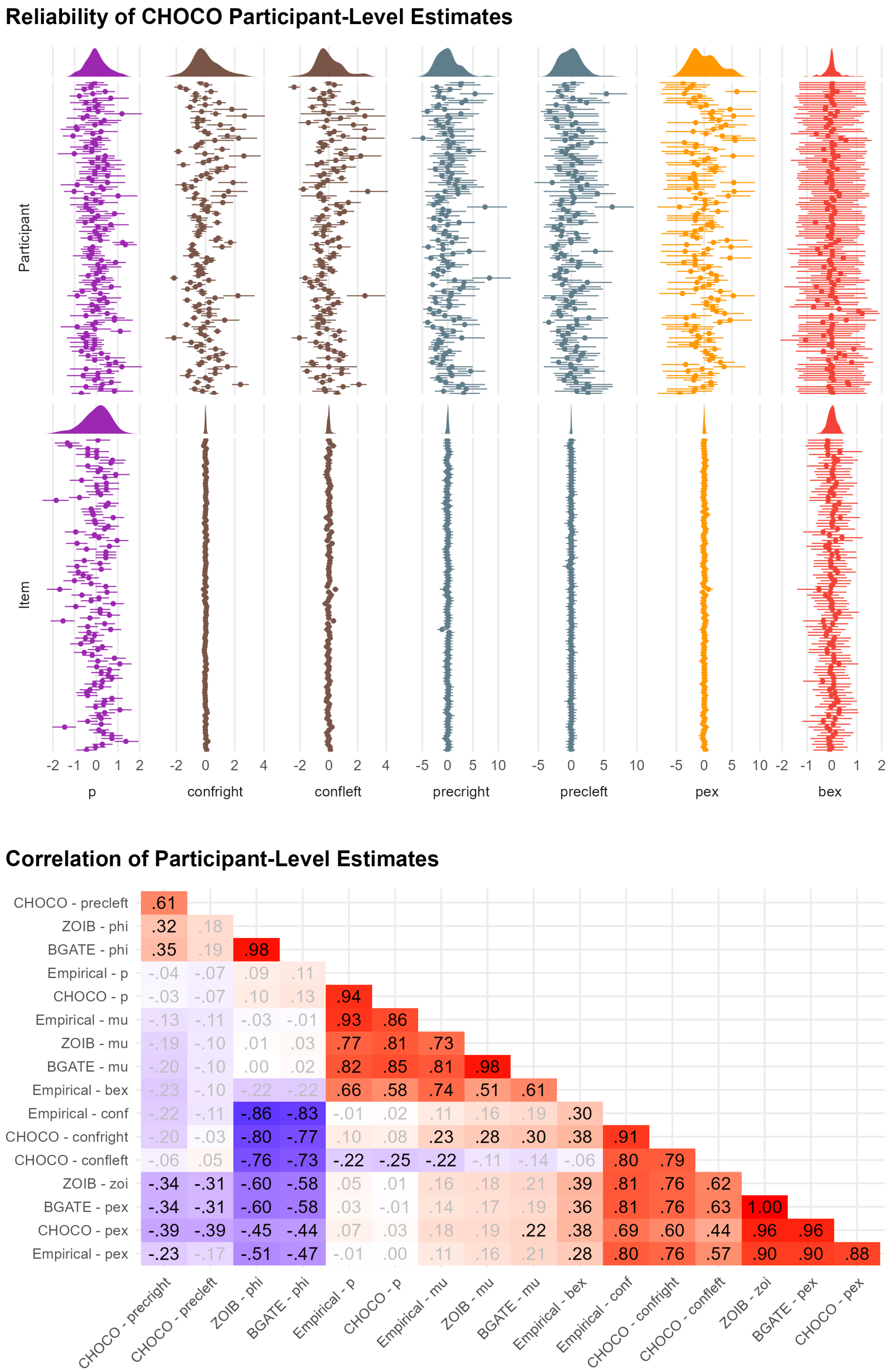
Study 1 revealed that the Choice-Confidence (CHOCO) model was a much better fit for bimodal bounded data, compared to other alternatives like the Zero-and-One Inflated Beta (ZOIB) and Beta-Gate (Ordered Beta) models. It also allowed for a deeper understanding through its interpretable parameters, offering insights into possibly distinct cognitive mechanisms, such as the probability of answering real *vs.* fake, and the associated confidence in these two choices. This was illustrated by modelling the effect of sex on all the CHOCO parameters.

Note that the observed gender differences are primarily presented as a proof-of-principle, to showcase the model's ability to capture group-level effects and to provide deeper insights compared to other models. However, given that they were based on different items (female and male faces), these differences might just be a reflection of stimuli characteristics rather than true sex dymorphism in the formation of reality beliefs.

Finally, we also show that the CHOCO model was able to capture reliable and interpretable individual-level parameters, supporting its value to measure inter-individual differences. An interesting dissociation emerged between participant- and item-level variability: the latter seemed mostly to be represented in the *p* parameter, while participants reliably varied in most of the components (aside from *bex*). This could suggest that external item characteristics primarily influence the probability of being judged as real *vs.* fake, while the expressed confidence is first and foremost an individual characteristic.

Figure 4

Top: the participant and item-level estimates for the CHOCO parameters, under the distribution of their point-estimates. Reliable effects are characterised by a higher between-group variability relative (the dispersion of the distribution of point-estimates) to its within-group variability (the average uncertainty of individual estimates represented by the error bar). For example, inter-individual variability in the parameters reflecting the confidence in left and right choices is reliably captured, as opposed to the inter-individual variability in the 'bex' parameter. Bottom: correlation matrix between participant-level estimates from different models and empirical indices (e.g., the raw proportion of responses on the right per participant). The CHOCO parameters are easily interpretable, strongly correlating with their empirical counterparts.



Study 2

The explosion of accessibility of state-of-the-art AI tools has made it effortless to generate realistic images, including human faces that are often indistinguishable from real ones (Bozkir et al., 2024; Miller et al., 2023; Nightingale & Farid, 2022). In this evolving landscape, understanding the cognitive mechanisms that underpin our judgments of reality becomes paramount. Despite the increasing prevalence of digitally altered or AI-generated content, humans still rely on certain heuristics to assess authenticity. One such heuristic might be facial attractiveness. Attractiveness appraisals are known to be automatic and unconscious (Hou et al., 2023; Hung et al., 2016; Luo et al., 2019), and carry strong real-life consequences, as demonstrated by the large body of literature on the "beauty premium"[4] (Gulati et al., 2024; Kukkonen et al., 2024; Little, 2021; Pandey & Zayas, 2021).

Although the role of attractiveness as a potential modulator of reality beliefs remains under-explored, Makowski, Te, et al. (2025) found significant associations between participants' realness ratings and facial attractiveness, with a potential sexual dymorphism: male participants judged attractive faces as being likely more real, whereas evidence suggested a milder and quadratic (U-shaped) relationship between attractiveness and reality beliefs for females. These findings offer a complementary perspective to those of Miller et al. (2023), who reported that participants used attractiveness as a distinguishing cue between real and AI-generated faces. These results highlight a possible bidirectional and context-dependent influence of attractiveness on reality judgments, of which the exact shape needs further investigation.

Methods

Participants

The first sample includes the same participants as study 1 (N = 141, see above). For the second sample (data and preprocessing information available at https://github.com/RealityBending/FakeFace2), 248 participants were initially recruited through academic platforms (SONA and SurveySwap). We removed 15 participants with data suggesting low-effort responding (no variation in their responses indicative of straightlining) as well as those (N=16) that did not believe in the experimental manipulation and were fully confident that all images were real or fake. Similarly to the first sample, we included all hetero and bisexual participants and stimuli from the opposite gender, resulting in a final sample included 189 participants (Mean age = 28.4, SD = 14.0, range: [18, 69]; Sex: 76.2% females). The study was approved by the University of Sussex Ethics Board (ER/ST633/1).

Procedure

For the second sample, the procedure was relatively similar to that of the first sample (described above in Study 1) with a few key differences.

The main difference was the introduction of an experimental manipulation: while for sample 1, participants were simply informed of the presence of AI-generated stimuli among photographs (not providing information as to specifically which image), the reality beliefs were directly manipulated in sample 2. At the beginning of the experiment, a cover story presented the study as a partnership with an AI startup aimed at testing the quality of a new face AI-generation algorithm. Following that, participants would see the 109 neutral-expression pictures (all real photographs) from the AMFD database (1 s), each preceded by a randomly assigned textual cue indicating whether the image was "AI-generated" or "Photograph" (2 s). Ratings of attractiveness, beauty and trustworthiness were collected after each image.

This phase of the experiment concluded with multi-choice questions asking participants to indicate whether they believed in the cover story. The second phase would start with a new set of instructions (falsely) revealing that the cues were "mixed up" (shuffled randomly), and that they would now be presented with the faces again (1 s) followed by an assessment of their own beliefs about whether the image was real or fake.

The second main difference was the subjective ratings' format, collected using a 7-point Likert scale ranging from 0 to 6 (which included a clear midpoint option), rather than a visual analog scale for sample 1. The 3 buttons on the left side (0, 1, 2) were colored in red and corresponded to the more-or-less pronounced belief that the image was "AI-generated", the 3 values on the right (4, 5, 6) for "Photograph" were colored in green, and the middle value (3), representing an undecided option, was colored in yellow.

Data Analysis

To compare the benefits of CHOCO models to a "traditional" analytic approach, we started by fitting a frequentist linear mixed model to predict reality beliefs with the formula $Real \sim Sex/poly(Attractive, 2) + (poly(Attractive, 2)|Participant) + (1|Item)$. The second degree orthogonal polynomial term was included to allow for potentially non-linear relationships (note that the first and second degree effects of orthogonal polynomials can be interpreted independently as the linear part and the "curvy" part of the relationship). For the CHOCO model, mildly informative and effect-agnostic (i.e., centered at zero) priors were used. The same formula was used for all parameters, except that

[4] As an eloquent example, Monk Jr et al. (2021) reported in a large representative US sample that the magnitude of earnings disparities among white women along the perceived attractiveness continuum exceeds in magnitude the canonical black-white race gap.

items were only included as random effects for p, and participants were not included for bex (based on the reliability analysis of Study 1).

For sample 2, the analysis was based on that of Sample 1. The main differences are 1) the inclusion of the "Condition" (whether the picture was presented as "Real" of "Fake" in the first phase of the experiment) as an additional predictor (entered as the only random slope for all participant random effects); 2) the inclusion of an additional parameters, *pmid*, modelling the probability of answering the middle-point of the Likert scale (representing an "undecided" option); 3) as they were effectively only 3 distinct values on each side of the scale, and to showcase the flexibility of the CHOCO model, we decided to *not* treat the extreme values as 0 and 1 (and model them via the separate parameters *pex* and *bex*, which would imply estimating the distributions from only 2 values), but instead to treat them as part of the continuous distribution. The 7 response options were rescaled to be evenly spaced between 0 and 1 excluded (i.e., [0.125, 0.875]). The *pex* and *bex* parameters were fixed to 0, making for a slightly more parsimonious model.

Results

As the complete model parameters tables are available at https://github.com/RealityBending/FictionChoco, we will focus on reporting noteworthy findings below.

Sample 1

In sample 1, the traditional approach suggested a significant linear relationship between the mean level of "Reality" and attractiveness for males only ($\beta_{\text{poly1}} = 3.42,\ 95\%\ CI[2.50, 4.34],\ p < .001$), the second largest effect being that of a quadratic link for women ($\beta_{\text{poly2}} = 1.82,\ 95\%\ CI[-0.27, 3.92],\ p = .09$). The CHOCO model revealed that, for males only, attractiveness had a significantly positive linear relationship with the probability p of judging faces as real ($P_{\text{poly1}} = 13.64,\ 95\%\ CI[8.42, 18.99],\ pd = 100\%$), and a quadratic relationship with the confidence in real judgments ($confright_{\text{poly2}} = 3.70,\ 95\%\ CI[0.80, 6.40],\ pd = 99.53\%$). Attractiveness was also associated with less confidence in fake judgments ($confleft_{\text{poly1}} = -5.49,\ 95\%\ CI[-8.84, -2.11],\ pd = 99.92\%$), a quadratic relationship with left precision ($precleft_{\text{poly2}} = -12.65,\ 95\%\ CI[-24.59, -0.36],\ pd = 97.86\%$), and related linearly with a stronger bias towards extreme Real responses ($bex_{\text{poly1}} = 9.56,\ 95\%\ CI[2.44, 16.73],\ pd = 99.55\%$). No significant relationship was found for females. The reliability of the effect of attractiveness (the random slopes) was very low for all parameters (D-vour < 0.01).

Sample 2

In Sample 2, the traditional approach suggested a significant linear relationship between the mean level of "Reality" and attractiveness for males ($\beta_{\text{poly1}} = 3.87,\ 95\%\ CI[2.91, 4.83],\ p < .001$) and females ($\beta_{\text{poly1}} = 1.88,\ 95\%\ CI[0.74, 3.01],\ p < .001$), with no effect of the Condition. The CHOCO model revealed that attractiveness had a significantly positive linear relationship with the probability p of judging faces as real for males ($P_{\text{poly1}} = 18.44,\ 95\%\ CI[11.36, 25.31],\ pd = 100\%$) and females ($P_{\text{poly1}} = 9.08,\ 95\%\ CI[1.90, 16.35],\ pd = 99.27\%$). It also had a linear relationship with the confidence in real judgments for males ($confright_{\text{poly1}} = 7.51,\ 95\%\ CI[3.90, 11.30],\ pd = 99.99\%$), as well as a significant quadratic relationship for females ($confright_{\text{poly2}} = 4.48,\ 95\%\ CI[0.74, 8.18],\ pd = 99.09\%$). Attractiveness also linearly decreased the confidence in fake judgments only for males ($confleft_{\text{poly1}} = -6.67,\ 95\%\ CI[-10.04, -3.38],\ pd = 100\%$). Marginal contrasts suggested that stimuli previously labelled as photographs increased the probability p of judging faces as real, only for females ($P\Delta_{\text{real - fake}} = 0.06,\ 95\%\ CI[0.00, 0.11],\ pd = 98.36\%$).

Discussion

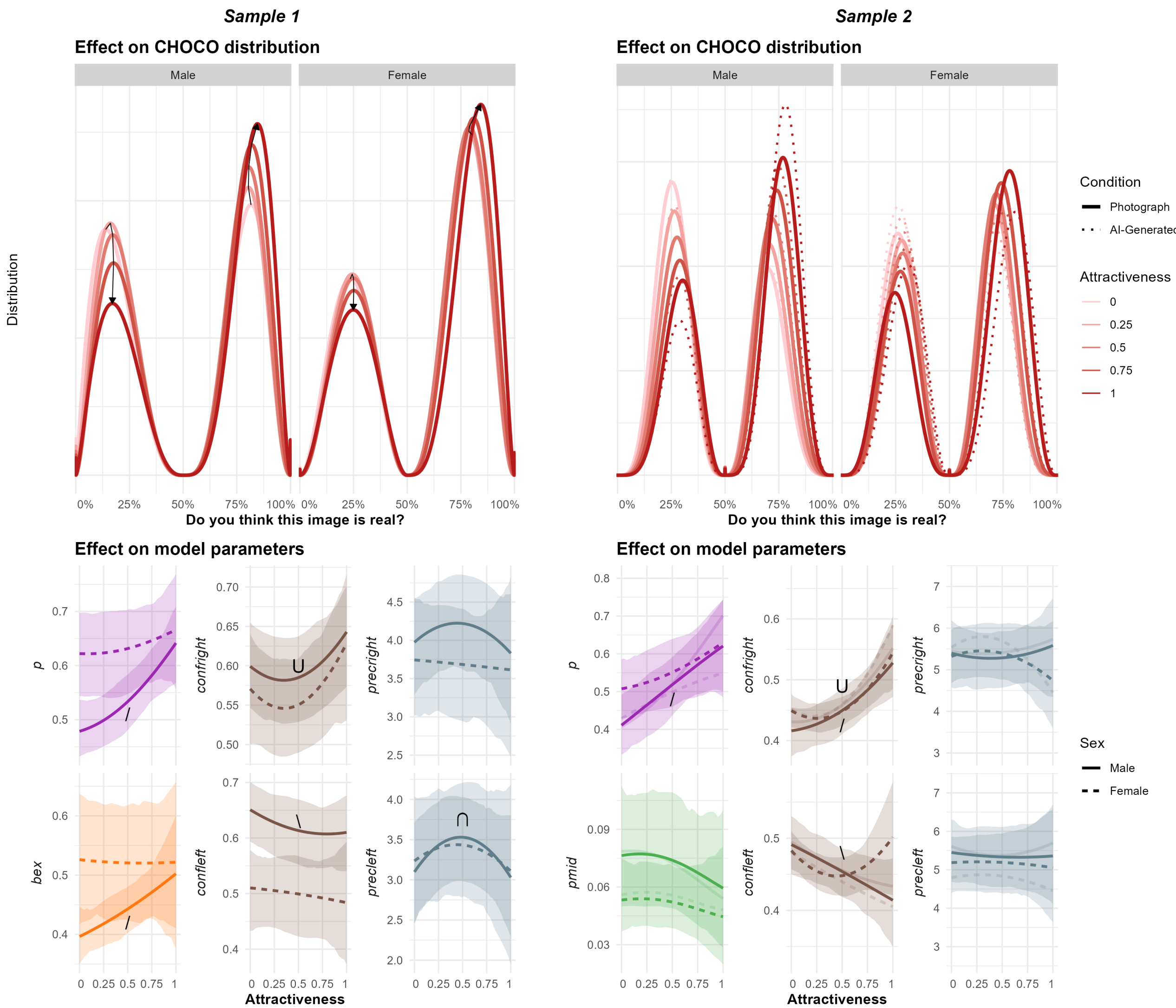
This study provides further evidence that attractive faces are more likely to be judged as real (*vs.* AI-generated). This effect was particularly strong and robust among male participants. For females, the effect was weaker in sample 1 but more pronounced in sample 2, which might partly reflect increased statistical power. An alternative possibility is that the second sample's experimental manipulation introduced conflicting cues (e.g., faces labelled "AI-generated") that could have disrupted intuitive heuristics, thereby increasing reliance on attractiveness as a diagnostic cue, particularly in ambiguous trials.

However, the mechanisms that underlie why attractiveness predicts reality judgments remains unclear. One possibility is that this positive link reflects a broader bias toward attributing positive qualities to attractive individuals, in-line with the substantial body of literature on the "beauty-is-good" stereotype, whereby attractive faces are judged as more trustworthy (Eagly et al., 1991), warmer and more approachable (Fiske et al., 2002), and perceived as more authentic and sincere (Little, 2021). These traits may implicitly overlap with qualities ascribed to "real" humans. In this sense, reality judgments could be an extension of existing social heuristics that conflate visual appeal with genuineness.

Alternatively, the effect might be primarily driven by attention. Attractive faces tend to capture and hold visual attention more effectively (Nakamura & Kawabata, 2014), which could lead to a deeper processing. This greater accumulation

Figure 5

The effect of attractiveness on reality beliefs. Top: the effect of different levels of attractiveness (shades of red) on the CHOCO distribution of the reality ratings in both samples, showing primarily that, for male participants, more attractive faces were judged more likely as a photograph rather than an AI-generated image. For the second sample, stimuli that were during the initial viewing presented as 'AI-generated' are represented via a dotted line. Bottom: The impact of attractiveness (x-axis) on different CHOCO distribution parameters, for male and female participants (the AI-generated condition is added as a transparent line for sample 2). Given the presence of polynomial terms, significant effects are denoted by a symbol representing the shape of the relationship (/ or \ for linear, U or inverse-U for quadratic links).



of evidence could influence the bias systematically towards a particular category ("reality") or perhaps, towards the "true" category of the stimulus (which we cannot delineate from our data as all our stimuli were actually real photographs). Alternatively, such attentional bias may boost perceptual fluency and subjective certainty, that would be predominantly reflected in the confidence parameter of the CHOCO model. The attention hypothesis could be formally tested via incorporating a reality judgment task of real and actual AI-generated faces within attentional paradigms to see whether the confidence and bias changes as a function of attentional engagement.

Importantly for the scope of this study, the CHOCO model allowed us to dissect this effect in greater detail compared to traditional analyses, revealing that attractiveness not only shifted the choice toward "real" judgments but also modulated the confidence and extremity of those judgments. With the second sample, we demonstrated the flexibility of this model by fitting it to discrete ratings with a mid-point - providing potential insight into epistemic uncertainty in decision-making tasks.

However, one might be concerned about the application of the CHOCO model (a mixture of two continuous Beta distributions) to ordinal data in Sample 2 (where a 7-point Likert scale was used). Ordinal ratings (limited number of discrete options represented numerically by integers) are commonly used in psychology, and often modeled as continuous. While this fact has spurred its own polarized debate (Liddell & Kruschke, 2018; Norman, 2010; Rausch & Zehetleitner, 2014; Sullivan & Artino Jr, 2013), our position is that the model used should ideally reflect the data *generating* mechanism rather than necessarily focus on the *observed* data[5] - although the former cannot always be easily inferred or known. For the data of Sample 2, we held the assumption that the underlying latent distribution was CHOCO distributed (as there is no reason to assume it would be different from Sample 1), and thus treated as continuous CHOCO-distributed data, despite the fact that it was collected on a 7-point scale. The motivation was to see if the model could extrapolate and reliably estimate all the parameters based on a limited number of data points but means in our case that, effectively, each Beta distribution was extrapolated from the frequency of only three unique values. While this is far from ideal, the CHOCO model still proved insightful, although it might have restricted its ability to detect finer-grain changes, including quadratic relationships.

General Discussion

This study introduces a new statistical model to analyze bimodal data, which can be observed when using subjective rating scales in which the two sides correspond to a different category (e.g., "false" vs. "true", "real" vs "fake", "positive" vs. "negative). The Choice-Confidence (CHOCO) model conceptualizes the data as a mixture of two distributions, one for each choice, and models the probability of choosing one or the other as well as the degree of confidence in each choice. We validated this model on real-life data by applying it to the reality beliefs of Makowski, Te, et al. (2025) as well as to a new sample, showing that it captures the underlying cognitive processes more accurately than alternative models (e.g., linear or ZOIB models), and provides interpretable psychological parameters. These parameters, such as the choice probability and respective confidence, offer a cognitively meaningful decomposition of subjective decisions, applicable to a wide range of tasks.

Beyond the statistical contribution, the study also replicates and expands findings on the mechanisms that underpin simulation monitoring, or judgments pertaining to beliefs about the real *vs.* simulated (or synthetic) nature of external stimuli. This process, important for navigating and making sense of our environment, is likely contributing to our sense of reality (the feeling and belief of being real in a real environment, Makowski, 2018), together with other mechanisms such as presence (the embodied feeling of being physically "in" an experience) and reality monitoring (the process of distinguishing between internally generated and externally perceived events, i.e., imagination *vs.* perception).

Interestingly, recent studies about the latter support a possible distinction at a neural level between a graded "reality signal" strength, primarily tracked by the fusiform gyrus, and its categorical thresholding supporting the binary classification of reality *vs.* imagination, supported by a frontal network of brain regions, including dorsomedial prefrontal cortex and the anterior insula (Dijkstra et al., 2025). Although tangential, these findings might provide potential neuroscientific empirical grounding for the CHOCO's model usefulness in investigating dimensions of the sense of reality, opening the doors for future research exploring the neural correlates of the CHOCO parameters.

The main empirical finding replicated in our study is that perceived facial attractiveness predicts the likelihood of believing that a face is real (*vs.* AI-generated). In both samples, males were more likely to identify highly attractive faces as real. The effect was weaker for females, possibly clouded by statistical power and/or the presence of other interacting moderators. Our work highlights how this key social heuristic not only biases trait perceptions (i.e., ratings of trustworthiness, competence, etc.) but also extends into other types of judgments, including reality beliefs.

Despite these promising findings, several limitations must be acknowledged. First, the stimuli shown to male and female participants were not identical, each group rated faces of the opposite sex, limiting our ability to make direct sex-

[5] Ideally, the data recording method should be aligned with the assumed generating mechanism, which is an experiment design issue rather than a statistical one.

based comparisons and fully answer the potential sexual dimorphism existing in the formation of reality beliefs. Second, all faces presented were real photographs, which could raise concerns about the validity of the procedure. This however was a deliberate design feature: our goal was not to assess the detectability of current AI-generated images and study true discrimination abilities, but rather to study the cognitive mechanisms that shape reality judgments assuming the simulation is perceptually flawless. Nevertheless, future work could leverage generative AI to systematically manipulate facial attributes, such as attractiveness, while holding other features constant, offering greater experimental control and the ability to test causal hypotheses about the role of attractiveness for simulation monitoring.

While our application focused on facial judgments, the CHOCO model has broader potential. Many real-world rating tasks - whether about emotions, morality, authenticity, political veracity, or aesthetic appeal—produce bimodal or skewed response distributions that traditional models fail to capture well. CHOCO offers a flexible, interpretable approach that accommodates both the binary outcome of decision-making and its related continuous evaluations. However, some methodological and practical questions remain to be answered.

Firstly, future studies should investigate the psychometric quality of the CHOCO model to derive practical guidelines for its optimal use. These include assessing the minimum amount of data required to reliably estimate and recover the different CHOCO parameters. When applying the model to ordinal data (such as Likert scales), another key question is the minimum number of unique response categories needed to detect subtle or nonlinear effects, such as quadratic modulation of confidence. Second, assessing the model's robustness when applied to unimodal or skewed data would extend its utility beyond strictly bimodal contexts and support its general applicability. Third, more parsimonious variants of the model could be explored, such as versions with a single shared precision parameter for both sides or formulations where the confidence on one side is modeled as a function of the other. Such simplifications may retain interpretability while reducing parameter overhead and improving model stability.

In the domain of reaction times, researchers distinguish between "descriptive" models (e.g., ex-Gaussian or log-normal distributions) that capture characteristic distributional shapes, and "data-generating" models like the Drift Diffusion Model (DDM, Ratcliff et al., 2016) or Linear Ballistic Accumulator (LBA, Brown & Heathcote, 2008), which simulate an assumed generative process (typically, sequential evidence accumulation). Drawing a comparison with this distinction, CHOCO was designed as a descriptive model to flexibly fit bimodal confidence data from subjective scales where responses implicitly reflect two categories. However, CHOCO remains agnostic about the underlying cognitive dynamics that generate those confidence ratings. In contrast, the field of metacognition has developed cognitive models that conceptualize confidence generation as a second-order inference. These include approaches derived from Signal Detection Theory, such as the meta-d' method which quantifies metacognitive sensitivity by assessing how well confidence discriminates between correct and incorrect decisions (Fleming, 2017; Maniscalco & Lau, 2012), as well as dynamic models like the Weighted Evidence and Visibility model or the Post-Decisional Accumulation model, which propose that confidence arises from mechanisms like post-decisional evidence sampling (Rausch et al., 2021). A critical distinction is that these models are typically applied to two-step paradigms, where participants first make a categorical decision and then separately report their confidence. Future studies could investigate the differences and potential overlap in the applicability area and insights provided by these two classes of models.

In conclusion, we developed and validated the CHOCO model, a mathematically grounded and practically flexible tool for modeling subjective judgments and delineating choice from confidence processes. It not only advances statistical modeling of decision-making data but opens new avenues for dissecting the cognitive mechanisms of belief, confidence, and reality perception.

Data Availability

Data, code and everything is available at https://github.com/RealityBending/FictionChoco. The CHOCO model is implemented in the *cogmod* R package (https://github.com/DominiqueMakowski/cogmod).

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