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Do We Find AI-Generated Less Emotional?

The Impact Of Reality Beliefs On Affective Responses

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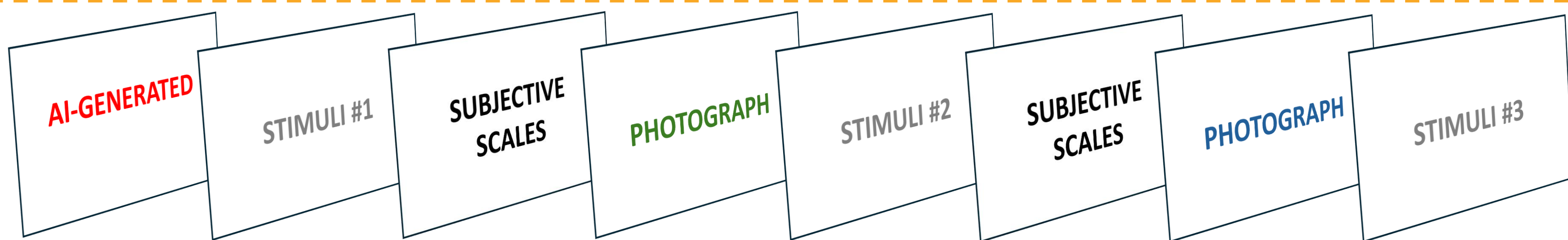
INTRODUCTION

- Advances in AI and immersive technology (e.g., VR) are making it increasingly difficult to distinguish between real and artificial content - a challenge with serious consequences, such as misinformation¹.
- For instance, deepfake technologies can generate realistic fake videos of politicians, spreading false narratives².
- In a “post-truth” era³, where emotions often outweigh facts, it is vital to understand how ambiguous or synthetic stimuli drive affect.

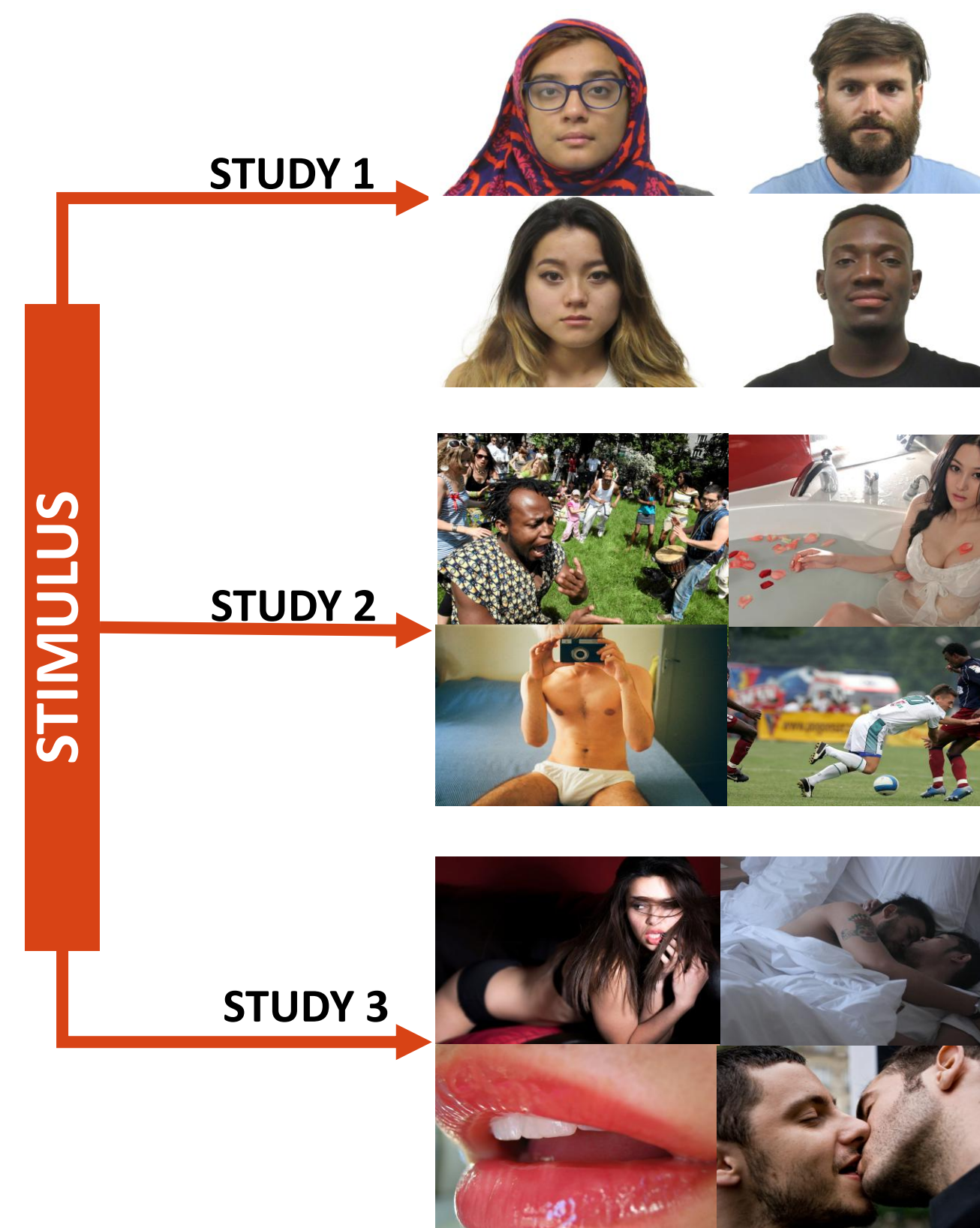
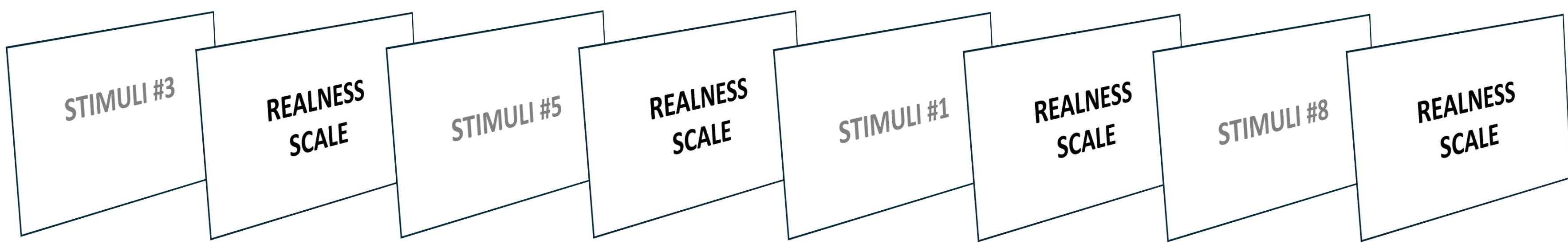
- Emotions shape how we interpret and respond to our environment⁴ and play a key role in how we process ambiguous or fictional content. Studies show that framing stimuli as fictional reduces emotional impact:

- ↓ Valence & intensity for neutral/negative videos⁵
- ↓ Intensity for negative pictures⁶
- ↓ Physiological arousal, subjective arousal, intensity & valence for negative and neutral images⁷

PHASE 1



PHASE 2



DATABASE: American Multiracial Face Database⁸

VARIABLE: Attractiveness

DATABASES: Nencki Affective Picture System⁹ AND NAPS Erotic subset (NAPS ERO¹⁰)

VARIABLE: Arousal

DATABASE: NAPS Erotic subset (NAPS ERO¹⁰)

VARIABLE: Arousal

“AI-Generated” beliefs leads to a decrease in emotional responses

RESULTS

STUDY 1 - FACES

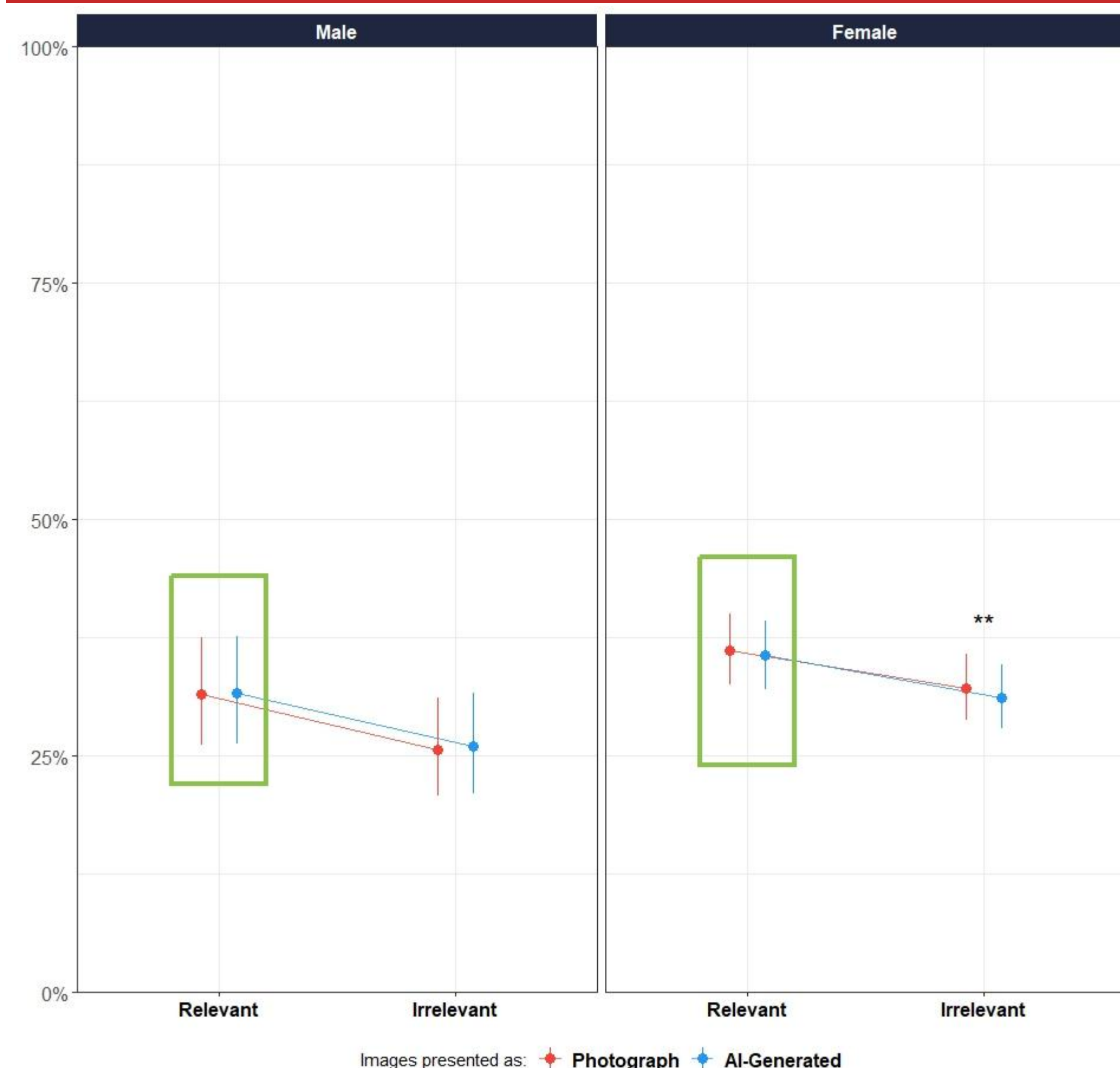


Figure 1. Estimated marginal means of attractiveness ratings across image relevance (relevant vs. irrelevant) and condition (photograph vs. AI-generated). Error bars represent 95% confidence intervals. Estimates are based on a generalized linear mixed model with participant- and stimulus-level random effects. ** $p < .01$.

- **N:** 206 participants (Mean age = 27.8, SD = 13.6, range: (18, 69); Gender: 76.7% women, 23.3% men)
- **Effect of condition:** Significant only for women, and only for *irrelevant* images (e.g., heterosexual women rating female faces); $\beta = -0.05$, 95% CI [-0.08, -0.001], $p = .006$.
- **Moderation by Honesty-Humility¹¹:** Among women, higher Honesty-Humility predicted lower attractiveness ratings for AI-labelled *irrelevant* images vs photos ($\beta = -0.03$, $p = .008$).

STUDY 2 - EROTIC + NON-EROTIC

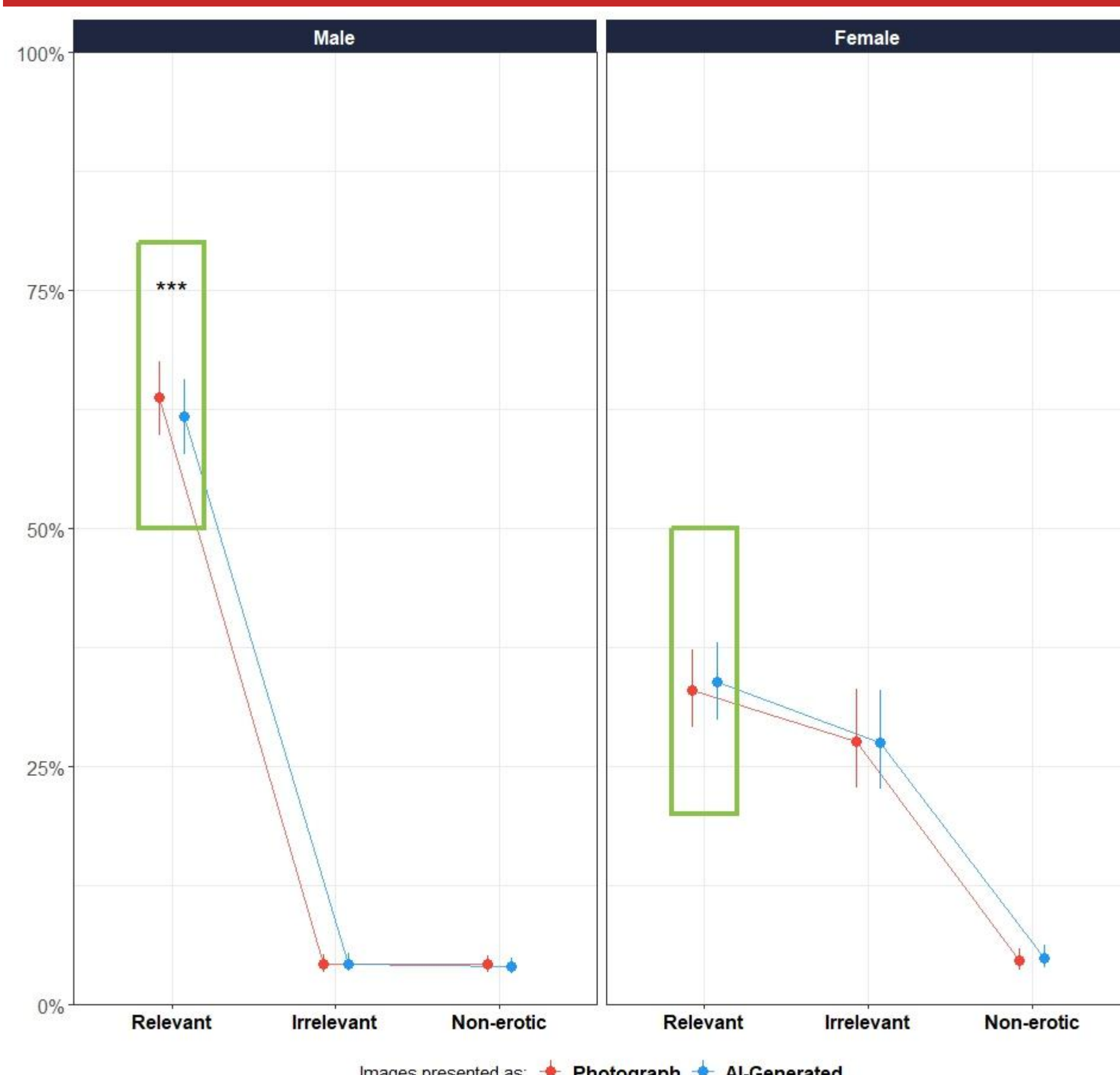


Figure 2. Estimated marginal means of arousal ratings across image relevance (relevant vs. irrelevant vs non-erotic) and condition (photograph vs. AI-generated). Error bars represent 95% confidence intervals. Estimates are based on a generalized linear mixed model with participant- and stimulus-level random effects. *** $p < .001$.

- **N:** 705 participants (M age = 30.2, SD = 11.8, range = 18–80); 35.7% women, 64.3% men.
- **Effect of condition:** Significant only for men, and only for *relevant* images (e.g., heterosexual men rating erotic images of women); $\beta = -0.07$, 95% CI [-0.13, -0.006], $p < .001$.
- **Moderation by AI-arousal feedback:** Men who believed AI images were less arousing rated them lower in arousal than photo-labelled images ($\beta = -0.16$, $p = .009$).

STUDY 3 - EROTIC

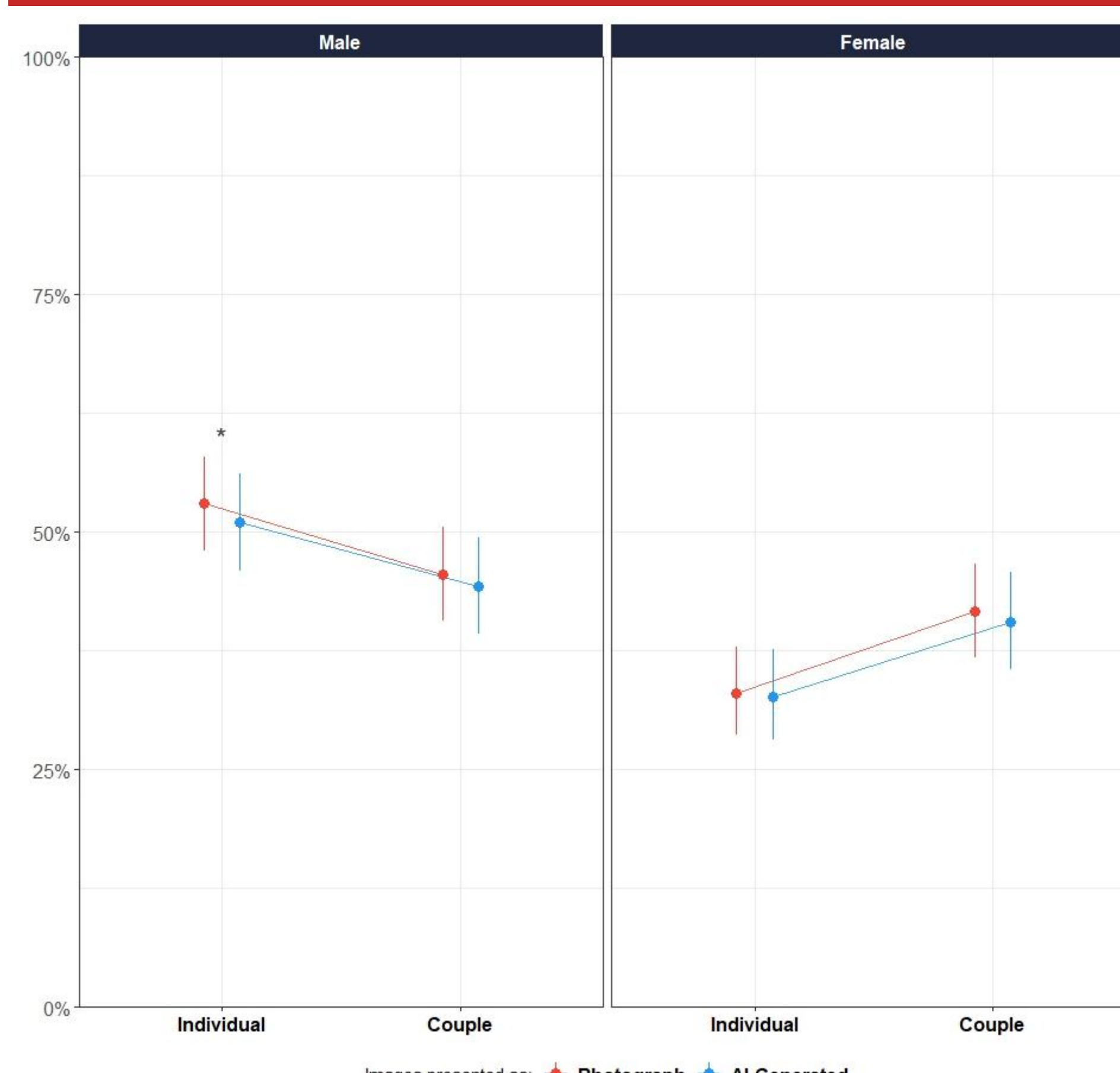


Figure 3. Estimated marginal means of arousal ratings across stimuli type - image of an individual or a couple - and condition (photograph vs. AI-generated). Error bars represent 95% confidence intervals. Estimates are based on a generalized linear mixed model with participant- and stimulus-level random effects. * $p < .05$. All pictures were relevant.

- **N:** 197 participants (M age = 36.5, SD = 13.1, range = 18–80); 48.2% women, 51.8% men.
- **Effect of condition:** Significant only for men, and only for *erotic images of individuals*; $\beta = -0.08$, 95% CI [-0.15, -0.01], $p = .019$.
- **Moderation by AI-attractiveness feedback :** Among men, those who believed AI images were more attractive also rated them as more arousing ($\beta = 0.14$, $p = .034$).

DISCUSSION

- Perceived artificiality reduces emotional responses, but only in specific gender and relevance contexts - women for irrelevant images (e.g., same-gender faces), and men for relevant erotic images.
- Among women, the effect was stronger for those high in Honesty-Humility, suggesting that individual moral traits influence reactions to artificial or fictional stimuli.
- Beliefs about AI played a key role: men who believed AI images were less arousing rated them lower, while others rated them higher when they believed AI images were more attractive.
- **Key takeaway:** emotional responses to “AI-generated” media are shaped not only by the content itself, but also by beliefs about its origin.
- **Next step:** assess physiological indices to test whether they align with these subjective patterns.

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