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Eerie edibles: Realism and food neophobia predict an uncanny valley in AI-generated food images

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ABSTRACT

This study investigates whether imperfect AI-generated food images evoke an uncanny valley effect, making them appear uncannier than either unrealistic or realistic food images. It further explores whether this effect is a nonlinear function of realism. Underlying mechanisms are examined, including food disgust and food neophobia. The study also compares reactions to moldy and rotten food with reactions to AI-generated food. Individual differences in food disgust and food neophobia are treated as moderators of food uncanniness. The results show that a cubic function of realism best predicts uncanniness, with imperfect AI-generated food rated significantly more uncanny and less pleasant than unrealistic and realistic food. Pleasantness followed a quadratic function of realism. Food neophobia significantly moderated the uncanny valley effect, while food disgust sensitivity did not. The findings indicate deviations from expected realism elicit discomfort, driven by novelty aversion rather than contamination-related disgust.

1. Introduction

Images of food are used in various contexts, such as advertising or clinical research on eating disorders (Giel et al., 2011; Vukmirovic, 2015). In advertising, image enhancements make food more appetizing, while in clinical research, controlled digital editing enables precise manipulation of appearance variables in food stimuli.

The quality of artificially generated content has recently spiked, achieving sufficient realism to find its way into many applications, both beneficial and sinister (Brooks et al., 2022; Malik et al., 2022; Passos et al., 2024; Salminen et al., 2022; Wu et al., 2023). The most convincing AI-generated media content is indistinguishable from real its counterparts (Brey et al., 2023; Diel et al., 2024; Groh, Epstein, Firestone, & Picard, 2022; Mirsky & Lee, 2021).

Beyond people, artificial intelligence (AI), specifically deep neural networks, can synthesize images and videos of various objects, including food—hereafter *AI food*. For example, OpenAI's text-to-image model, *DALL-E*, can generate detailed and realistic food images.

AI food has various applications and has already been used to replace real food images in advertisements and restaurant menus (Jackson, 2023). AI food may also support clinical research on eating disorders by using AI-generated stimuli to study food perception (e.g., palatability, estimated calories), for example, in patients with anorexia nervosa or binge eating disorder, whose perceptions differ from the healthy population (Giel et al., 2011). Furthermore, AI's ability to generate novel food appearances can enable researchers to create unnatural foods for clinical studies. These stimuli can control for familiarity while investigating factors like readiness-to-eat thresholds or calorie estimation tendencies when comparing unhealthy and healthy eating behaviors or individuals with and without eating disorders.

However, anecdotal reports indicate AI food often appears wrong, weird, or off-putting (Walhout, 2023), and early research indicates that AI food, when correctly labeled, is rated more negatively than real food images (Califano & Spence, 2024; Zelený et al., 2024). This negative evaluation may share some causes with the unnerving feelings elicited by artificial humans, called the *uncanny valley* effect (Mori, 2012). However, the relation between AI food and the uncanny valley effect remains unexamined (Diel et al., 2022; Kätsyri et al., 2015; Zhang et al., 2020; however, see Yamada et al., 2012).

In his 1970 essay, Mori (2012) proposed that, as we make robots and other entities appear more human, our affinity for them initially increases. However, past a certain point, they risk appearing cold and eerie, turning our affinity into aversion. From 2005, empirical research has reproduced this uncanny valley effect—not only for robotic and

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virtual simulations of humans but across a range of other categories, including animals (Löffler et al., 2020; Schwind et al., 2018; Sierra Rativa et al., 2022; Steckenfinger & Ghazanfar, 2009; Takahashi et al., 2015; Yamada et al., 2013) and inanimate objects (Diel & MacDorman, 2021; MacDorman & Chattopadhyay, 2016). However, we are especially sensitive to imperfections in human appearance, amplifying the creepiness of our digital doubles (Chattopadhyay & MacDorman, 2016).

Imperfections in AI-generated content may produce a similar uncanny valley effect. Moreover, the effect's underlying mechanisms may partially explain aversion to AI food, given that nonhuman animals, inanimate objects, and even buildings have been shown to elicit the uncanny valley effect, though to a lesser extent than humans (Diel & Lewis, 2022a, 2022b; Diel & MacDorman, 2021), as discussed next.

1.1. *Disease avoidance*

According to disease avoidance theory, the uncanny valley effect arises from an evolved sensitivity to signs of threat, specifically disease, which elicit disgust-motivated avoidance (MacDorman & Ishiguro, 2006; Moosa & Ud-Dean, 2010). Feeling disgust would motivate avoidance reactions towards indicators of disease (Curtis et al., 2011). Uncanny entities resemble diseased humans, activating protective mechanisms that promote survival. Studies have found images of diseased humans elicit uncanniness (Diel & MacDorman, 2021), disgust partially predicts the perceived uncanniness of humanoid robots (Ho et al., 2008), and an individual's disgust sensitivity predicts the uncanny valley effect (MacDorman & Entezari, 2015).

The uncanny valley effect may be one manifestation of a broader disgust-driven avoidance system that evolved to minimize health risks, particularly in food selection (Curtis et al., 2011). Spoiled, contaminated, or moldy foods elicit disgust to prevent ingestion of harmful substances (Darwin, 1872; Rozin & Fallon, 1987). Similarly, food neophobia—the aversion to unfamiliar foods like wild mushrooms—functions as a protective mechanism against potential toxins (Allen, 2012). Individual differences in food aversion are shaped by internalized norms and negative arousal toward novel foods (Curtis & de Barra, 2018; Jaeger et al., 2023; Koch et al., 2021). These differences extend to alternative food sources, such as cultured meat and insect protein (Hartman & Siegrist, 2017; Ruby et al., 2015; Siegrist et al., 2018).

Just as the uncanny valley effect may arise when humanoid figures deviate from expected human appearance in ways that signal disease, anomalies in AI food images may similarly activate disease avoidance mechanisms. However, these mechanisms are unlikely to be activated by abstract depictions of food. Abstract depictions, despite appearing visually unconventional, do not sufficiently resemble real food. Other human-oriented mechanisms meant to explain the uncanny valley effect are also unlikely to apply to AI food. This includes evolutionary aesthetics, the theory that the effect results from an evolved mechanism for evaluating human attractiveness and rejecting reproductively unfit sexual targets (Laue, 2017; MacDorman et al., 2009; MacDorman & Ishiguro, 2006). Unlike humanoid robots or diseased individuals, AI food images may lack the necessary humanlike cues to activate these avoidance mechanisms, instead eliciting food-specific disgust.

1.2. *Violations of internalized norms*

Observing violations of social norms triggers negative emotional and physical responses, often called moral disgust (Chapman & Anderson, 2013). Analogously, uncanny entities may elicit moral disgust through their norm-violating appearance and behavior (Laakasuo, 2023; Laakasuo et al., 2021; Olivera-La Rosa et al., 2023; Villacampa, Ingram, Corradi, & Olivera-La Rosa, 2019). The appearance, production, and consumption of food reflect cultural norms and customs, and violations of these norms may also trigger moral disgust (Gollwitzer et al., 2017; Koch et al., 2021). Atypical AI food may violate norms of food appearance, eliciting moral disgust, negative evaluations, and rejection. However, it is unclear to what degree moral disgust involves visceral disgust for food.

1.3. *Specialized processing*

Negative judgments may arise when stimuli appear atypical, especially within specialized categories (Diel & MacDorman, 2021; Kätsyri et al., 2015). Specialized categories cover familiar stimuli, like food or faces, that are often crucial for survival or social functioning. These categories are specialized because human perceptual and cognitive systems have evolved or adapted to process them with heightened efficiency and accuracy (Kanwisher, 2000).

Specialized processing of familiar categories manifests as categorical perception, perceptual narrowing, and configural processing. Categorical perception, also known as the perceptual magnet effect, entails equal-sized changes in a stimulus along a continuum appearing larger between categories than within a category. It has been observed in transitions from images of 3D computer models to photographs of real people (Cheetham et al., 2011; Looser & Wheatley, 2010). Category perception could explain heightened sensitivity to the appearance of liminal objects like androids, computer animation, and AI food (MacDorman & Chattopadhyay, 2016; Moore, 2012; but see Burleigh & Schoenherr, 2014).

The processing of specialized categories also exhibits perceptual expertise, honed by experience, an effect known as perceptual narrowing (Gauthier et al., 1999; Kelly et al, 2007; Pascalis et al., 2002; Scott et al., 2007; Simpson et al., 2010). Through heightened sensitivity to specialized categories, perceptual narrowing can make stimuli appear unfamiliar despite their physical similarity to known stimuli, which could explain the uncanny valley effect (Chattopadhyay & MacDorman, 2016; Lewkowicz and Ghazanfar, 2006).

Configural processing involves the rapid, holistic processing of familiar stimuli like human faces, with attunement to the relations among their features. Once first-order relations are learned (e.g., eyes above nose and mouth), they provide a configural structure for processing second-order relations (e.g., eye distance or nose-to-mouth ratio; Maurer et al., 2002). Configural processing enables subtle deviations from expected configurations to be noticed, a potential trigger for the uncanny valley effect (Chattopadhyay & MacDorman, 2016; Diel & MacDorman, 2021; Diel et al., 2023; Kätsyri, 2018).

Specialization occurs for objects whose recognition and differentiation are crucial for survival, such as food. Discriminating subtle differences in appearance helps identify healthy food, as poisonous or spoiled food often shows only minor visual deviations. Specialized perceptual strategies for detecting deviations enhance survival but increase false positives. This sensitivity could explain why farmers, retailers, and consumers discard perfectly edible but visually imperfect food—so-called *ugly food* (Hartmann et al., 2021)—or why people negatively evaluate visually imperfect AI food. Thus, AI food is expected to be negatively evaluated due to its close similarity to, yet deviation from, real food. This effect aligns with the uncanny valley, where intermediate realism is less preferred to high or low realism.

1.3.1. *Research question and hypotheses*

As AI food finds increasing use in advertising and other areas, understanding how it is perceived gains importance. The uncanny valley framework offers insight. Our study investigates this research question: Does visually imperfect AI food fall into an uncanny valley, and if so, what mechanisms or individual differences contribute to its negative evaluation?

First, food images varying in realism—real, virtual, and AI-generated—were rated on uncanniness and realism to determine if uncanniness plotted against realism forms an uncanny valley. AI-generated images were also rated to assess whether they were uncannier than real and unrealistic images. Unrealistic depictions of food paralleled unrealistic humanoid depictions in uncanny valley research, described as abstract, cartoonish, or stylistic (Diel et al., 2022; Hanson et al., 2005; MacDorman and Chattopadhyay, 2016; Schwind et al., 2017). Thus, hypotheses 1 and 2 were framed as follows:

1. *Uncanny valley hypothesis:* When plotted against levels of realism, the uncanniness of food is better explained by a quadratic or cubic function than a linear function.
2. *AI-food hypothesis:* Images of visually imperfect AI food are uncannier than real or unrealistic images of food.

Second, mechanisms underlying the negative evaluation of AI food were investigated. For disgust-related explanations (disease avoidance and norm violation), individual differences in food disgust sensitivity (Haidt et al., 1994; Hartman & Siegrist, 2017; Olatunji et al., 2007) or food neophobia (Pliner & Hobden, 1992) were expected to predict food uncanniness because previous research has shown disgust sensitivity heightens the uncanniness of androids (MacDorman & Entezari, 2015). Furthermore, AI-generated food should be processed similarly to moldy and rotten food, which would then fall into an uncanny valley. Thus, hypotheses 3 to 5 were framed as follows:

3. Individual differences in food disgust predict food uncanniness.
4. Individual differences in food neophobia predict food uncanniness.
5. Images of moldy and rotten food fall into an uncanny valley of food.

Finally, given the potential use of AI food in investigating how individuals with obesity or eating disorders process food images, an exploratory investigation examined the association between AI food ratings and body mass index (BMI).

2. Methods

A pilot study was conducted before the main experiment. Both are summarized in Table 1.

2.1. Pilot study

A pilot study with 12 participants from a German university was conducted to select an optimal range of AI foods. A total of 99 images were generated using three different types of food prompts: *unrealistic* (e.g., abstract, cartoonish, or stylistic), *imperfect* (e.g., distorted), and *realistic*. Ninety-nine images were selected, which was the stimulus limit of the online platform.

Participants rated each image according to six scales ranging from 1 to 100: *langweilig–schaurig* (boring–eerie), *unheimlich–reizlos* (uncanny–plain), *hässlich–schön* (ugly–pretty), *angenehm–abstoßend* (pleasant–repulsive), *abstrakt–fotorealistisch* (abstract–photorealistic), and *lebensecht–künstlerisch* (lifelike–artistic). German translations of validated semantic differential scales from Ho and MacDorman (2017) were used. Each pair of scales was averaged into its respective *uncanniness*, *pleasantness*, and *realism* index. Opposing pairs like boring–eerie and uncanny–plain were similarly valanced to decorrelate *uncanniness* from other constructs. The pilot study's results are summarized in Fig. 1.

Table 1
Pilot study and main experiment methods.

Pilot Study	Main Experiment
12 participants	**95 participants** $d = 0.28$, $1 - \beta = 0.8$, $M_{\text{age}} = 31.28$ ($SD_{\text{age}} = 9.47$), 64 male, 27 female, 4 other **Two questionnaires** Food disgust scale: 32 items, ranged 1–100 (Hartman & Siegrist, 2017) Food neophobia: 10 items, ranged 1–100 (Siegrist et al., 2013) **Post-hoc body mass index analysis**
99 AI foods: generated with unrealistic, imperfect, or realistic prompts	**38 stimuli:** the 6 most realistic, 6 least realistic, and 20 imperfect of increasing uncanniness, taken from the pilot, and 6 rotten (Kalluri, 2018)
Six semantic differential scales, ranged 1–100 (Ho & MacDorman, 2017): eeriness (boring–eerie, uncanny–plain, $r = 0.81$), pleasantness (ugly–pretty, pleasant–repulsive, $r = 0.82$), realism (abstract–photorealistic, lifelike–artistic, $r = 0.65$)	**Three semantic differential scales,** ranged 1–100: uncanny–plain, pleasant–repulsive, abstract–photorealistic **Calorie scale** **Willingness to consume two-alternative forced choice task**

2.2. Participants

In the main experiment, a power analysis determined the required sample size following standard experimental practice (Brysbaert, 2019; Lakens, 2022). Based on Diel and MacDorman (2021), a minimum effect size of $d = 0.26$ was used for the uncanniness of distorted inanimate objects. With a power of 0.8 and this small effect size, 95 participants were sufficient for the experiment.

Participants were recruited online via Prolific and SurveyCircle. Prolific allows verified users to take part in research studies to ensure quality data (Douglas et al., 2023). SurveyCircle allows participants to collect points by participating in studies.

Participants were $M_{\text{age}} = 31.28$ ($SD_{\text{age}} = 8.47$), with 64 participants identifying as male, 27 as female, and 4 as other. Participants were primarily German speakers living in Germany as German nationals; 76 identified as White, six as Mixed, two as Asian, and the rest did not provide information. Forty-seven were employed full-time, 15 were part-time, nine were unemployed, six conducted non-paid work, five reported other employment status, and the remainder did not provide information.

2.3. Materials

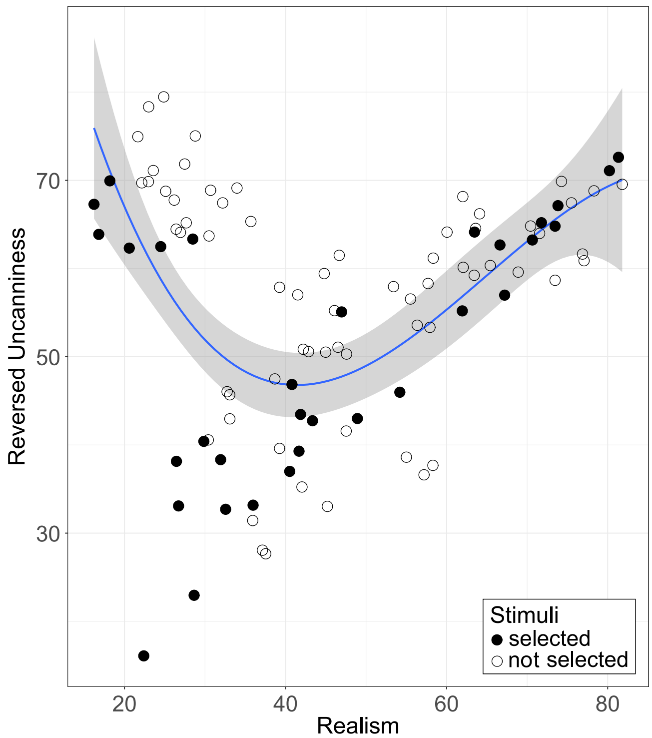
2.3.1. Rating scales

Rating scales were German translations of the scales used to measure an uncanny valley effect (Ho & MacDorman, 2017). The scales consist of three indices: *realism*, *warmth*, and *eeriness*. Because intercorrelations between the items in the pilot study were high for each variable (uncanniness: 0.81, pleasantness: 0.82, realism: 0.65) and to decrease participant workload, one item per variable was used: *unheimlich–reizlos* (uncanny–plain), *angenehm–abstoßend* (pleasant–repulsive), and *abstrakt–fotorealistisch* (abstract–photorealistic).

2.3.2. Questionnaires

German translations of the disgust sensitivity scale and the food neophobia questionnaire were used to assess their respective constructs (Hartman & Siegrist, 2017; Siegrist, Hartmann, & Keller, 2013). For food disgust, participants were asked on 32 scales how disgusting they found a specific situation (e.g., "to eat with dirty silverware in a restaurant"). For food neophobia, participants were asked on 10 scales how much they agreed with a specific statement (e.g., "I am very selective about food").

Full scales for both questionnaires were used. However, participants indicated their choice by moving a slider with the cursor, replacing the original Likert scales with continuous scales, ranging from 1 to 100. Continuous scales were adopted to minimize anchoring effects, avoid information loss from binning data into Likert response categories, and allow more powerful parametric tests requiring interval rather than ordinal data; these advantages enhance the analysis of interaction effects with significance tests by improving statistical power (Chyung et al., 2018). The Food Disgust mean was $M = 39.91$, $SD = 14.52$ (transformed to original scale: $M = 2.97$, $SD = 1.68$; Lane, 2013), and the Food Neophobia mean was $M = 28.23$, $SD = 18.21$ (transformed to original scale: $M = 2.65$, $SD = 2.04$; Lane, 2013).



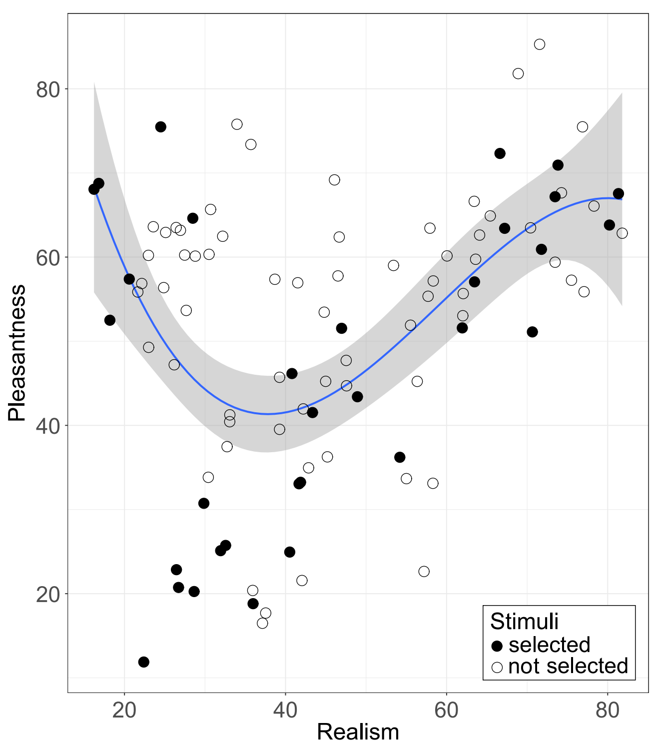


Fig. 1. Pilot study results (12 participants). Uncanniness (top) and pleasantness (bottom) ratings plotted against realism ratings across 99 AI-generated food stimuli. The plotted regression line depicts a *U*-shaped function similar to the uncanny valley. The gray band represent its standard error. Stimuli marked *selected* were used in the main experiment.

Cronbach's alpha and total omega, which accounts for multidimensionality, were calculated to estimate questionnaire reliability (Kalkbrenner, 2023). The Food Disgust Scale, α = .91, $\omega_t = 0.94$, and Food Neophobia Questionnaire, α = .87, $\omega_t = 0.91$, showed excellent reliability. Frequency distributions of food disgust, food neophobia, and BMI appear in the Appendix.

2.4. *Stimulus selection*

In the pilot study, AI food was generated using *unrealistic*, *imperfect*, and *realistic* prompts. Based on average ratings, the six least realistic and six most realistic stimuli were selected for the main study to ensure the uncanny valley curve covered a broad range of realism. In addition, 20 imperfect food stimuli were selected along a linear function of increasing uncanniness with decreasing realism. Fig. 1 plots selected and nonselected stimuli with increasing realism. In addition, six images of rotten food were presented from the database "fruits, fresh and rotten, for classification" (Kalluri, 2018). Thus, a total of 38 stimuli were used in the study. Fig. 2 depicts these stimuli ordered by increasing realism, excluding rotten stimuli for copyright reasons. Stimuli were edited to whiteout the background.

2.5. *Procedure*

A qualitative debriefing indicated pilot study participants experienced a high workload. Hence, the number of stimuli and rating scales were reduced.

Participants performed the experiment online. After providing electronic informed consent and completing the Food Disgust Scale and Food Neophobia Questionnaire, they viewed all 38 stimuli in random order. For each stimulus, participants first rated the meal on the three uncanniness scales, followed by the calorie scale and the two-alternative forced choice task on willingness to consume. Participants had unlimited time to view each stimulus and respond to each scale. Stimuli were presented full screen and centered to control for positional biases (Manippa et al., 2021).

2.6. *Statistical analysis and data availability*

Linear mixed-effects models were fitted with participant as a random effect to allow for individual differences in intercepts and slopes. Analyses were conducted using R (ver. 4.1.2) and the *lmer4* package (Bates et al., 2015). Because uncanniness, pleasantness, and realism are not independent (Ho & MacDorman, 2017), outliers were removed using Mahalanobis distance for uncanniness (421 values), pleasantness (424 values), and realism scales (643 values) out of 3,610 values each. Indices were calculated by averaging the respective items. Interscale reliability was assessed via intercorrelations. Planned contrasts were used to calculate differences between conditions. In addition, a post-hoc analysis examined participants' BMI as a predictor of AI food ratings.

2.7. *Ethics statement*

The study was approved by the Ethics Committee of the University of Duisburg-Essen's Medical Faculty in June 2024 (no. 24-11879-BO). The study has been conducted according to the Declaration of Helsinki.

2.8. *Data availability*

Data, analysis scripts, and stimuli are available at https://osf.io/x2y8h/.

3. Results

Descriptive results for each stimulus are reported in Table A1.

3.1. *An uncanny valley*

Scale correlations were $r = 0.12$ between uncanniness and realism, $r = -0.72$ between uncanniness and pleasantness, and $r = 0.15$ between pleasantness and realism.

Fig. 2. Main experiment stimuli appear in order from low (1) to high realism (38), excluding rotten foods. Stimuli 1 to 6 are unrealistic, 32 and 34 to 38 are realistic, and the remaining stimuli are imperfect. Full data for each stimulus are reported in Table A1.

Mixed-effects models with participant as the random effect were conducted with hierarchical linear, quadratic, and cubic terms of realism as fixed-effect predictors of uncanniness. For both uncanniness and pleasantness models, assumptions of residual normality and homoscedasticity were violated though independence was not. Thus, robust estimations of mixed-effects models were conducted. A linear ($t(83) = 5.93, p < .001$), quadratic ($t(2853) = 9.25, p < .001$), and cubic function were fitted to predict uncanniness ($t(2585) = -2.95$, $p < .001$). The cubic function had the best fit among them, $\chi^2 = 10.62$, $p = .001$, AIC = 27,023, BIC = 27,070, LRT = −13,503, $R^2_m = 0.06$, $R^2_c = 0.22$, better than the quadratic, AIC = 27,031, BIC = 27,073, LRT = −13,508, $R^2_m = 0.06$, $R^2_c = 0.24$, and linear function, $\chi^2 = 91.60$, $p < .001$, AIC = 27,110, BIC = 27,146, LRT = −13,549, $R^2_m = 0.03$, $R^2_c = 0.20$.

For pleasantness, the linear ($t(102) = -4.77, p < .001$) and quadratic ($t(2796) = -11.72$, $p < .001$) terms were significant, whereas the cubic term was not ($t(2636) = 0.41$, $p = .404$). The quadratic function, $\chi^2 = 119{,}67$, $p < .001$, AIC = 27,704, BIC = 27,745, LRT = −13,845, $R^2_m = 0.06$, $R^2_c = 0.18$, had a better fit than the linear function, AIC = 27,821, BIC = 27,867, LRT = −13,905, $R^2_m = 0.02$, $R^2_c = 0.12$. The models are depicted in Figs. 3 and 4.

Mixed-effects models with participant as the random effect and stimulus type as the fixed effect significantly predicted uncanniness, $F(3,132) = 128.54$, $p < .001$, and pleasantness, $F(3,152) = 620.96$, $p < .001$. Planned contrasts showed that imperfect AI food was significantly more uncanny than realistic, $t(94) = 20.39$, $p < .001$, $d = 1.08$, and unrealistic AI food with large effect sizes, $t(94) = 15.97$, $p < .001$, $d = 0.95$. The same pattern was observed when comparing pleasantness ratings of imperfect AI food with realistic, $t(94) = 27.50$, $p < .001$, $d = 1.46$, and unrealistic AI food, $t(94) = 21.12$, $p < .001$, $d = 1.26$. Thus, hypotheses 1, 2, and 5 were supported. The data are plotted in Fig. 5.

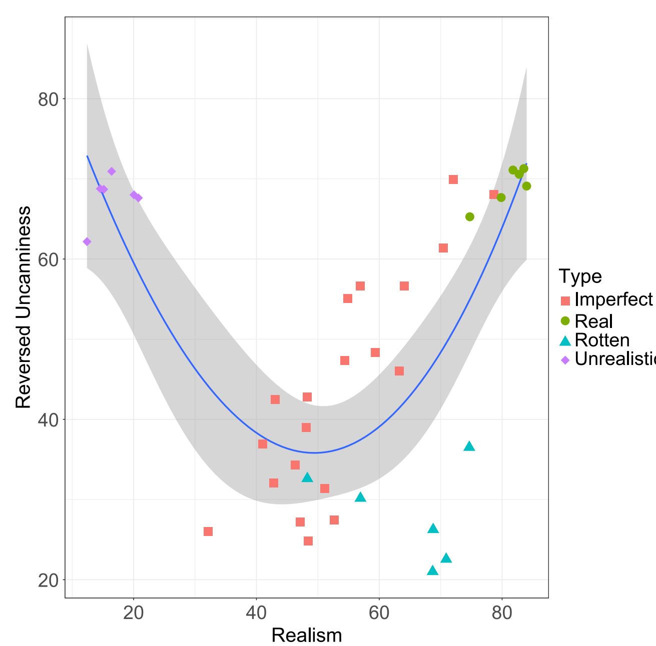


Fig. 3. Cubic model of food image uncanniness plotted against realism, grouped by food category (95 participants, 26 food stimuli). The gray band represents the 95% confidence interval of the regression line.

3.2. Individual difference analysis

Food disgust and food neophobia were added as moderators of the uncanny valley effect. Using mixed-effects models with participant as

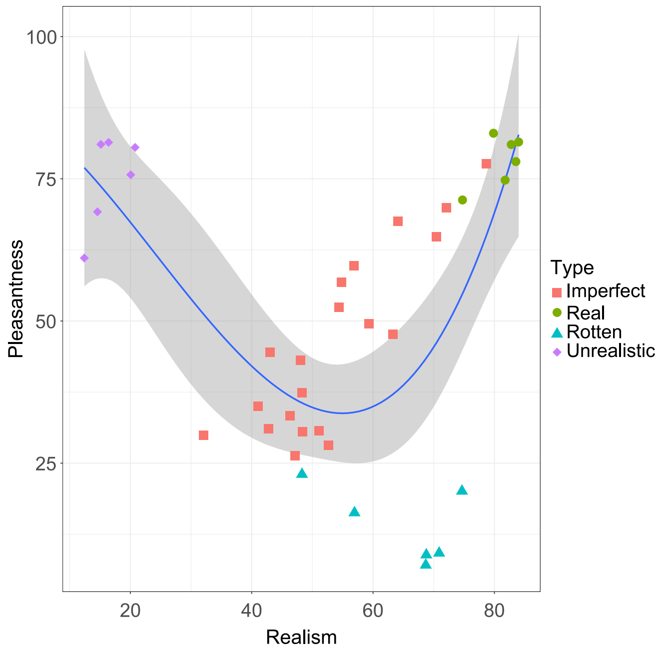


Fig. 4. Cubic model of food image realism plotted against pleasantness, divided by food category (95 participants, 26 food stimuli). The gray band represents the 95% confidence interval of the regression line.

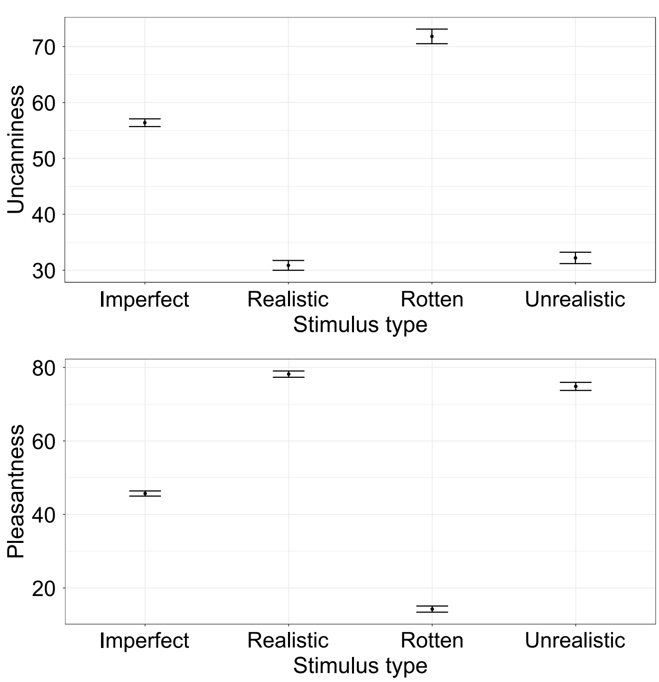


Fig. 5. Average uncanniness (A) and pleasantness (B) ratings across stimulus conditions in alphabetical order (95 participants, 26 food stimuli). Error bars indicate standard errors.

the random effect and the individual difference measure and cubic realism as fixed effects revealed food neophobia, $t(1832) = -2.15$, $p = .029$, $R^2_c = 0.52$, significantly moderated the cubic realism effect on uncanniness with a large effect size, while food disgust was nonsignificant, $t(2573) = -0.05$, $p = .959$. Hence, hypothesis 4 was supported, while hypothesis 3 was not.

A post-hoc analysis found that BMI significantly interacted with the cubic function of realism on uncanniness ($t(2695) = 3.18$, $p = .001$), indicating that participant BMI may moderate the observed uncanny valley of food. However, a clear trend was not observed.

4. Discussion

Mori (2012) proposed the uncanny valley in 1970, observing how imperfections in humanlike figures could elicit eeriness. Since then, his concept has been extended to animals and inanimate objects (Diel & MacDorman, 2021; Löffler et al., 2020; MacDorman & Chattopadhyay, 2016; Schwind et al., 2018; Yamada et al., 2012, 2013). In this study, plotting the uncanniness and pleasantness of AI and other foods against their realism resulted in the same *U*-shaped curve, thereby extending the uncanny valley to food. Reinforcing this, imperfect AI food was significantly more uncanny and less pleasant than unrealistic and realistic AI food. Thus, hypotheses 1 and 2 were supported.

These findings indicate realistic yet deviating depictions of stimuli elicit uncanniness (Diel & Lewis, 2024). By contrast, cartoonlike food and other abstract depictions do not provoke discomfort. They are easily processed as nonthreatening or playful representations (MacDorman & Chattopadhyay, 2016). Additionally, images of rotten food were perceived as uncanny and less pleasant than unrealistic and realistic images of AI food.

Disgust, anxiety, and fear elicit the uncanniness of humanlike robots (Ho et al., 2008; MacDorman & Entezari, 2015), potentially as indicators of disease motivating avoidance (Curtis et al., 2011; Moosa & Ud-Dean, 2010). For food, disgust may indicate a risk of foodborne illness, making accurate discrimination between safe and spoiled food crucial for survival (Rozin & Fallon, 1987). In contrast, food neophobia may arise from arousal caused by uncertainty about whether foods are safe to eat (e.g., due to unfamiliar features or ingredient combinations). However, while rotten food fell into an uncanny valley, supporting hypothesis 5, food disgust sensitivity did not predict an uncanny valley of food; thus, hypothesis 3 was not supported.

This study used a food-specific disgust scale because food has been found to elicit contamination-related disgust. However, AI food may still elicit disgust unrelated to food, which would explain nonsignificant individual differences in food disgust. Instead, uncanny valley-related disgust may be associated with reminders of death, contamination, or animals, moral disgust caused by norm violation, or sexual disgust (Chapman & Anderson, 2013; MacDorman & Ishiguro, 2006; Olatunji et al., 2007). Thus, the results do not rule out a relation between disgust and the uncanny valley of food but perhaps only specific food-related features.

Food neophobia, however, significantly predicted the cubic effect of realism on uncanniness and pleasantness, supporting hypothesis 4. This indicates that, for AI food, novelty avoidance may contribute to the uncanny valley. It may have evolved to protect against the hazardous effects of consuming unfamiliar substances (Allen, 2012). Eeriness in the uncanny valley may stem from expectation violation and novelty avoidance (Kawabe et al., 2017; MacDorman & Ishiguro, 2006; Sasaki et al., 2017; Saygin et al., 2012; Urgen et al., 2018). McAndrew and Koehnke (2016) proposed that creepiness arises from ambiguous threats, with unpredictable or nonnormative behaviors eliciting unease. This concept can be applied to food neophobia, where unfamiliar or ambiguous foods trigger similar feelings of discomfort due to their unpredictability.

High arousal may underlie the uncanny valley of food observed in individuals with food neophobia. This trait elicits anxiety and aversive arousal responses to unfamiliar foods perceived as dangerous due to their novelty, complexity, or intense flavors (Fox et al., 2018; Jaeger et al., 2023; Spinelli et al., 2021). Foods most likely to elicit negative arousal are more strongly rejected by neophobic individuals (Jaeger et al., 2021). Thus, AI food's atypical appearance may intensify the uncanny valley effect in individuals with food neophobia.

Indeed, facial electromyography responses during avatar interactions and pupillary responses while viewing humanlike robots reveal distinct physiological arousal patterns consistent with the uncanny valley effect (Bailey & Blackmore, 2022; Reuten et al., 2018). Uncanny responses may thus increase with the higher, negatively experienced arousal elicited by the stimulus, moderated by individual differences (MacDorman & Entezari, 2015). Moderating individual differences may be specific to the stimulus domain (e.g., fear of clowns or disgust sensitivity for humanoids) or general (e.g., emotional instability or aversion to deviancy; Diel & Lewis, 2024b; Pollick, 2010; Tyson et al., 2023). If so, food neophobia serves as a domain-specific moderator of eerie reactions toward AI food caused by higher arousal ratings (Jaeger et al., 2023). In sum, the results indicate that an uncanny valley of food exists and that it may be related to a fear of unfamiliar food rather than heightened disgust towards signs of contamination.

AI food is replacing real food in marketing, yet the consumer's response is not always favorable (Califano & Spence, 2024; Jackson, 2023; Zeleny et al., 2024). This study provides insight into how and why AI food can be assessed negatively by revealing an uncanny valley of food with neophobia as a moderator. Specifically, AI food with imperfect, inconsistent, or deviating features may fall into an uncanny valley due to its novelty, which individuals may shun as a potential hazard.

A post-hoc analysis revealed that BMI significantly moderated the uncanny valley of food. A more positive evaluation of imperfect food, including AI-generated food, may result in a "flatter" valley. It could also heighten willingness to eat, leading to weight gain and higher BMI levels. Research has already shown that food disgust proneness correlates negatively with BMI (Houben & Havermans, 2012; Spinelli et al., 2021; Watkins et al., 2016). In contrast, disgust sensitivity and food selectivity predict anorexia nervosa (Aharoni & Hertz, 2012; Davey et al., 1998). In anorexia nervosa, impaired neural reward processing lowers the appeal of calorie-dense foods, reinforcing restrictive eating behaviors that contribute to severe weight loss and a lower BMI.

AI food may serve as a valuable tool in clinical research. Pictorial stimuli of real food are already used in research on eating disorders and pathological eating behaviors (Giel et al., 2011; Pimpini et al., 2022). These stimuli could be replaced or extended with AI-generated food. For example, individuals with obesity tend to underestimate calories (Chandon & Wansink, 2007), so AI food could be used to compare calorie estimation between obese and normal-weight participants. Under control and hunger conditions, high-BMI individuals with high disgust sensitivity might rate AI food lower when not hungry and display increased emotional or physiological reactivity when hungry. Additionally, AI food images can be used to investigate both restrained and dysregulated eating behaviors in individuals with binge eating disorder, whose heightened disgust sensitivity impairs behavioral inhibition (Brassard et al., 2023).

This study mainly relied on AI-generated food images. To further investigate the relation between food neophobia and an uncanny valley of food, future research could test whether individuals with high food neophobia experience eeriness towards real food that typically elicits neophobic responses, such as culturally unfamiliar food, seafood, strongly spiced or flavored food, and food from unusual meat sources (Jaeger et al., 2021). Food perceptions vary widely across cultures (Rottman et al., 2019). Cultural norms, food exposure, and personal experiences may influence the perception of AI food. Thus, future studies could examine how cultural and individual differences in food preferences and experiences influence the uncanniness of AI food. A diverse diet reduces food neophobia in nonhuman mammals owing to high variability of available safe food in the environment (Modlinska, 2022). In humans, exposure to diverse foods may lessen an uncanny valley of food, moderated by food neophobia. It is worth exploring this topic in a crosscultural survey.

A limitation is that participants' familiarity with AI images was not controlled. Familiarity may increase participants' acceptance of AI food or may, on the contrary, sensitize their perception of potential errors in AI-generated content, decreasing acceptance. Furthermore, food features that may influence ratings, such as fattiness or savoriness, were not controlled between conditions, nor were participants' dietary preferences. Hence, the effects of these factors on food uncanniness ratings remain unclear. Future research may attempt to replicate these findings while controlling for stimulus properties and participant dietary preferences.

5. Conclusion

This study shows AI-generated food images exhibit an uncanny valley effect, where imperfectly realistic food is eerier and less pleasant than unrealistic or highly realistic food. The relation between realism and uncanniness followed a cubic function, while pleasantness followed a quadratic function. Food neophobia, but not food disgust sensitivity, moderated this effect, indicating AI food discomfort is driven more by novelty aversion than contamination concerns. Images of moldy and rotten food also fell into an uncanny valley, further showing that deviations from expected realism in food stimuli elicit uncanniness.

The findings have implications for AI food applications in advertising, marketing, and clinical research. As AI food becomes more prevalent, understanding consumer reactions is crucial for acceptance. Given the interaction between AI food ratings and BMI, future research could investigate AI food perception in individuals with eating disorders, focusing on food-related anxiety, arousal, calorie estimation, and restrictive or dysregulated eating. Future research could also explore cultural influences on the uncanny valley of food, familiarity with AI-generated images, and food-related individual differences beyond neophobia and disgust. Controlling for dietary preferences and food characteristics like texture and flavor may further clarify the uncanny valley of food.

CRediT authorship contribution statement

Alexander Diel: Writing – review & editing, Visualization, Validation, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Tania Lalgi:** Writing – review & editing, Visualization, Resources, Investigation, Formal analysis, Data curation. **Martin Teufel:** Writing – review & editing, Validation, Supervision, Resources. **Alexander Bäuerle:** Writing – review & editing, Validation, Supervision, Conceptualization. **Karl MacDorman:** Writing – review & editing, Visualization, Validation, Resources, Formal analysis, Conceptualization.

Ethical statement

1) This material is the authors' own original work, which has not been previously published elsewhere.
2) The paper is not currently being considered for publication elsewhere.
3) The paper reflects the authors' own research and analysis in a truthful and complete manner.
4) The paper properly credits the meaningful contributions of co-authors and co-researchers.
5) The results are appropriately placed in the context of prior and existing research.
6) All sources used are properly disclosed. Literally copying of text must be indicated as such by using quotation marks and giving proper reference.
7) All authors have been personally and actively involved in substantial work leading to the paper and will take public responsibility for its content.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

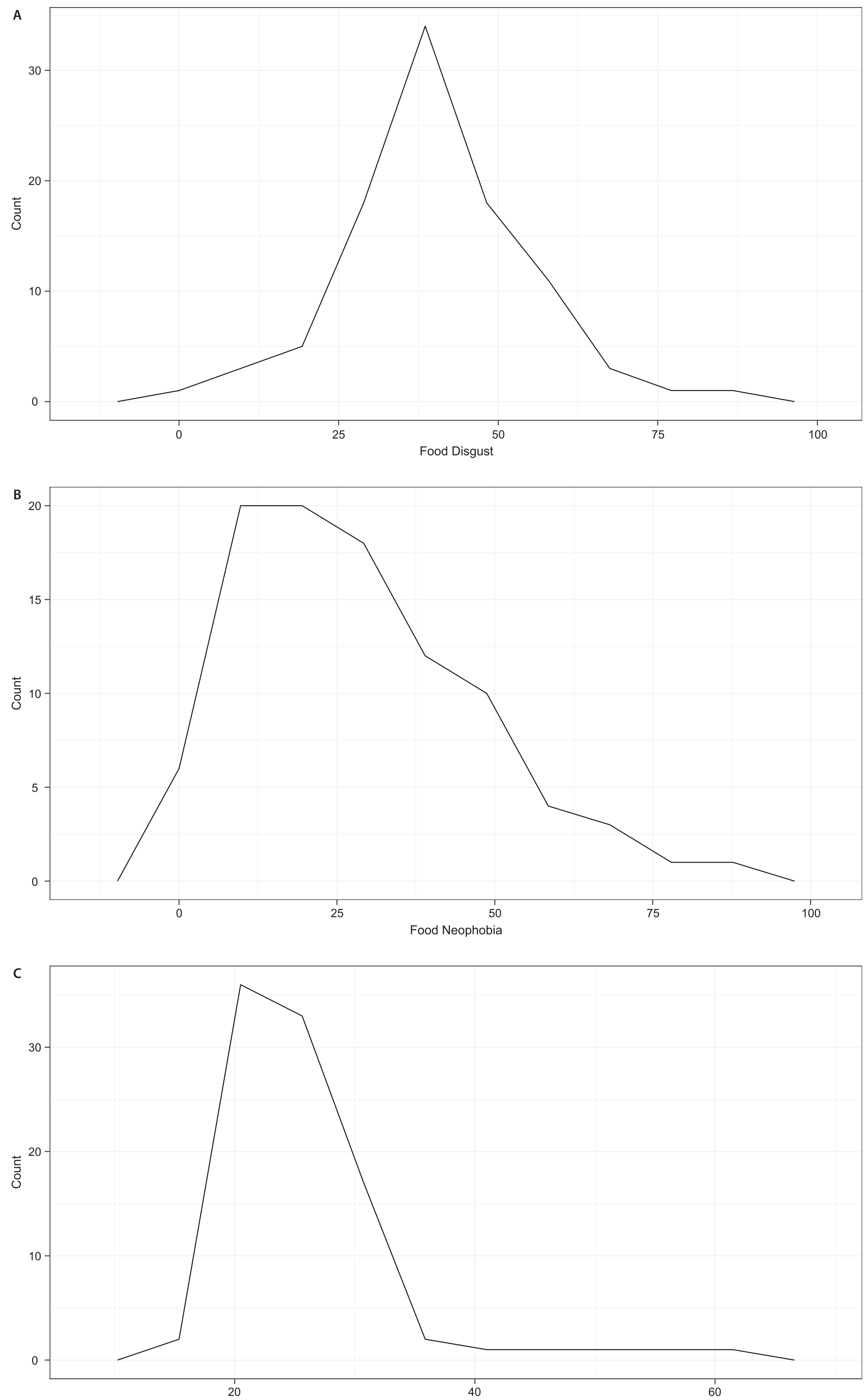

Fig. A1. Frequency distributions for food disgust (A) and food neophobia (B) ratings and BMI (C).

Table A1
Descriptive data (mean and standard errors) of the food stimuli from the main experiment (category, realism, eeriness, warmth, willingness to eat), ordered by level of realism.

Stimulus	CategoryF	Realism	Eeriness	Warmth	Willingness to eat
1	Stylized	12.41 (2.20)	37.83 (2.42)	61.07 (2.63)	0.44 (0.04)
2	Stylized	14.57 (2.52)	31.23 (2.71)	69.19 (2.58)	0.68 (0.04)
3	Stylized	15.13 (3.25)	31.31 (1.90)	81.06 (1.91)	0.83 (0.04)
4	Stylized	16.42 (2.72)	29.06 (1.90)	81.41 (1.89)	0.81 (0.04)
5	Stylized	20.06 (3.42)	31.99 (2.03)	75.71 (2.12)	0.74 (0.04)
6	Stylized	20.78 (3.04)	32.38 (1.90)	80.52 (1.89)	0.83 (0.03)
7	Imperfect	32.10 (2.46)	73.97 (2.05)	29.88 (1.66)	0.08 (0.03)
8	Imperfect	41.01 (2.16)	63.06 (2.13)	35.02 (2.03)	0.23 (0.03)
9	Imperfect	42.79 (2.55)	67.96 (2.19)	31.02 (2.05)	0.23 (0.04)
10	Imperfect	43.06 (2.34)	57.53 (2.32)	44.54 (1.88)	0.34 (0.04)
11	Imperfect	46.35 (2.45)	65.71 (2.72)	33.33 (2.80)	0.31 (0.04)
12	Imperfect	47.15 (2.57)	72.80 (2.47)	26.34 (2.20)	0.28 (0.04)
13	Imperfect	48.08 (2.32)	61.00 (2.10)	43.08 (2.07)	0.40 (0.04)
14	Rotten	48.29 (2.14)	67.39 (2.52)	23.03 (1.73)	0.13 (0.03)
15	Imperfect	48.29 (1.92)	57.20 (2.50)	37.40 (2.23)	0.18 (0.04)
16	Imperfect	48.40 (2.86)	75.18 (1.90)	30.55 (2.21)	0.25 (0.04)
17	Imperfect	51.11 (2.34)	68.64 (2.29)	30.72 (1.99)	0.19 (0.03)
18	Imperfect	52.64 (2.40)	72.54 (1.88)	28.15 (1.89)	0.18 (0.03)
19	Imperfect	54.39 (2.68)	52.63 (2.22)	52.37 (2.40)	0.48 (0.05)
20	Imperfect	54.83 (2.57)	44.89 (2.48)	56.81 (2.46)	0.53 (0.05)
21	Imperfect	56.87 (2.56)	43.36 (2.15)	59.67 (2.33)	0.53 (0.04)
22	Rotten	56.94 (2.69)	69.84 (2.77)	16.27 (1.60)	0.05 (0.02)
23	Imperfect	59.37 (2.03)	51.63 (2.20)	49.55 (2.21)	0.45 (0.05)
24	Imperfect	63.30 (2.06)	53.96 (2.32)	47.68 (2.41)	0.51 (0.05)
25	Imperfect	64.10 (2.35)	43.38 (2.44)	67.50 (2.46)	0.64 (0.04)
26	Rotten	68.69 (2.53)	78.99 (2.58)	7.07 (1.53)	0.02 (0.02)
27	Rotten	68.78 (2.26)	73.75 (2.90)	8.87 (1.34)	0.02 (0.02)
28	Imperfect	70.44 (2.05)	38.61 (2.22)	64.82 (1.92)	0.65 (0.05)
29	Rotten	70.90 (3.13)	77.44 (2.74)	9.18 (1.63)	0.02 (0.02)
30	Imperfect	72.05 (2.10)	30.05 (2.35)	69.93 (2.06)	0.80 (0.04)
31	Rotten	74.66 (2.31)	63.49 (2.83)	20.08 (1.95)	0.14 (0.03)
32	Real	74.74 (2.09)	34.73 (2.09)	71.28 (2.16)	0.77 (0.04)
33	Imperfect	78.66 (2.13)	31.94 (2.01)	77.66 (1.74)	0.87 (0.03)
34	Real	79.85 (1.84)	32.33 (1.92)	83.01 (1.62)	0.85 (0.03)
35	Real	81.77 (1.53)	28.90 (1.80)	74.76 (1.67)	0.81 (0.03)
36	Real	82.78 (1.74)	29.43 (1.77)	81.02 (1.77)	0.86 (0.03)
37	Real	83.54 (1.85)	28.71 (1.62)	78.03 (1.61)	0.86 (0.03)
38	Real	84.00 (1.81)	30.90 (1.89)	81.46 (1.63)	0.85 (0.03)

Data availability

Stimuli, data, and analysis script are publicly available at https://osf.io/x2y8h/.

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