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Artificial intelligence, body image comparison, and perceived aesthetic bias: a correlational study of weight-based digital exclusion

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Abstract

This study examines how perceptions of aesthetic discrimination based on body weight are associated with self-reported experiences in digital environments mediated by artificial intelligence (AI). Drawing on social comparison and objectification theories and on the sociotechnical literature on algorithmic bias, the study adopts a cross-sectional correlational design with a non-probability sample of 284 adult social media users in Ecuador. The analysis addresses associations among perceived algorithmic aesthetic intervention, body comparison with AI-generated representations, and self-reported feelings of body-related exclusion. Perceived AI-based photographic enhancement was positively associated with feelings of body-related exclusion ($\rho = 0.24$, $p < .001$), and comparison of one's own body image with AI-generated representations was positively associated with the perception of automated aesthetic enhancement ($\rho = 0.32$, $p < .001$). Participants who compared themselves with AI-generated images, and those reporting greater exclusion, were also the most likely to identify these systems as generating predominantly thin or athletic bodies ($\rho = -0.20$, $p < .001$, and $\rho = -0.17$, $p = .005$, on a scale whose lowest code is that response). Taken together, the results indicate that participants who perceive AI as intervening aesthetically in bodily images also report greater engagement in body comparison and stronger feelings of exclusion, and that those most engaged with AI-generated representations are also the most likely to recognise the narrowness of the bodies these systems produce. The findings are interpreted as perceptual evidence relevant to debates on algorithmic aesthetic standardisation, and they indicate the need for audit-based, longitudinal and instrument-validated designs.

Keywords Artificial intelligence · Perceived algorithmic bias · Body image · Social comparison · Objectification · Weight stigma · Digital culture · Cross-sectional survey · Ecuador

Introduction

Artificial intelligence now mediates a substantial share of the images through which bodies are seen and evaluated online. Algorithmic systems organise the production, circulation and ranking of visual content, and a critical literature argues that this mediation shapes the aesthetic horizons against which users assess their own appearance (Bucher, 2017; Gillespie, 2014). Within that literature, aesthetic discrimination associated with body weight has attracted particular attention, since weight stigma is well documented offline and its digital expressions may reach large audiences at low cost (Adelardi, 2022; Strings, 2019).

Several strands of work converge on the claim that these environments favour a narrow range of bodily appearances. Audits of computer-vision and text-to-image systems report that generated and highly ranked imagery skews towards thin and athletic phenotypes (Bianchi et al., 2023; Buolamwini

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& Gebru, 2018; Luccioni et al., 2023), and studies of editing and filtering tools describe how automated retouching adjusts bodily proportions towards a narrow ideal (Javornik et al., 2022). Whether such regularities amount to a distinct algorithmic aesthetic regime, and what consequences they carry for how users experience their own bodies, remains a matter of theoretical argument rather than of settled empirical fact. The present study does not test that argument at the level of system behaviour. It examines how users perceive it, and it makes no claim that artificial intelligence determines, establishes or defines standards of bodily beauty.

This study makes three contributions. First, it specifies a perceptual level of analysis: rather than inferring algorithmic behaviour from platform outputs, it measures how users interpret AI-mediated aesthetic intervention and how those interpretations relate to body comparison and to feelings of exclusion. Second, it situates those interpretations within an explicit theoretical model that articulates social comparison theory (Festinger, 1954; Wood, 1989), objectification theory (Fredrickson & Roberts, 1997) and the tripartite influence model of body image (Thompson et al., 1999) with sociotechnical accounts of algorithmic systems (Gillespie, 2014; Selbst et al., 2019), thereby identifying the psychological mechanisms through which AI-mediated imagery may become a comparison target. Third, it provides evidence from an under-represented Latin American setting, given that most quantitative research on social media and body image has been conducted in Anglophone and European samples (Vandenbosch et al., 2022). The study does not claim to establish causal effects; its scope is confined to associations among self-reported perceptions.

This scenario raises the question that guides the research: how do users perceive the involvement of artificial intelligence in aesthetic discrimination based on body weight, and how are those perceptions associated with body comparison and with feelings of exclusion? Three subordinate lines of inquiry follow. The first concerns how individuals identify algorithmic intervention in the environments they use daily and what role they attribute to AI in the circulation of weight-related aesthetics. The second focused on how such perceptions relate to body self-image and to emotions of acceptance, belonging or exclusion in digital space. The third one related to whether these perceptions are distributed unevenly across sociodemographic positions.

Theoretical framework

Theoretical mechanisms: social comparison, objectification and algorithmic mediation

The psychological mechanism assumed throughout this study is upward social comparison. Social comparison theory holds that individuals evaluate their own attributes against those of others, and that comparison with targets perceived as superior on a valued dimension tends to produce negative self-evaluation (Festinger, 1954; Wood, 1989). Applied to body image, upward appearance comparison is a consistent correlate of body dissatisfaction in both offline and online settings (Fardouly et al., 2015; Rodgers et al., 2015). Objectification theory adds that repeated exposure to appearance-focused environments encourages self-objectification, that is, the habitual adoption of an observer's perspective on one's own body, with documented consequences for body shame and appearance anxiety (Fredrickson & Roberts, 1997). The tripartite influence model identifies media, peers and family as the channels through which appearance ideals are internalised (Thompson et al., 1999); digital platforms compress these channels into a single interface, so that mediated ideals and peer feedback are encountered simultaneously and continuously (Perloff, 2014).

The question is whether AI-mediated imagery constitutes a theoretically distinct case or merely a further instance of media exposure. Three features suggest that it is distinct. The first is the algorithmic assembly of the comparison set: earlier image-editing technologies modified individual images, whereas recommender systems determine which images a given user encounters, so that the comparison set is personalised and differs across users (Bucher, 2017; Gillespie, 2014). The second is target ambiguity: generative models produce photorealistic bodies with no referent, which removes the attainability cue that ordinarily moderates the impact of upward comparison, since a target that does not exist cannot be discounted as an atypical case (Kleemans et al., 2018). The third is attributed agency: users increasingly treat algorithmic output as the judgement of a machine rather than of a person, and machine judgements are frequently granted a heuristic objectivity that human ones are not (Logg et al., 2019; Sundar, 2008, 2020). Where a retouched magazine photograph can be attributed to an editorial decision, an algorithmically curated feed may be read as an impartial description of which bodies are valued.

These features imply three candidate mechanisms. The first is comparison-set curation: personalised ranking may increase the frequency and homogeneity of upward appearance comparisons without any deliberate search on the user's part. The second is automated self-alteration: filters and enhancement tools return an optimised version of the user's own body, generating an intrapersonal comparison between the biographical and the computationally corrected self, and thereby extending the self-objectification pathway to a target that is simultaneously self and ideal. The third is attributed algorithmic evaluation: the belief that a system

is ranking one's appearance, whether or not it in fact does so, may itself generate appearance anxiety and perceived exclusion, consistent with work on the algorithmic imaginary (Bucher, 2017; Eslami et al., 2015). The present study measures perceptions relevant to the second and third mechanisms; it does not observe the first, which would require platform-level data on what each participant was actually shown.

Whether AI-specific exposure produces outcomes that differ in kind, rather than in degree, from those of traditional media exposure remains an open empirical question that a cross-sectional perceptual survey cannot settle. The present design can establish whether perceived AI intervention is associated with body comparison and exclusion within a general adult sample. Adjudicating between an AI-specific and a generic media pathway requires designs that manipulate the source attribution of otherwise identical images, or that measure AI-mediated and non-AI-mediated exposure separately over time. This constraint is stated here and returned to in Sect. 6.

Three terms used in the remainder of the article are defined at the outset. Algorithmic aesthetic regime is used descriptively, to designate the configuration of ranking, filtering and generative processes through which bodily appearances obtain differential visibility on a platform; the expression names an object of inquiry and not a demonstrated causal force (Anikina, 2020). Perceived algorithmic aesthetic bias denotes a user's belief that such processes systematically favour particular body types (Bucher, 2017; Eslami et al., 2015) and is distinguished throughout from actual algorithmic bias, which can be established only through audits of system behaviour (Bianchi et al., 2023; Raji & Buolamwini, 2019). Body-related exclusion is the concise analytic label for the respondent's direct report of having felt excluded or judged on social media because of their body. It is treated as a bounded experiential indicator rather than as a measure of clinically significant distress or documented platform exclusion (Papaioannou & Monaghan, 2023).

Aesthetic discrimination based on body weight in digital culture

Aesthetic discrimination in the domain of body weight is discussed in the literature through two related concepts: fat hatred (Ronconi et al., 2024) and fatphobia (Adelardi, 2022). In digital environments the first has been described not as an isolated prejudice but as a visual principle that ranks individuals by degree of thinness (Aparicio-Martín, 2015), so that fat bodies are pathologised or rendered invisible; on this reading, such discrimination is an outcome of modern aesthetic configurations of the body rather than a system error (Albet-Castillejo, 2020). Fatphobia refers more narrowly to rejection of and discrimination against people with fat bodies (Adelardi, 2022; Del Mar et al., 2025), sustained by stereotypes that associate higher body weight with a lack of willpower or unhealthy habits (Strings, 2019) and reported across educational, social and workplace settings.

Within visual culture, fat hatred has been analysed as a form of lateral surveillance in which users themselves act as agents of normalisation (Piñeyro, 2016, 2019), and digital networks as environments that penalise bodily dissidence through segregation or omission (Guerrero-Salazar, 2020; Ronconi et al., 2024). These dynamics are described as gendered, intensifying appearance demands on feminised bodies (Álvarez-Castillo, 2015), and as embedded in an attention economy that rewards normative thinness (Clay & Brickell, 2022). Platform optimisation logics have also been argued to marginalise narratives of body acceptance except in commodified form (Cohen et al., 2021), and to render fat bodies visible mainly when framed within a narrative of transformation towards thinness (Allende-Allende, 2020; Noble, 2018; Wanniarachchi et al., 2022).

Weight-based discrimination online has also been read as an extension of biopolitics, with the algorithm treated as an agent of biological normality (Noble, 2018). The term *digital biopolitics* is used here in the specific Foucauldian sense adopted by Albet-Castillejo (2020), namely the governance of populations through norms of health and bodily conduct that subjects come to apply to themselves. The claim is theoretical rather than measured: it describes an interpretive framework for reading platform design, not an established property of any particular system. Within that framework, the ostensible detachment of online interaction from physical presence has been argued to intensify rather than diminish concern with appearance, turning weight into a metric of social validation (Adelardi, 2022; García-Díaz et al., 2024; Ring Carlson, 2022).

Empirical work in this tradition documents weight-based online harassment as a systemic practice of exclusion from shared public space rather than as isolated individual behaviour (Lobaton, 2022; Wanniarachchi et al., 2023), and content analyses report that representations of fatness in digital media are frequently associated with a lack of self-control (Arcila-Calderón et al., 2020, 2024; Gibson, 2022). Arcila-Calderón et al. (2020) describe the resulting configuration as *fat hatred by design*, an analytical expression conveying the argument that interfaces are not neutral with respect to bodily volume; it is reported here as their formulation and not as a claim about demonstrated design intent. On this account, aesthetic discrimination is an emergent property of systems optimised for visual uniformity and user retention (Aparicio-Martín, 2015; Birhane, 2021; Strings, 2019) rather than a deliberate objective of their designers.

Consistent with weight-stigma scholarship, terminology is selected according to analytic context and respect for the people described (Meadows & Daníelsdóttir, 2016). Fat hatred and fatphobia name the critical concepts defined above, while fat is retained when discussing the cited fat studies literature and its identity-affirming vocabulary. In the study's own analytic prose, higher-weight bodies serves as the neutral descriptive term. Body diversity refers inclusively to variation in body size, shape and form, including but not limited to higher-weight representation. Overweight and obesity appear only when reproducing clinical language or the questionnaire category 'with obesity (diagnosed or self-perceived).' These choices give each term a clear function and support consistent, context-sensitive reporting.

Artificial intelligence, algorithms, and bias in the production of bodily visibility

Critical scholarship characterises AI systems not as neutral instruments but as sociotechnical artefacts that carry the aesthetic assumptions of their developers and training corpora (Birhane, 2021; Costanza-Chock, 2020). Computer-vision models are commonly trained on image sets in which thin bodies function as the statistical and aesthetic norm (Buolamwini, 2023; Noble, 2018), and audits of text-to-image systems report a tendency to generate thin or athletic figures in response to appearance-neutral prompts (Bianchi et al., 2023; Luccioni et al., 2023). Comparable patterns have been reported for AI-generated imagery in sport and physical education (Díaz Barahona & Marín Liébana, 2025).

A second body of work concerns tools that modify images rather than generate them. Filters and enhancement applications smooth textures and adjust bodily proportions towards a narrow ideal, and their use has been associated with reduced self-acceptance among some users (Aparicio-Martín, 2015; García-Díaz et al., 2024; Javornik et al., 2022). Wanniarachchi et al. (2022) characterise the automation of appearance correction as a form of aesthetic normalisation; the expression is theirs, it denotes a critical reading of the technology rather than a measured property of it, and it is reported here in that sense. Related work on self-perception in AI-mediated environments reports comparable concerns among Latin American users (Manjarrés, 2024).

At the level of distribution, classification and ranking systems have been shown to associate normative appearance with engagement metrics (Ali et al., 2019), and audits report that images of thin bodies receive higher levels of algorithmic promotion (Birhane, 2021). Moderation systems have been reported to conflate the display of higher-weight bodies with sexualised content, reducing the reach of fat activist accounts (Abid et al., 2021; Álvarez-Castillo, 2015; Del Mar et al., 2025). The opacity of these systems means that users cannot readily determine why particular bodies become less visible in their feeds (Birhane, 2021; Noble, 2018), which has prompted calls for auditing and regulatory frameworks attentive to embodiment (Buolamwini, 2023; Costanza-Chock, 2020).

Taken together, this literature describes a feedback dynamic in which systems reproduce the appearance regularities present in their training data, and in which the resulting outputs form part of the material from which subsequent models learn (Javornik et al., 2022; Luccioni et al., 2023). The emergence of AI-generated influencers has been discussed in similar terms, as introducing appearance standards with no biological referent (Adelardi, 2022; Palomino-Flores et al., 2026). Two cautions are warranted. First, this evidence concerns system outputs rather than user experience. Second, the strength of the documented regularities varies across models, tasks and audit protocols, so general statements about what artificial intelligence does are correspondingly imprecise. The present study addresses neither question directly; it measures what users report perceiving.

Social perception of AI and bodily experience in digital environments

A smaller literature addresses how users experience these systems. Users have been described as attributing evaluative authority to algorithmic feedback, reading metrics of visibility as judgements on their appearance (Birhane, 2021; Ugarte, 2021), and as reporting a sense of inadequacy when their bodies do not receive the engagement that normative bodies attract (Papaioannou & Monaghan, 2023; Taylor et al., 2023). These accounts do not describe passive reception: users develop working theories of platform behaviour and act on them, adjusting posts and poses in an attempt to gain visibility (Bucher, 2017; Ellison, 2020).

Sociodemographic position appears to modulate these perceptions. Perceived discrimination varies by gender, age and socioeconomic position (Aparicio-Martín, 2015; Gordon, 2020; Strings, 2019), including discrimination attributed to algorithmic systems (Arcila-Calderón et al., 2020; Costanza-Chock, 2020), and young women in particular report greater appearance-related pressure in digital environments (Allende-Allende, 2020; Tiggemann & Slater, 2013).

Qualitative work reports that appearance satisfaction becomes entangled with legibility to the system: system approval is internalised as personal validation (Luccioni et al., 2023; Papaioannou & Monaghan, 2023), and people with higher-weight bodies describe sustained monitoring of how their images circulate (Adelardi, 2022; Guerrero-Salazar, 2020). This monitoring has been characterised as affective labour that users with bodies aligned with the thin

or athletic ideal are not required to perform (Álvarez-Castillo, 2015; Del Mar et al., 2025; Lind, 2020). Difficulty in distinguishing unaltered from digitally altered images has likewise been linked to body dissatisfaction (Cohen et al., 2021; Kleemans et al., 2018).

Reduced representation of body diversity has in turn been associated with disengagement and platform abandonment among users with higher-weight bodies (Ring Carlson, 2022; Wanniarachchi et al., 2023), with consequences that some authors frame as a matter of health equity (Noble, 2018; Taylor et al., 2023). These accounts are largely qualitative or theoretical, and the affective outcomes they describe have rarely been measured directly in general adult samples.

Two observations follow from this review and motivate the empirical design that follows. The first is that the literature is asymmetrically distributed: claims about the behaviour of algorithmic systems rest largely on audits and content analyses, whereas claims about users' experience of those systems rest largely on qualitative and theoretical work, with comparatively few quantitative studies measuring perception directly. The second is that the two levels are routinely conflated, so that evidence about system outputs is used to license claims about subjective experience and vice versa. The present study addresses the second level only. It measures what a sample of users perceive, compare and report feeling, and examines how those measures covary.

Method

Objectives and hypotheses

The general objective of this research is to analyse the relationship between AI-mediated aesthetic manipulation tools on social media, perceptions of aesthetic bias associated with the ideal of thinness, body comparison and direct reports of body-related exclusion or judgment, while considering gender, age and level of education. The analysis is organised around three theory-derived directional hypotheses and one explicitly exploratory question.

Social comparison and objectification theories predict that engagement with appearance optimising environments is associated with heightened appearance self-evaluation, and that this association is stronger among people socialised into greater appearance surveillance (Fredrickson & Roberts, 1997; Perloff, 2014). Research on gendered appearance pressure and on formal education as a resource for critical media and algorithmic literacy provides the directional basis for the following hypotheses (Tiggemann & Slater, 2013; Vandenbosch et al., 2022).

H1: Women will report more frequent use of appearance modifying social media filters and a stronger perception that AI promotes thin bodies as the aesthetic norm than men.

H2: Higher educational attainment will be associated with stronger recognition of perceived AI aesthetic bias, a greater likelihood of identifying AI generated output as predominantly thin or athletic, and stronger support for training AI systems with a broader diversity of bodies.

H3: Greater perceived AI-mediated aesthetic intervention will be associated with a higher likelihood of body comparison with AI-generated representations and of reporting body-related exclusion or judgment on social media. Participants reporting comparison or exclusion will also be more likely to identify AI output as predominantly thin or athletic.

RQ1: Does perceived AI aesthetic bias vary across age groups after educational attainment is taken into account? Age is treated as an exploratory question because the available literature does not support an unambiguous directional prediction for a general adult sample. H1, H2 and H3 are associational predictions. The cross-sectional design supports neither causal ordering nor a claim that the hypotheses were confirmed beyond this sample.

Design

The study adopts a quantitative, cross-sectional correlational design, which is appropriate for examining the strength and direction of associations between variables without intervening in the conditions under which they occur (Wherry, 2014). It supports an assessment of how self-perceived body weight, filter use, comparison with AI-generated images and perceived algorithmic aesthetic bias covary within the sample, and provides the basis for the hypothesis tests reported in Sect. 4. It does not support inference about the direction of any of these associations.

Instrument, pilot test and content validation

A structured survey was used as the data collection technique, enabling the systematic gathering of information on perceptions, experiences, and digital practices related to artificial intelligence and bodily representation. The instrument consisted of 20 questions organized into four thematic blocks. The first block addressed sociodemographic variables and included four questions designed to identify basic characteristics of the participating population, such as gender, age, and level of education. The second block focused on body self-perception and comprised three questions that explored subjective perceptions of body weight

Table 1 Descriptive statistics for the variables entering the analyses ($N = 284$)

Statistics						
	N valid	*N* missing	Mdn	P25	P75	IQR
Sociodemographic characteristics						
Gender	284	0	1	1	2	1
Age	284	0	3	2	5	3
Level of education	284	0	3	1	4	3
Variables entering the analyses						
Body-altering social media filters	284	0	1	1	2	1
AI improves photos	284	0	1	1	3	2
AI thin bodies	284	0	2	2	3	1
Aesthetic bias	284	0	3	2	3	1
AI body types	284	0	2	1	3	2
Training AI with diverse bodies	284	0	3	1	3	2
Comparison of real image with AI	284	0	1	1	2	1
Body-related exclusion or judgment	284	0	1	1	2	1
Panel B. Frequency distribution						
Frequency distribution						
	Response category	f	%	Valid %		
Sociodemographic characteristics						
Gender	Woman	198	69.7	69.7		
	Man	82	28.9	28.9		
	Non-binary	4	1.4	1.4		
Age (bands)	18–20 years	34	12.0	12.0		
	21–25	89	31.3	31.3		
	26–30	41	14.4	14.4		
	31–35	40	14.1	14.1		
	36–40	25	8.8	8.8		
	41–45	22	7.7	7.7		
	46–50	10	3.5	3.5		
	51–55	10	3.5	3.5		
	56–60	9	3.2	3.2		
	61–65	4	1.4	1.4		
Level of education	Complete secondary	93	32.7	32.7		
	Technical / technological	24	8.5	8.5		
	Undergraduate	84	29.6	29.6		
	Postgraduate	83	29.2	29.2		
Variables entering the analyses						
Body-altering social media filters	Never	169	59.5	59.5		
	Occasionally	95	33.5	33.5		
	Frequently	20	7.0	7.0		
AI improves photos	No	185	65.1	65.1		
	Not sure	25	8.8	8.8		
	Yes	74	26.1	26.1		
AI thin bodies	No	63	22.2	22.2		
	Not sure	99	34.9	34.9		
	Yes	122	43.0	43.0		
Aesthetic bias	No	35	12.3	12.3		
	Not sure	83	29.2	29.2		
	Yes	166	58.5	58.5		
AI body types	Thin / athletic	115	40.5	40.5		
	Diverse	68	23.9	23.9		
	Have not noticed	101	35.6	35.6		
Training AI with diverse bodies	Indifferent	82	28.9	28.9		
	No	53	18.7	18.7		
	Yes	149	52.5	52.5		
Comparison of real image with AI	No comparison made	178	62.7	62.7		

Table 1 (continued)

Statistics						
	N valid	*N* missing	Mdn	P25	P75	IQR
	Yes, no effect	52	18.3	18.3		
	Yes, felt better	38	13.4	13.4		
	Yes, felt worse	16	5.6	5.6		
Body-related exclusion or judgment	No	192	67.6	67.6		
	Not sure	36	12.7	12.7		
	Yes	56	19.7	19.7		

Mdn = median; P25 and P75 = 25th and 75th percentiles; IQR = interquartile range. Response categories are numbered in the order shown, and medians and percentiles are computed on those numerical codes. Percentages in the % column are computed on the total sample (N = 284) and those in the Valid % column on the number of valid cases for each variable; the two coincide for every variable except age. Percentages may not sum to 100 owing to rounding

Table 2 Spearman correlations between gender, use of body-altering filters, and the perception of thinness as an aesthetic norm (n = 280)

Variable	ρ with gender	*p*
Use of body-altering filters on social media	−0.21	< 0.001
Perception that AI promotes thin bodies as the norm	−0.16	0.006

n = 280 (respondents identifying as women or men). Gender is coded 1 = woman, 2 = man, so that negative coefficients indicate higher scores among women. ρ = Spearman's rank-order correlation coefficient

Table 3 Spearman correlation between age and perceived aesthetic bias (N = 284)

Variables	ρ	*p*
Age and perceived aesthetic bias	0.17	0.005

N = 284. ρ = Spearman's rank-order correlation coefficient. Age and educational attainment are associated in this sample; the adjusted model reported in Table 4 shows that this bivariate association does not survive control for educational attainment

Table 4 Spearman correlations among feelings of body-related exclusion and perceptions of bodily representation in artificial intelligence (N = 284)

Variable	1	2	3
1. Body-related exclusion or judgment	—	0.24**	−0.17**
2. Perception that AI enhances photographs		—	−0.15**
3. Perceived body-type composition of AI output			—

N = 284. Coefficients are Spearman's rank-order correlations. Variable 3 is coded 1 = thin or athletic bodies, 2 = diverse bodies, 3 = have not noticed, so that negative coefficients indicate a greater likelihood of identifying AI output as thin or athletic. **p < .01 (two-tailed)

Table 5 Spearman correlations between body comparison with ai-generated images and perceptions of ai-based bodily representation (N = 284)

Variable	ρ	*p*
Perceived body-type composition of AI output	−0.20	< 0.001
Support for training AI with diverse bodies	0.13	0.033
Perception that AI enhances photographs	0.32	< 0.001

N = 284. Coefficients are Spearman's rank-order correlations with body comparison with AI-generated representations, coded 1 = no comparison, 2 = comparison without change, 3 = comparison, felt better, 4 = comparison, felt worse. The perceived body-type composition of AI output is coded 1 = thin or athletic bodies, 2 = diverse bodies, 3 = have not noticed

and satisfaction with one's physical image. The third block addressed digital experiences mediated by artificial intelligence and included six questions related to the use of filters, comparison with AI-generated images, and aesthetic pressure derived from interaction with digital content. Finally, the fourth block examined perceptions of algorithmic bias and aesthetic discrimination and included five questions aimed at assessing the perception that artificial intelligence reproduces bodily stereotypes and promotes thinness as the dominant aesthetic standard.

Prior to final administration, the instrument underwent a pilot test conducted between August 18 and September 18, 2025, involving 43 participants selected to reflect the sociodemographic profile of the target population. The pilot identified semantic ambiguities, structural inconsistencies and difficulties in item comprehension. Content validation was also conducted by five university faculty members with more than 15 years of experience in psychology and information and communication technologies, who assessed the relevance, clarity and coherence of the items in relation to the research objectives. The resulting revisions improved terminology, item order and wording. Together, the pilot and expert review provided evidence of face and content validity for the item-level indicators. Cronbach's alpha was 0.80 for the complete set of administered items and is retained as an overall instrument descriptor; it is not used to make reliability claims about any individual item (Tables 1, 2, 3, 4, 5 and 6).

Measurement and variable definition

The focal variables are labelled differently across the body image and algorithmic fairness literatures; their operational definitions are therefore stated explicitly. Perceived AI aesthetic bias is the respondent's belief that AI systems favour

Table 6 Exploratory ordinal logistic regressions for perceived aesthetic bias and feelings of body-related exclusion ($n=280$)

Ordinal logistic regression (proportional odds)				
Predictor	b	SE	OR [95% CI]	*p*
Model 1. Perceived aesthetic bias ($n=280$)				
Woman (vs. man)	+0.364	0.258	1.44 [0.87, 2.39]	0.159
Level of education	+0.266	0.111	1.30 [1.05, 1.62]	0.017
Age band	+0.078	0.064	1.08 [0.95, 1.23]	0.220
McFadden pseudo-R^2 = 0.029				
Model 1b. Perceived aesthetic bias, age omitted ($n=280$)				
Woman (vs. man)	+0.339	0.257	1.40 [0.85, 2.32]	0.186
Level of education	+0.330	0.098	1.39 [1.15, 1.69]	0.001
McFadden pseudo-R^2 = 0.026				
Model 2. Body-related exclusion or judgment ($n=280$)				
AI improves photos	+0.383	0.151	1.47 [1.09, 1.97]	0.011
Compared with AI image (yes vs. no)	+0.833	0.276	2.30 [1.34, 3.95]	0.003
Woman (vs. man)	+0.690	0.313	1.99 [1.08, 3.68]	0.028
Level of education	−0.131	0.109	0.88 [0.71, 1.09]	0.229
McFadden pseudo-R^2 = 0.026				

b = log-odds coefficient; *OR* = odds ratio; CI = confidence interval. Level of education and age band enter as ordered integer scores. Outcomes are coded 1 = no, 2 = not sure, 3 = yes, so that an odds ratio above 1 indicates higher odds of an affirmative response. All three models are estimated on the 280 respondents who identified as women or as men; the four non-binary respondents are excluded because the group is too small to enter a binary gender term. Threshold parameters are omitted from the table

particular body types in the images they generate, recommend or enhance. It is a report of perceived bias rather than an audit of system behaviour. Body-related exclusion is operationalised by the direct item, 'Have you felt excluded or judged on social media because of your body?' with the response options no, not sure and yes. The variable therefore records a clearly bounded experience in the study context; it is not presented as a comprehensive scale of social exclusion, body dissatisfaction or psychopathology. Body comparison with AI-generated representations records whether respondents compared their own image with AI-generated images and the reported valence of that comparison. Perceived body-type composition records which bodies respondents most frequently notice in AI-generated images, distinguishing thin or athletic bodies, diverse bodies and not having noticed. Table 7 reproduces the complete operational definitions and response coding.

Table 7 Operational Definitions and Response Coding of the Main Analytical Variables

Variable	Operational definition	Response coding
Body-altering social media filters	Self-reported use of social-media tools or filters intended to modify bodily appearance.	1 = Never; 2 = Occasionally; 3 = Frequently
Perceived AI enhancement of photographs	Respondent's perception that AI systems aesthetically enhance or modify photographs.	1 = No; 2 = Not sure; 3 = Yes
Perception that AI promotes thin bodies	Respondent's perception that AI promotes thin bodies as the dominant or normative aesthetic standard.	1 = No; 2 = Not sure; 3 = Yes
Perceived AI aesthetic bias	Respondent's belief that AI systems systematically favour particular body types in the images they generate, recommend, or enhance. This measure captures perceived rather than demonstrated algorithmic bias.	1 = No; 2 = Not sure; 3 = Yes
Perceived body-type composition of AI output	Body types respondents report most frequently noticing in AI-generated images.	1 = Thin or athletic; 2 = Diverse; 3 = Have not noticed
Support for training AI with diverse bodies	Respondent's normative judgement regarding whether AI systems should be trained using a broader diversity of body types.	1 = Indifferent; 2 = No; 3 = Yes
Body comparison with AI-generated representations	Whether respondents have compared their own body image with AI-generated representations and the reported valence of that comparison.	1 = No, I have never made that comparison; 2 = Yes, but it did not affect me; 3 = Yes, and I felt better with the generated image because I looked thinner; 4 = Yes, and I felt worse with the generated image because it altered my body or weight
Body-related exclusion or judgment	Direct self-report of having felt excluded or judged on social media because of one's body. It is treated as a bounded experiential indicator rather than a clinical or multidimensional exclusion scale.	1 = No; 2 = Not sure; 3 = Yes

The item-level measurement strategy matches the study's exploratory and perceptual scope. Methodological guidance does not treat single items as automatically inadequate: it distinguishes narrow, concrete and unambiguously worded experiences from broad or multidimensional psychological constructs, for which multi-item scales are generally preferable (Allen et al., 2022; Bergkvist & Rossiter, 2007). In this study, the five-expert content review and 43-participant pilot established relevance, clarity and comprehensibility for the intended questions. The body-related exclusion item also behaved coherently across complementary analyses: its association with perceived AI enhancement was observed in both rank-based and coding-free tests, while perceived enhancement and reported body comparison remained associated with the item in the adjusted ordinal model. This convergence supports its interpretation as an exploratory indicator of the specified experience, although it is not presented as a full psychometric validation or a latent clinical measure. Within-scale internal consistency and factor structure are not applicable to an individual item, and the instrument-level alpha of 0.80 is therefore not invoked as construct-level evidence.

The response formats were selected to match the content of each question. The three-category items distinguish absence or disagreement, uncertainty and presence or agreement; the comparison item additionally preserves whether the comparison had no reported effect or was followed by a more or less favourable self-evaluation. Retaining 'not sure' treats uncertainty as substantive information rather than forcing a binary answer. Because these categories are discrete and do not represent equal numerical intervals, analyses retain the original response structure, report category distributions and pair rank-based results with chi-square tests and Cramér's V when order is ambiguous. This strategy permits transparent analysis of the observed categorical responses; future studies can add broader response ranges and multi-item measures when greater differentiation of frequency or intensity is the primary aim.

Participants, sampling procedure and ethical safeguards

The final administration of the instrument yielded 284 valid responses. The sampling strategy is described here as non-probability sampling. The questionnaire was distributed as an open link through digital channels and participation was voluntary and self-selected; consequently no sampling frame was constructed, no randomised selection procedure was applied, and the probability of selection for any member of the target population is unknown. The target population was defined as adults resident in Ecuador who use social media, a population for which no enumerable frame exists. Of the 284 respondents, 264 (93.0%) reported residing in Ecuador and 20 (7.0%) elsewhere; the latter are retained in the analyses, and the sample is accordingly described as predominantly, rather than exclusively, Ecuadorian. Recruitment proceeded by open dissemination of the survey link through digital channels, and because the link could be forwarded freely the number of individuals who received or viewed the invitation is unknown; a response rate therefore cannot be computed, and the 284 cases analysed are all the complete responses received during the fieldwork period. No claim of representativeness is therefore made for the sample (Hernández-Ávila & Escobar, 2019).

Eligibility was restricted to adults aged 18 years or older. This adult-only eligibility criterion was communicated through the recruitment and consent information; no separate automated age-gating item was included in the questionnaire. The first age band in the original questionnaire, labelled '20 years or under,' was intended to group adult respondents aged 18–20 years. No participants younger than 18 were included in the final analytical sample. The revised manuscript therefore reports this category consistently as '18–20 years.'

Self-selected online samples over-represent individuals with higher digital engagement and, typically, higher educational attainment, and they under-represent those with limited connectivity (Bethlehem, 2010; Wright, 2005). The design supports the examination of associations among variables within the sample, which is the stated analytical aim, but it does not support inference to the Ecuadorian population, and no such inference is drawn. In addition, several variables that plausibly condition perceptions of AI and bodily representation are unavailable to the analyses reported below.

Prior to participation, all respondents provided informed consent through a mandatory digital consent form included at the beginning of the questionnaire. Participants were informed about the objectives of the study, the voluntary nature of participation, confidentiality guarantees and the anonymous treatment of the data in accordance with personal data protection regulations. Specifically, they were told that the study examined perceptions, experiences and knowledge concerning higher-weight bodies and other body types underrepresented in AI-mediated digital environments, particularly in relation to perceived algorithmic bias, weight-based discrimination and aesthetic exclusion. Only individuals who explicitly agreed to participate were allowed to continue. No personally identifiable information was collected, and all responses were processed exclusively for academic and research purposes under secure data-management procedures. Participation was limited to adults aged 18 years or older, and no minors were included in the study.

The verified distribution by gender was 198 women, 82 men and 4 non-binary respondents. These counts sum to the full sample of 284 and are used consistently in Sect. 4.1 and Table 1. Analyses comparing women and men use $n = 280$ because the four non-binary respondents could not form a statistically stable comparison group. The gender imbalance limits the precision of estimates for men and precludes reliable inference for non-binary participants. Formal data collection took place between 5 October 2025 and 5 February 2026. The questionnaire was administered through Microsoft Forms.

Analytical strategy

Once data collection was completed, the data were cleaned, coded and organised in an analysis matrix for statistical processing in the Statistical Package for the Social Sciences (SPSS). Because the variables are ordinal or categorical and the normality assumption was rejected for every variable examined, the analysis proceeded with non-parametric procedures: Spearman's rho for bivariate association, the Mann–Whitney U test for two-group comparisons, and the Kruskal–Wallis test with Dunn post hoc comparisons and Bonferroni correction for comparisons across more than two groups. Effect sizes are reported for every inferential test, the coefficient $r = Z/\sqrt{N}$ for two-group comparisons (Rosenthal, 1991) and epsilon squared, computed as $\varepsilon^2 = H/(n-1)$, for Kruskal–Wallis tests (Tomczak & Tomczak, 2014). A single definition is applied consistently within each family of tests, and effect sizes are interpreted following the benchmarks discussed by Cohen (1988) and the calibration guidance of Funder and Ozer (2019). Correlation coefficients and test statistics are reported to two decimal places, and effect-size indices to three, because several of the latter fall below 0.10, where two-decimal rounding would obscure differences between comparisons.

Kruskal-Wallis results are reported as H(df), where df is the number of compared groups minus one; thus $H(3) = 17.70$ denotes a statistic evaluated on three degrees of freedom across four educational strata. This use of H is unrelated to H1, H2 and H3, the labels designating the three research hypotheses.

The analysis matrix assigns consecutive integers to the categories of each item in the order in which they were stored, and for four variables that order is not monotone with respect to any underlying continuum. The perceived body-type composition of AI output is coded 1 = thin or athletic, 2 = diverse, 3 = have not noticed; support for training AI with diverse bodies is coded 1 = indifferent, 2 = no, 3 = yes; body comparison with AI-generated representations is coded 1 = no comparison, 2 = comparison without change, 3 = comparison, felt better, 4 = comparison, felt worse; and self-perceived body weight retains "not sure" and "prefer not to answer" as its two highest codes. Because a non-committal or non-applicable option occupies an interior or terminal position in each of these sequences, the corresponding Spearman coefficients and mean ranks index association but do not describe movement along a scale, and they are interpreted in Sect. 4 by reference to the underlying category distributions rather than as directional gradients. Wherever such a variable enters an analysis, a chi-square test of independence with Cramer's V is reported alongside the rank-based statistic as a coding-free check. The variables coded no / not sure / yes, namely perceived aesthetic bias, the perception that AI promotes thin bodies, the perception that AI enhances photographs and feelings of body-related exclusion, together with the ordered filter-use item and the ordered education and age bands, are unaffected by this consideration.

The theoretical model outlined in Sect. 2.1 proposes a process in which body comparison may link perceived AI intervention with body-related exclusion. The present study tests the prespecified associations within that model but does not estimate mediation or a structural pathway. All variables were measured simultaneously, and cross-sectional mediation can yield biased estimates of the longitudinal parameters of interest (Maxwell & Cole, 2007). A direct mechanism test would therefore require temporal separation and a measurement design developed for that purpose, including multi-item measures where constructs are multidimensional. The ordinal logistic regressions reported in Sect. 4.5 address a different question: whether the principal bivariate associations remain after the sociodemographic composition of the sample is taken into account. Their coefficients are interpreted as adjusted associations rather than as causal or mediational effects.

The theoretical framework treats gender, age and education as social positions that may be interdependent. In the present analyses these variables are entered jointly as main effects, which estimates each association while holding the others constant but does not estimate their interactions. Inspection of the joint distributions confirmed several low-frequency gender by age and gender by education cells. Because the study was not stratified for these joint subgroups and interaction contrasts were not prespecified, post hoc product terms would not provide a stable test of intersectionality. The manuscript therefore distinguishes the current adjusted analysis from a direct intersectional test. Future work can test these combinations through stratified or quota-controlled recruitment, prespecified interaction contrasts and adequate numbers in each joint subgroup.

Results

Descriptive statistics

Before the inferential analyses, the distribution of the principal variables was summarised. The analytical sample comprised 284 respondents: 198 women (69.7%), 82 men (28.9%) and 4 non-binary participants (1.4%). Every descriptive table and inferential analysis uses these verified counts. Use of appearance modifying filters was reported as never by 74.4% of men and 53.0% of women, occasional by 23.2% of men and 37.9% of women, and frequent by 2.4% of men and 9.1% of women. Women also more frequently reported that AI promotes thin bodies as the aesthetic norm.

The data set contains no missing values on any variable entering the analyses. All tests are computed on the full sample of 284, except the two-group comparisons by gender, which are computed on the 280 respondents who identified as women or as men. Table 1 reports the complete descriptive statistics. The remaining variables, namely perceived AI enhancement of photographs, the perceived body-type composition of AI output, support for training AI with diverse bodies, and feelings of body-related exclusion, were recorded on three- and four-category ordinal scales. Normality was assessed for every variable within every comparison subgroup using the Kolmogorov–Smirnov test with Lilliefors correction and the Shapiro–Wilk test, and the distributions departed significantly from normality in all cases ($p < .001$),

Relationships between sociodemographic variables and aesthetic perceptions

Gender

The correlation analysis identified significant associations between sociodemographic variables, namely gender, level of education, and age, and several variables related to the perception of body standards and digitally mediated aesthetic manipulation (Table 2). Regarding gender, significant correlations were observed with variables associated with the aesthetic manipulation of body image. Particularly, gender was associated with bodily alteration through social media filters, as well as with the perception of thinness as the predominant aesthetic norm in digital environments. These results suggest that experiences and perceptions related to body standards and image-modification tools may vary according to participants' gender.

Regarding gender and its relationship with aesthetic alteration through social media filters and the perception of thinness as an aesthetic norm in digital environments, a significant negative correlation was identified between gender and the use of body-altering filters on social media ($\rho = -0.21$, $p < .001$, $n = 280$). This finding suggests variation across gender groups in the use of digital tools designed to modify bodily appearance. Similarly, gender showed a significant negative correlation with the perception of thinness as an aesthetic norm ($\rho = -0.16$, $p = .006$, $n = 280$), indicating that perceptions of dominant body standards in digital environments may vary according to this sociodemographic variable.

Regarding gender and filter use, the Mann-Whitney U test showed a statistically significant difference between women and men ($U = 6288.00$, $Z = -3.42$, $p < .001$, $n = 280$). Women had higher mean ranks (149.74) than men (118.18), consistent with the category distributions. The effect size was $r = .20$ and is interpreted as small. Statistical significance should therefore not be confused with a large gender difference.

Figure 1 shows the distribution of appearance-modifying filter use by gender. The "Never" category includes a higher proportion of men (74.4%) than women (53.0%). By contrast, women show higher proportions in the occasional (37.9%) and frequent (9.1%) filter-use categories, whereas these proportions are lower among men (23.2% and 2.4%, respectively).

Regarding gender and thinness as an aesthetic norm, a Mann–Whitney U test was also applied to examine whether this perception differed by gender, specifically in relation to the view that artificial intelligence promotes thin bodies as the aesthetic norm. The results show that women ($N = 198$) had a higher mean rank (mean rank = 148.42) than men ($N = 82$; mean rank = 121.38), suggesting that women were more likely to agree with this statement. The statistical analysis indicated that this difference was statistically significant ($U = 6550.00$, $Z = -2.73$, $p = .006$). The effect size was $r = .16$, corresponding to a small effect. This indicates that, although gender is significantly associated with the perception that artificial intelligence promotes thin bodies as the bodily standard, the magnitude of this difference is limited.

Figure 2 shows the distribution of responses to the statement "AI promotes thin bodies as the norm" by gender. As observed, women show a higher proportion of affirmative responses ("Yes") than men, who are more concentrated in the "No" and "Not sure" categories. This pattern suggests that women are more likely to perceive artificial intelligence as promoting thin bodies as an aesthetic standard.

Level of Education

Before conducting the comparative analyses, the distributional normality of the variable's *aesthetic bias*,

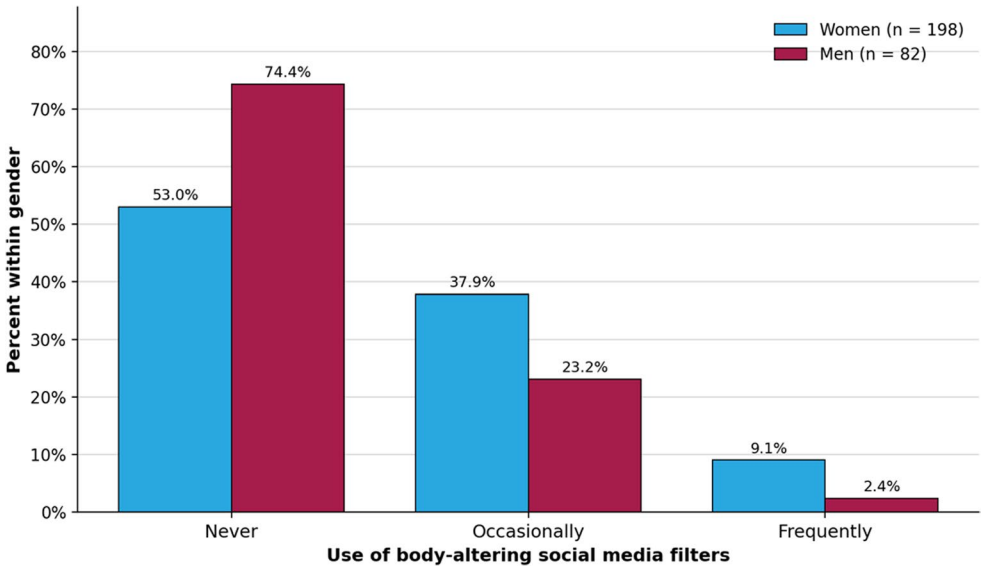


Fig. 1 Distribution of body-altering filter use on social media by gender. *Note*. $n = 280$ (198 women and 82 men). Mann-Whitney U = 6288.00, Z = -3.42, $p < .001$, $r = .20$. The effect size is small

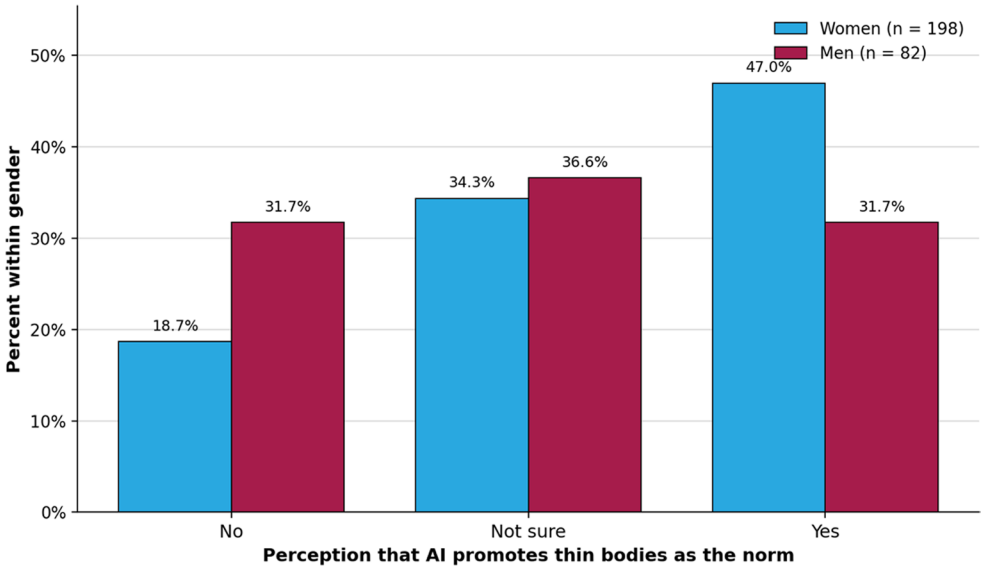


Fig. 2 Gender differences in the perception that artificial intelligence promotes thin bodies as the normative ideal. Note. $n = 280$. Mann–Whitney $U = 6550.00$, $Z = -2.73$, $p = .006$, $r = .16$

AI-generated body types, and *training AI with diverse bodies* was assessed across different educational levels using the Kolmogorov–Smirnov and Shapiro–Wilk tests. In all educational groups, the distributions departed significantly from normality ($p < .001$ in both tests), indicating that the assumption of normality was not met. Accordingly, non-parametric procedures were applied, specifically the Kruskal–Wallis test, to examine differences across educational levels in the variables under study.

Figure 3 shows small associations between educational attainment and perceived aesthetic bias (rho = 0.22) and support for training AI systems with diverse bodies (rho = 0.23). These coefficients are described as weak or small, not moderate. Education is also weakly associated with the perceived body-type composition of AI output (rho = −0.16). Because that variable is coded 1 = thin or athletic, 2 = diverse

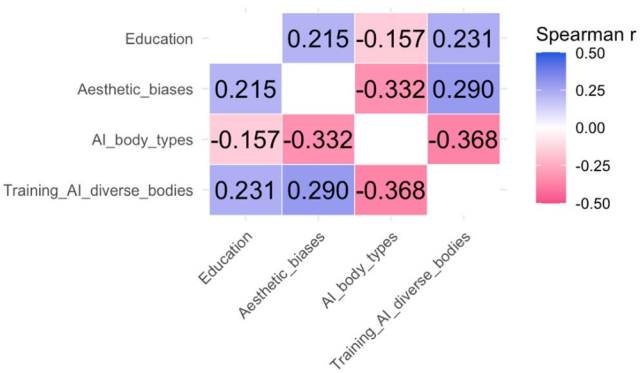


Fig. 3 Heatmap of spearman correlations between level of education and perceptions of ai-generated body representations. Note. $N = 284$. Cells display Spearman's correlation coefficients between variables. The diagonal values, representing self-correlations, are omitted for clarity. Blue tones indicate positive correlations, whereas pink tones indicate negative correlations, with color intensity reflecting the strength of the relationship

and 3 = have not noticed, the negative sign indicates that participants with higher educational attainment were more likely to identify AI output as thin or athletic and less likely to report diversity or inattention. The associations indicate limited differences in recognition and support, not large educational effects.

To examine whether academic level was associated with perceptions of aesthetic bias and AI-generated bodily representations, the nonparametric Kruskal–Wallis test was applied. This procedure enables the comparison of more than two independent groups when the assumption of normality is not met, using mean ranks as the basis for comparison. The analysis included four educational levels: complete secondary education, technical or technological education, undergraduate university education, and postgraduate studies.

Perceived aesthetic bias differed across educational levels, H(3) = 17.70, $p < .001$, epsilon squared = 0.063. Participants with postgraduate education had the highest mean rank (170.08), followed by undergraduate education (134.57), complete secondary education (130.40), and technical or technological education (121.77). The effect is interpreted as small. Educational level therefore accounts for only a limited share of the observed variation, despite the statistically significant omnibus test.

Regarding the variable *AI-generated body types*, the Kruskal–Wallis test also identified significant differences across educational levels ($H(3) = 12.78$, $p = .005$, $\varepsilon^2 = 0.045$). Analysis of the mean ranks indicated that participants with undergraduate university education had the highest value (mean rank = 156.14), followed by those with complete secondary education (mean rank = 153.68). By contrast, participants with technical or technological education had a lower mean rank (mean rank = 132.79), whereas individuals with postgraduate studies had the lowest value (mean rank = 118.98). Because this variable is coded 1 = thin or athletic, 2 = diverse and 3 = have not noticed, the ordering of the mean ranks does not express a gradient of approval and is read here from the underlying distribution. Participants with postgraduate studies identified the bodies generated by artificial intelligence as thin or athletic more often than any other group (57.8%) and reported bodily diversity least often (15.7%), whereas among participants with complete secondary education the three options were distributed almost evenly (31.2%, 30.1% and 38.7% respectively). The association is confirmed by a chi-square test of independence, which does not depend on the numerical codes, $\chi^2(6) = 22.28$, $p = .001$, Cramér's $V = 0.20$. The estimated effect size ($\varepsilon^2 = 0.045$) corresponds to a small effect, suggesting that the observed differences, although statistically significant, are limited in magnitude.

Finally, the analysis showed statistically significant differences across educational levels in the variable training AI with diverse bodies ($H(3) = 15.69$, $p = .001$, $\varepsilon^2 = 0.055$). The mean ranks indicated that participants with postgraduate studies had the highest value (mean rank = 167.37), followed by those with undergraduate university education (mean rank = 142.21). By contrast, participants with technical or technological education (mean rank = 128.58) and complete secondary education (mean rank = 124.15) had lower mean ranks. These results suggest that participants with more advanced educational levels show greater willingness to support the incorporation of bodily diversity into the training of artificial intelligence systems. The direction of this finding does not depend on the numerical coding of the variable, which places the non-committal option below rather than between the two substantive responses: affirmative support rises monotonically from 36.6% among participants with complete secondary education to 72.3% among those with postgraduate studies, while explicit rejection falls from 31.2% to 6.0% across the same groups, and a chi-square test of independence yields $\chi^2(6) = 29.29$, $p < .001$, Cramér's $V = 0.23$. The estimated effect size ($\varepsilon^2 = 0.055$) likewise corresponds to a small effect, indicating that educational level explains only a limited proportion of the observed variability.

Figure 4 shows differences in the mean ranks of the three variables analyzed according to educational level. An increasing trend is observed for *aesthetic bias* and support for *training AI with diverse bodies* as educational level rises, with the highest values found among participants with postgraduate studies. By contrast, the variable *AI-generated body types* follows an inverse pattern: the mean rank declines markedly among participants with postgraduate education. Given the coding of the variable, that decline corresponds to a concentration of postgraduate respondents in the 'thin or athletic' category rather than to lower acceptance of the bodily models, and it is therefore consistent with, rather than opposed to, the educational gradient observed for perceived aesthetic bias. Overall, the figure shows that educational level is related to differences in the perception of aesthetic bias and in attitudes toward bodily diversity in artificial intelligence systems.

Age

Perceived aesthetic bias is a three-category ordinal variable, so nonparametric procedures were selected independently of subgroup normality tests. The two oldest age bands were sparse, with 9 respondents aged 56 to 60 and 4 aged 61 to 65. Estimates for these groups, including mean ranks and distributional diagnostics, are consequently unstable. The Kruskal-Wallis comparison across all ten age bands is

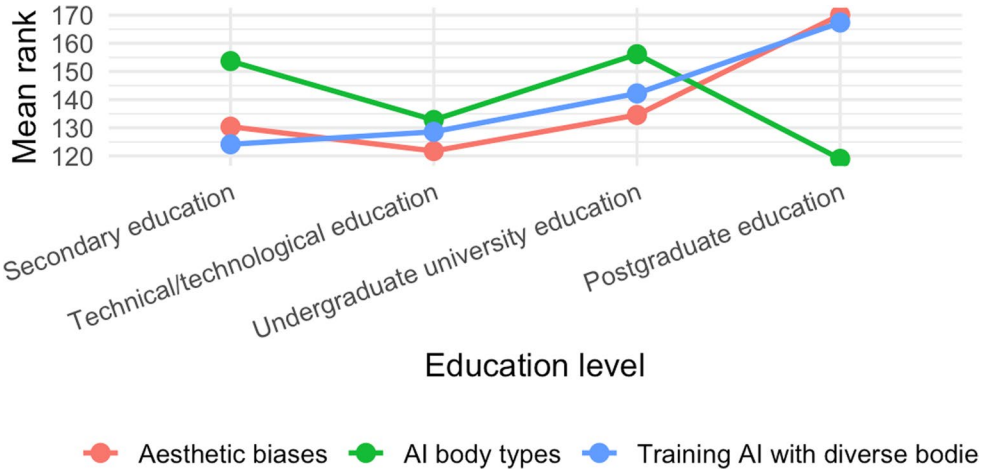


Fig. 4 Differences in mean ranks across educational levels in perceptions of AI-generated body representations. Note. $N = 284$. Kruskal–Wallis tests: perceived aesthetic bias, $H(3) = 17.70$, $\varepsilon^2 = 0.063$; perceived body-type composition of AI output, $H(3) = 12.78$, $\varepsilon^2 = 0.045$; support for training AI with diverse bodies, $H(3) = 15.69$, $\varepsilon^2 = 0.055$

therefore treated as exploratory, and no pairwise post hoc tests are interpreted in the absence of a significant omnibus result.

As reported in Table 4, Spearman's correlation indicates a positive and statistically significant relationship between age and the perception of aesthetic bias ($\rho = 0.17$, $p = .005$, $n = 284$). The coefficient is of low magnitude, accounting for under 3% of the shared variance between the two variables, and it does not survive further scrutiny. Age and educational attainment are strongly associated in this sample ($\rho = 0.56$, $p < .001$), and once educational attainment is held constant the association with age disappears: within the postgraduate group $\rho = 0.05$, $p = .649$, and among all other participants $\rho = 0.02$, $p = .823$. The ordinal regression reported confirms this, returning an adjusted odds ratio for age of 1.08 ($p = .220$) while the educational coefficient remains significant. The bivariate association is therefore reported as an expression of the joint distribution of age and educational attainment rather than as evidence of an age gradient in perceived aesthetic bias.

The omnibus comparison of perceived aesthetic bias across the ten age bands did not reach conventional significance, $H(9) = 16.05$, $p = .066$, epsilon squared = 0.057. The smallest mean ranks occurred among participants aged 18–20 years (112.26) and 61 to 65 (109.75), while the highest occurred in the 46 to 50 and 51 to 55 groups (176.60 in both). Because this non-monotone pattern is concentrated partly in small groups, it may reflect sampling instability. No age-group difference is claimed. Age was also entered as an ordered predictor in the adjusted model, where it was not significant after educational attainment was considered.

Figure 5 describes the distribution of perceived aesthetic bias across age bands. The 46 to 50 and 51 to 55 groups each contain only 10 respondents, the 56 to 60 group contains 9, and the 61 to 65 group contains 4. Apparent differences involving these bands should therefore not be interpreted as stable age effects. The omnibus Kruskal-Wallis test was not significant, and the figure is retained solely as a transparent description of the data.

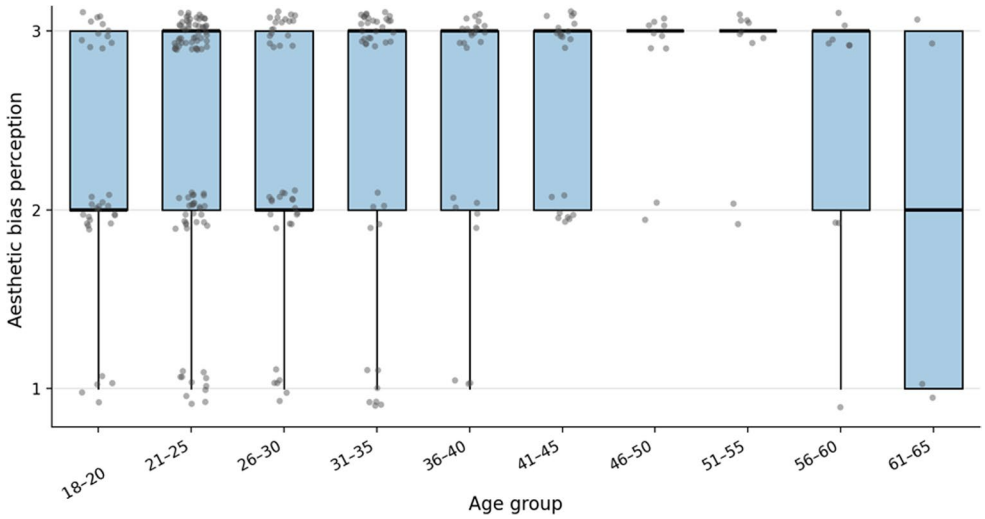


Fig. 5 Distribution of perceived aesthetic bias across age groups. Note. $N = 284$, ten age bands. Kruskal–Wallis $H(9) = 16.05$, $p = .066$, $\varepsilon^2 = 0.057$

Relationship between aesthetic manipulation and psychosocial effects

Feelings of exclusion

The normality assumption for feelings of body-related exclusion was assessed as a function of two variables: the perception that AI enhances photographs and the perception of the body types generated by AI. To this end, the Kolmogorov–Smirnov and Shapiro–Wilk tests were applied. The results show that, across all response groups ("No," "Not sure," and "Yes"), the distributions of feelings of body-related exclusion yielded significance values below 0.001 in both tests, indicating significant departures from normality. This pattern was observed both for the variable related to AI-based photograph enhancement and for the variable referring to the body types represented by AI.

Table 5 presents the Spearman correlation matrix, showing the associations between feelings of body-related exclusion and two variables related to bodily representation in artificial intelligence systems: the perception that AI enhances photographs and the perception of the body types generated by AI. The results indicate a positive and statistically significant correlation between feelings of body-related exclusion and the perception that AI enhances photographs ($\rho = 0.24$, $p < .001$). This finding suggests that participants who were more likely to perceive artificial intelligence as enhancing or modifying images also reported stronger feelings of exclusion in relation to their own bodies.

A negative and statistically significant correlation was also observed between feelings of body-related exclusion and the perception of AI-generated body types ($\rho = -0.17$, $p = .005$). Because the response options of this variable are coded 1 = thin or athletic, 2 = diverse and 3 = have not noticed, the coefficient is not an evaluative gradient: it indicates that stronger feelings of body-related exclusion are associated with a greater tendency to identify the bodies produced by these systems as thin or athletic, and with a lower likelihood of reporting either bodily diversity or inattention to the matter. In addition, a negative correlation was identified between the perception that AI enhances photographs and the perception of AI-generated body types ($\rho = -0.15$, $p = .009$), indicating that participants who consider AI to enhance images are likewise more likely to identify the body types produced by these technologies as thin or athletic. Taken together, these results show that feelings of body-related exclusion are significantly associated with the way participants perceive bodily modifications and representations generated by artificial intelligence, suggesting that perceptions of these technologies may be linked to subjective experiences related to body image.

To examine potential differences in feelings of body-related exclusion according to perceptions of bodily representation in artificial intelligence systems, the non-parametric Kruskal–Wallis test was applied. This procedure was selected on the basis of the results obtained from the previously conducted normality tests, which showed significant departures from the normal distribution, thereby discouraging the use of parametric tests.

Feelings of body-related exclusion differed according to the perception that AI enhances photographs, $H(2) = 16.33$, $p < .001$, epsilon squared = 0.058. This is a small effect. Mean ranks rose from respondents who answered no (131.44), through those who were unsure (145.78), to those who answered yes (169.04). A chi-square test supported the association, chi-square$(4) = 26.55$, $p < .001$, Cramér's V = 0.22. The result indicates a limited association between two self-reported categorical responses and does not establish that perceived AI intervention causes exclusion.

Second, the analysis also identified statistically significant differences in feelings of body-related exclusion according to the perceived body-type composition of AI output ($H(2) = 8.54$, $p = .014$, $\varepsilon^2 = 0.030$), a small effect indicating a lower-intensity relationship between the variables analysed. The mean ranks revealed that participants who reported that these systems predominantly generate thin or athletic bodies reported the highest levels of body-related exclusion (mean rank = 156.67), followed by those who reported bodily diversity (mean rank = 134.79) and by those who had not attended to the matter (mean rank = 131.55). Because the three response options are not orderable with respect to one another, the corresponding distribution is given directly: 51.8% of participants who reported feeling excluded, and 55.6% of those who were uncertain, identified the output as thin or athletic, against 34.4% of those who reported no such feeling. The association is weak and only marginally significant on a chi-square test of independence, $\chi^2(4) = 9.55$, $p = .049$, Cramér's $V = 0.13$, and is accordingly treated as suggestive. Here too the statistics reported previously ($H(2) = 8.15$, with mean ranks of 151.49 and 124.75) were obtained with the roles of the two variables reversed.

Taken together, these results indicate that perceptions of AI-mediated bodily representation covary with self-reported body-related exclusion. They do not establish that image-generation or image-modification systems cause exclusion or reproduce aesthetic bias. The observed associations instead identify questions for longitudinal studies using validated multi-item measures and for audits that compare user perceptions with system outputs.

Figure 6 shows the distribution of feelings of body-related exclusion according to the perception that artificial intelligence enhances or modifies photographs. The graph combines violin plots, representing distribution density;

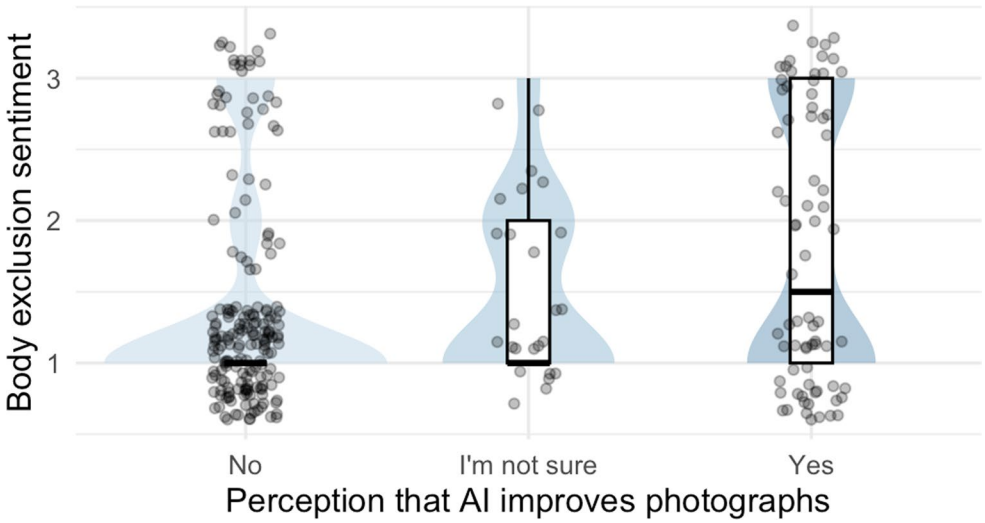


Fig. 6 Distribution of feelings of body-related exclusion according to perceptions of AI-enhanced photographs. Note: $N = 284$. Kruskal–Wallis $H(2) = 16.33$, $p < .001$, $\varepsilon^2 = 0.058$

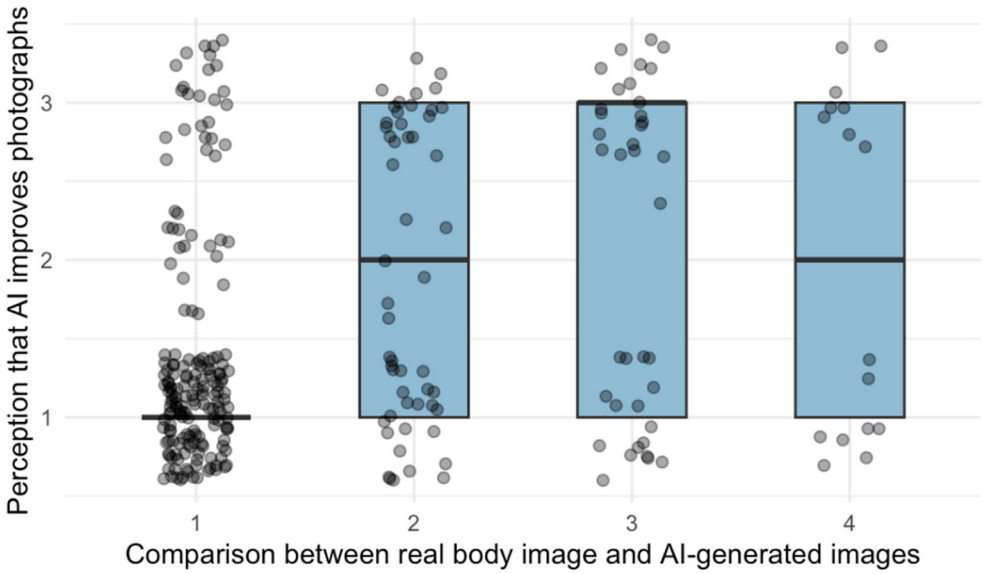


Fig. 7 Differences in the perception that ai enhances photographs across body-image comparison groups. Note. $N = 284$. Kruskal–Wallis $H(3) = 30.03$, $p < .001$, $\varepsilon^2 = 0.106$. Group 1 = no comparison; Groups 2–4 = comparison reported

boxplots, indicating the median and interquartile range; and individual points, corresponding to participants' observations. Overall, participants who perceive artificial intelligence as enhancing photographs show relatively higher values of feelings of body-related exclusion, reflected in a greater concentration of observations at the upper levels of the scale. By contrast, the group that does not perceive this algorithmic enhancement shows a distribution more concentrated at lower values, suggesting comparatively lower levels of body-related exclusion.

Body comparison with AI-generated images

To assess the normality assumption for the variables included in the analysis, the Kolmogorov–Smirnov test with Lilliefors correction and the Shapiro–Wilk test were applied. This procedure considered the categories of the variable *comparison of real body image with AI-generated representations*, as well as its relationship with the variables *perception that AI enhances photographs*, *training AI with diverse bodies*, and *body types represented by AI*. The results show that, across all categories analyzed, the significance values obtained in both tests were below 0.001, indicating that the distributions of the variables departed significantly from normality. This pattern was observed consistently across participant groups, regardless of whether participants reported not having compared their body image with AI-generated representations or indicated that they had experienced positive or negative effects after such comparison.

The Spearman correlation matrix examines the relationship between comparison of body image with AI-generated representations and three dimensions related to bodily representation in AI systems: AI-generated body types, the perceived need to train AI with diverse bodies, and the perception that AI enhances photographs.

Table 6 reports three associations. First, a significant negative correlation was observed between comparison of body image with AI-generated representations and the evaluation of the body types produced by these systems ($\rho = -0.20$, $p < .001$). Given the coding of this variable, the coefficient indicates not a less favourable evaluation but a greater tendency to identify the output as thin or athletic: the proportion doing so rises from 34.8% among participants who had never compared to 62.5% among those who reported feeling worse after the comparison, while the proportion reporting that they had not noticed falls from 42.7% to 6.2% across the same groups ($\chi^2(6) = 14.02$, $p = .030$, Cramér's $V = 0.16$). Second, a weak positive correlation was identified between such comparison and the perceived need to train artificial intelligence systems with diverse bodies ($\rho = 0.13$, $p = .033$); given its magnitude, and given that it does not reach significance on a chi-square test of independence ($\chi^2(6) = 9.04$, $p = .171$, Cramér's $V = 0.13$), this association is treated as suggestive rather than as an established pattern. Third, comparison of body image with AI-generated representations showed the strongest association observed in the study, with the perception that artificial intelligence enhances photographs ($\rho = 0.32$, $p < .001$), indicating that participants who have compared their appearance with AI-generated representations are also more likely to attribute an aesthetic-modification role to these technologies.

In addition, the results indicate that comparison of body image with AI-generated representations is associated with greater awareness of aesthetic modification processes and with a greater tendency to identify the body types produced by these systems as thin or athletic. At the same time, it is linked to stronger recognition of the need to promote bodily diversity in the training of generative models. These associations highlight the role that interactions with image-generation technologies may play in shaping perceptions and evaluations related to body standards in digital environments.

To examine whether perceptions related to bodily representation in artificial intelligence systems varied according to participants' experiences of comparison between real body image and AI-generated representations, the nonparametric Kruskal–Wallis test was applied. The results revealed statistically significant differences in the three variables analyzed.

Differences were identified in the perceived need to train artificial intelligence systems with diverse bodies ($H(3) = 8.01$, $p = .046$, $\varepsilon^2 = 0.028$). Although the effect size was small, the mean ranks suggest that participants who reported feeling better after comparing their body image with AI-generated representations showed relatively higher levels of support for training AI systems with diverse bodily representations (mean rank = 170.11) than those who had not engaged in this type of comparison (mean rank = 136.75). This is the one comparison in the study whose result depends on the numerical coding of the outcome, in which the non-committal option is assigned the lowest value: a chi-square test of independence, which is free of that assumption, does not reach significance ($\chi^2(6) = 9.04$, $p = .171$, Cramér's $V = 0.13$). The difference is therefore reported for completeness and is not carried into the interpretation.

In addition, significant differences were observed in the perception that artificial intelligence enhances photographs ($H(3) = 30.03$, $p < .001$, $\varepsilon^2 = 0.106$), the largest effect observed in the study; a chi-square test of independence agrees, $\chi^2(6) = 40.06$, $p < .001$, Cramér's $V = 0.27$. The mean ranks indicate that participants who reported experiences of body comparison with AI-generated representations showed higher values for this perception. Specifically, those who reported feeling better with the generated image had the highest ranks (mean rank = 177.08), followed by those who reported feeling worse because of modifications to their body or weight (mean rank = 170.25). By contrast, participants who had never engaged in this type of comparison showed considerably lower values (mean rank = 125.32).

Significant differences were also identified in the perception of the body types represented by artificial intelligence ($H(3) = 12.38$, $p = .006$, $\varepsilon^2 = 0.044$). In this case, the mean ranks were highest among participants who had not compared their body image with AI-generated representations (mean rank = 153.71) and lowest among those who reported feeling worse after the comparison (mean rank = 97.59). Given the coding of the variable, the descending ranks correspond to an increasing tendency to identify AI-generated bodies as thin or athletic among those who had compared, and to a sharply decreasing tendency to report not having noticed; the association is supported by a chi-square test of independence, $\chi^2(6) = 14.02$, $p = .030$, Cramér's $V = 0.16$. These results suggest that AI-mediated body comparison experiences are associated with differences in how participants perceive processes of bodily representation in algorithmic systems, particularly regarding aesthetic image modification, bodily diversity in model training, and the evaluation of body types generated by these technologies.

Figure 7 presents the distribution of the perception that artificial intelligence enhances photographs according to different experiences of comparison between real body image and AI-generated representations. Each boxplot summarizes the distribution of responses within each category, while the points represent participants' individual observations.

Overall, participants who had not compared their body image with AI-generated representations (Group 1) showed lower values in the perception that artificial intelligence enhances photographs, with responses more concentrated at the lower levels of the scale. By contrast, the groups that

reported experiences of comparison with AI-generated representations (Groups 2, 3, and 4) showed medians and distributions shifted toward higher values on the scale.

Particularly, participants who reported feeling better with the generated image (Group 3) showed a greater concentration of responses at the upper levels of the scale, suggesting a more favorable perception of AI's capacity to enhance photographs. Similarly, those who reported feeling worse after the comparison (Group 4) also showed relatively high values, although with greater dispersion in their responses.

Magnitude of the observed effects

Taken together, the correlations are small except for the association of rho = 0.32 between body comparison and perceived AI enhancement, which is moderate under conventional benchmarks. Correlations near 0.20, including the coefficients of 0.22 and 0.24, are described as small or weak. Epsilon-squared values range from 0.028 to 0.106 and indicate small to moderate omnibus differences. These magnitudes are compatible with stronger unmeasured determinants and do not warrant describing AI-mediated aesthetic intervention as a dominant influence.

Statistical significance is attainable for associations of this size in a sample of 284, and the interpretation offered in Sect. 5 therefore rests on the magnitude and direction of the coefficients rather than on p values alone. Three associations are of interpretive interest because they are the largest and the most consistent: the association between body comparison with AI-generated representations and perceived AI enhancement of photographs ($\rho = 0.32$; $H(3) = 30.03$, $\varepsilon^2 = 0.106$), the association between perceived AI enhancement and feelings of exclusion ($\rho = 0.24$; $H(2) = 16.33$, $\varepsilon^2 = 0.058$), and the educational gradient in perceived aesthetic bias ($H(3) = 17.70$, $\varepsilon^2 = 0.063$). The remaining associations, in particular the correlation of 0.126 between body comparison and support for training AI with diverse bodies, are weak and are treated as suggestive only. The adjusted models reported in Sect. 4.5 show that the first two of the three survive control for gender and educational attainment, and that the bivariate association between age and perceived aesthetic bias does not.

Exploratory adjusted models

The preceding analyses are bivariate and cannot show whether the observed associations reflect the composition of the sample. Three exploratory ordinal logistic regressions are therefore reported with outcomes on their original three-point response scales and with the 280 respondents who identified as women or men. The models enter the sociodemographic predictors jointly, so the coefficients represent mutually adjusted main-effect associations. Interaction terms were not prespecified or estimated, and these models are not described as intersectional tests. This distinction aligns the empirical claim with the design while preserving intersectionality as a framework for future, specifically powered analyses.

Model 1 provides an adjusted assessment of the educational prediction in H2 and the age question in RQ1. With gender and age held constant, each step in educational attainment was associated with higher odds of reporting perceived aesthetic bias, OR = 1.30, $p = .017$. Age was not significant after adjustment, OR = 1.08, $p = .220$. Model 1b, which omits age, returned OR = 1.39, $p = .001$ for education. Gender was not significant in either model. These results support the limited educational prediction but not an independent age pattern.

Model 2 provides an adjusted assessment relevant to H3. Feelings of body-related exclusion remained associated with perceiving that AI enhances photographs, OR = 1.47, $p = .011$, and with having compared one's body with an AI-generated representation, OR = 2.30, $p = .003$, after adjustment for gender and educational attainment. Women reported higher odds of exclusion, OR = 1.99, $p = .028$, while education was not significant, $p = .229$. These are adjusted associations within the sample and do not establish causal effects or intersectional patterns.

Three qualifications apply. The models explain a modest share of the variation (McFadden pseudo-R^2 between 0.026 and 0.063), which is consistent with the effect sizes reported in Sect. 4.4 and with the presence of substantial unmeasured determinants. The proportional odds assumption was inspected by fitting separate binary logistic models at each cut point of the outcome in Model 2; the coefficients retain their sign and approximate magnitude across cut points, with the comparison indicator showing the largest divergence, so the pooled coefficients should be read as averages across thresholds. Third, the models adjust only for the sociodemographic variables recorded in the instrument. Because baseline body dissatisfaction, social media intensity and frequency of AI tool use were not measured, adjustment for sample composition does not amount to adjustment for confounding in general, and the coefficients are accordingly interpreted as adjusted associations rather than as estimates of an effect.

Discussion

The study measured self-reported perceptions and experiences in a cross-sectional, non-probability sample. It did not audit any recommender system, did not analyse the outputs of any generative model, and did not observe platform-level

moderation decisions. Statements about actual algorithmic behaviour, such as the claim that particular systems downrank particular bodies or that training corpora systematically under-represent them, are therefore not findings of this study. Where such statements appear below they are drawn from the audit and content-analysis literature and are attributed to it (Bianchi et al., 2023; Buolamwini & Gebru, 2018; Luccioni et al., 2023; Raji & Buolamwini, 2019). The contribution of the present study is to document how users perceive and affectively respond to environments that this literature describes. The two levels are complementary but not interchangeable, and the distinction between perceived AI-related bias and actual algorithmic bias is maintained throughout the article.

Perception, recognition and the limits of inference

Perceived aesthetic bias increased with educational attainment ($H(3) = 17.70$, $\varepsilon^2 = 0.063$), and support for training AI systems with diverse bodies followed the same gradient ($H(3) = 15.69$, $\varepsilon^2 = 0.055$). The bivariate association with age ($\rho = 0.17$) does not survive adjustment for educational attainment (Sect. 4.5) and is not interpreted here as an age effect. The most economical reading is that recognising aesthetic bias functions as a competence rather than as an index of exposure: the participants most likely to name it are those with greater access to the critical vocabulary in which algorithmic systems are discussed (Bucher, 2017). This interpretation carries a consequence that runs against the framing of the previous version of this manuscript. If perceived bias indexes critical literacy, a low score does not indicate the absence of exposure; it may indicate exposure without recognition. The perception measure and the phenomenon to which it refers are therefore not interchangeable, and the study cannot establish which participants were in fact most exposed.

A second result complicates any straightforward account of AI as an unrecognised influence. The perceived body-type composition of AI output was negatively associated both with body comparison ($\rho = -0.20$, $p < .001$) and with feelings of exclusion ($\rho = -0.17$, $p = .005$). Once the coding of that variable is taken into account, both coefficients point the same way: participants who compared themselves with AI-generated images, and those who reported greater exclusion, were the most likely to identify the output as thin or athletic and the least likely to report not having noticed what kinds of bodies these systems produce. Participants are thus not passive recipients of algorithmic representation; they attend to it and name its regularities. This is consistent with accounts of the algorithmic imaginary in which users form explicit theories about system behaviour and act upon them (Bucher, 2017; Eslami et al., 2015), and it qualifies the deterministic framing common in critical work on algorithmic aesthetics. It also raises a question the present data cannot answer: whether critical evaluation attenuates the affective impact of exposure, or whether, as the positive association between perceived enhancement and exclusion suggests, recognising a standard as artificial does not exempt one from being measured against it.

The central association of the study, between perceived AI enhancement of photographs and feelings of body-related exclusion ($\rho = 0.24$; $H(2) = 16.33$, $\varepsilon^2 = 0.058$), admits at least three readings that the design cannot distinguish. Perceiving AI as aesthetically interventionist may heighten sensitivity to bodily standards; feeling excluded may increase attention to, and therefore detection of, such intervention; or both may follow from a third variable, most plausibly prior body dissatisfaction, which was not measured.

Reported exclusion rises monotonically across the three response categories, from participants who denied that AI enhances photographs (mean rank = 131.44) through those who were uncertain (mean rank = 145.78) to those who affirmed it (mean rank = 169.04). Uncertainty therefore occupies an intermediate rather than a neutral position: participants who did not know whether their images were being algorithmically adjusted reported more body-related exclusion than those who believed they were not. One interpretation, consistent with work on the algorithmic imaginary, is that not knowing whether one's image is being algorithmically adjusted is itself a condition of appearance-related unease, since it removes the possibility of attributing a perceived discrepancy either to oneself or to the system (Bucher, 2017). This reading is post hoc, and the item was not designed to test it; it is offered as a hypothesis for designs that measure algorithmic uncertainty directly.

The strongest association in the study links body comparison with AI-generated representations to the perception that AI enhances photographs ($\rho = 0.32$; $H(3) = 30.03$, $\varepsilon^2 = 0.106$). This association held for participants who reported feeling better after the comparison (mean rank = 177.08) as well as for those who reported feeling worse (mean rank = 170.25), both markedly above non-comparers (mean rank = 125.32). The variable therefore appears to index engagement with AI-mediated imagery rather than the affective outcome of that engagement. The distinction matters for the mechanism proposed in Sect. 2.1: it is the occurrence of the comparison, not its valence, that tracks the perception of automated aesthetic intervention. Whether the valence has consequences that this study did not capture, for body dissatisfaction or for subsequent platform use, remains open.

One asymmetry in these results is worth stating plainly. Higher educational attainment was associated with greater recognition of aesthetic bias, yet nothing in these data indicates that the participants who recognised it reported lower

levels of body-related exclusion. Recognition and protection appear to be separable, which is a testable proposition rather than a demonstrated one.

Socioaffective correlates and digital identity

Gender differences were observed in the use of appearance-modifying filters ($U=6288.00$, $Z=-3.42$, $p < .001$, $r = .20$) and in the perception that AI promotes thin bodies as the norm ($U=6550.00$, $Z=-2.73$, $p = .006$, $r = .16$), with women scoring higher on both. These differences are consistent with the appearance-surveillance pathway described by objectification theory (Fredrickson & Roberts, 1997) and with the gendered internalisation of appearance ideals documented in social media research (Fardouly et al., 2015; Perloff, 2014). Their magnitude, however, is small: gender accounts for approximately 4% of the variance in filter use, and reported filter use among men is far from negligible, with 25.6% reporting occasional or frequent use. Framing appearance pressure as an exclusively feminine phenomenon would misdescribe the distribution observed here.

The association between body comparison and the perceived body-type composition of AI output deserves emphasis. Participants who compared themselves with AI-generated imagery were markedly more likely to report that these systems generate thin or athletic bodies ($\rho = -0.20$, on a scale whose lowest code is that response), and markedly less likely to report not having noticed. The most plausible reading is that comparison and recognition are distinct from endorsement: a representation can be identified as narrow and remain comparison-relevant. This reading is consistent with experimental findings that disclosure labels on manipulated images do not reliably eliminate their effects on body image (Kleemans et al., 2018), although the present study includes no manipulation and cannot test the proposition.

Countervailing affordances: AI as a contested sociotechnical system

The account developed so far, and the literature on which it draws, treats AI predominantly as a technology that reproduces restrictive appearance norms. A balanced assessment requires acknowledging that the same technical capacities support outcomes of the opposite kind, and that which outcome obtains is a function of training data, design choices, governance arrangements and user practice rather than of the technology as such (Barocas et al., 2023; Selbst et al., 2019).

First, generative systems can be prompted, fine-tuned or curated to produce representation of body types that conventional media pipelines have excluded, and the marginal cost of doing so is considerably lower than that of commissioning conventional photography; the constraint is compositional and economic rather than technical. Second, algorithmic curation is not intrinsically homogenising: the same ranking machinery that concentrates attention on normative appearance can, under different objective functions, surface body-diverse and body-neutral content, and experimental work indicates that exposure to body-positive material has measurable short-term benefits for mood and body satisfaction (Cohen et al., 2019). Third, the auditability of automated systems is a genuine asset relative to the diffuse editorial judgement they partly replace: bias in a model can be measured, reported and contested in ways that bias in a magazine picture desk could not (Mehrabi et al., 2021; Raji & Buolamwini, 2019). Fourth, communities excluded from mainstream representation have historically used platform affordances tactically, and although the difference did not survive a coding-free test in the present sample, participants who reported comparison experiences were descriptively the most supportive of reforming the systems in question.

These possibilities are not symmetric with the concerns discussed above. The evidence that current systems skew toward narrow appearance norms is considerably stronger than the evidence that they are being redirected, and nothing in the present data speaks to their realisation. They are noted because a framing in which algorithmic outcomes are treated as fixed properties of the technology forecloses precisely the design and policy questions that, on the sociotechnical account adopted here, are the ones that matter. The corresponding empirical question, which this study cannot answer, is whether user-level perceptions of the kind measured here shift when platform objectives change.

Limitations and future research

All variables were measured at a single point in time, so no temporal ordering can be established between perceived AI intervention, body comparison and feelings of exclusion. The associations reported are compatible with the mechanism proposed in Sect. 2.1, with its reverse, and with confounding, and none of these can be preferred on the present evidence. Establishing directionality requires at minimum a multi-wave panel design; establishing causal effect requires experimental manipulation of the source attribution and the AI provenance of otherwise equivalent images. No causal claim is made anywhere in this article.

All measures are self-reports collected through a single instrument in a single administration, which raises the risk that common method variance inflates the observed associations (Podsakoff et al., 2003). Perceived aesthetic bias and perceived exclusion in particular may share method-specific variance arising from a general disposition to evaluate digital environments negatively, and no marker variable

was included that would permit this to be estimated. Self-reported filter use and self-reported comparison are additionally subject to recall and social desirability effects, and participants' capacity to identify AI-generated content was assumed rather than verified.

The focal variables were operationalised as direct categorical indicators appropriate to the study's exploratory, perceptual aim and to the breadth of the 20-item survey. Evidence of face and content validity was strengthened through the 43-participant pilot and five-expert review. Because each variable is analysed at item level, within-scale internal consistency and factor structure are not applicable to the individual item; the overall alpha of 0.80 is not used as stand-alone evidence of construct validity (Cronbach & Meehl, 1955; Flake & Fried, 2020). Interpretation therefore remains tied to the exact item wording and response categories. Future replication can extend the evidence through test-retest assessment and convergence with validated multi-item instruments, as recommended for single-item validation (Allen et al., 2022).

The voluntary online sample is weighted toward women and participants with tertiary education and is not intended to represent the Ecuadorian population. It is suitable for the reported within-sample association and adjusted main-effect analyses, but it was not designed for precise gender by age or gender by education comparisons. The manuscript therefore does not interpret the adjusted models as tests of intersectional processes. A direct examination of these combinations should use stratified or quota-controlled recruitment, prespecified interaction contrasts and adequate numbers in every joint subgroup. Replication in additional cultural settings would also clarify the transferability of the observed associations.

Several potentially relevant covariates were not included, including frequency of AI tool use, exposure to AI-generated imagery, baseline body dissatisfaction and socioeconomic position; future models can examine their contribution directly. The present response formats were tailored to the content of the questions and preserve substantively meaningful distinctions among absence or disagreement, uncertainty and presence or agreement, as well as the reported valence of body comparison. They support transparent analysis of categorical patterns but do not provide the same fine-grained differentiation of frequency or intensity as broader scales. The analyses therefore retain the original categories and report distributions, with coding-free chi-square tests and Cramér's V used when ordinal placement is ambiguous. Future studies can complement these indicators with wider response ranges and multi-item measures for questions that require greater measurement granularity.

Finally, the study measures perception and offers no evidence about algorithmic behaviour. Establishing whether the systems in question do in fact differentially rank, generate or moderate bodies of different sizes requires algorithm audits, computational experiments with controlled prompts, platform-level analyses of reach, and systematic content analysis of generated outputs (Bianchi et al., 2023; Raji & Buolamwini, 2019). The most informative next step for this line of research would combine such methods with the perceptual measures used here, in order to determine whether users' perceptions track actual system behaviour and to identify the conditions under which the two diverge. A mixed design of this kind, using validated instruments, a probability-based or quota-controlled sample and at least two measurement waves, would address the principal limitations identified above.

Conclusions

This study examined how adult social media users in a predominantly Ecuadorian sample perceive AI-mediated bodily representation. Perceived AI enhancement of photographs was weakly associated with the direct item on body-related exclusion or judgment, rho = 0.24. Body comparison with AI-generated representations was moderately associated with perceived enhancement, rho = 0.32. Perceived body-type composition was weakly associated with comparison, rho = −0.20, and with the exclusion item, rho = −0.17. On the coding used, participants reporting comparison or exclusion were more likely to identify AI output as thin or athletic. These small to moderate associations are interpreted at the level of the observed categorical responses.

The results indicate covariation, not causal influence. They do not show that AI produces body-related exclusion, that recognition of aesthetic bias protects users, or that the observed patterns extend to the Ecuadorian population. Differences by gender and education were small, the age pattern was not significant after adjustment, and the available sample does not permit intersectional inference.

The findings motivate, but do not prescribe, future research. Audit and survey combinations, multi-wave designs, validated multi-item instruments and samples designed for interaction analysis are needed to separate perception from system behaviour and establish temporal ordering. The present data neither demonstrate that weight-based stigma will persist nor evaluate the effectiveness of educational, clinical or platform interventions. They identify limited associations that can inform the design of those subsequent tests.

Appendix 1. Measurement items, response options and coding

The table below reports every item retained in the analysis data set. For each item it gives the name under which the variable appears in the analysis matrix, the thematic block of the instrument to which it belongs (Sect. 3.3), the construct it operationalises, the complete set of response options with the numerical code assigned to each, and the section in which it is examined. Items retained in the data set but not entering any reported analysis are listed for completeness and marked accordingly. All constructs are measured by single items; the implications for construct validity are discussed in Sect. 3.4, and the consequences of the coding for the rank-based statistics are set out in Sect. 3.6. The verbatim wording of each item, in the original Spanish and in English translation, is provided in the supplementary material.

Item (analysis label)	Block	Construct operationalised	Response options and numerical coding
Country	1	Sociodemographic characteristic	Recorded as free choice from a country list: Ecuador (264), Spain (5), Mexico (2), Dominican Republic (2), Colombia (1), other or unspecified (9); one case blank
Gender	1	Sociodemographic characteristic	1 = woman; 2 = man; 3 = non-binary
Age	1	Sociodemographic characteristic	1 = 18–20 years; 2 = 21–25; 3 = 26–30; 4 = 31–35; 5 = 36–40; 6 = 41–45; 7 = 46–50; 8 = 51–55; 9 = 56–60; 10 = 61–65
Level of education	1	Sociodemographic characteristic	1 = complete secondary; 2 = technical or technological; 3 = undergraduate (licenciatura or ingeniería); 4 = postgraduate (specialisation, master's or doctorate)
Self-perceived body weight	2	Body self-perception	1 = below what I consider adequate; 2 = adequate for my build; 3 = above what I consider adequate; 4 = with obesity, diagnosed or self-perceived; 5 = not sure; 6 = prefer not to answer
Body-related exclusion or judgment	2	Direct self-report of body-related exclusion or judgment on social media	1 = no; 2 = not sure; 3 = yes
AI and fat hatred	2	Normative judgement on AI and weight stigma	1 = strongly agree; 2 = agree; 3 = disagree; 4 = strongly disagree
Frequency of social media use	3	Digital practice	Several times a day (229); several times a week (30); once a day (20); almost never (5); the "never" option was not selected by any respondent
Frequency of posting	3	Digital practice	1 = every day; 2 = several times a week; 3 = once a week; 4 = occasionally, less than once a week; 5 = never post
Body-altering social media filters	3	Use of appearance-modifying tools	1 = never; 2 = occasionally; 3 = frequently
Comparison of real image with AI	3	Body comparison with AI-generated representations	1 = no, I have never made that comparison; 2 = yes, but it did not affect me; 3 = yes, and I felt better with the generated image because I looked thinner; 4 = yes, and I felt worse with the generated image because it altered my body or weight
Emotion towards AI-modified images	3	Affective response to self-representation through AI	1 = indifference; 2 = insecurity or frustration; 3 = I have never used AI to represent myself; 4 = pride or satisfaction
Enhanced version on social media	3	Self-presentation practice	1 = no, I show myself as I am; 2 = sometimes; 3 = yes, constantly
Aesthetic bias	4	Perceived algorithmic aesthetic bias (general)	1 = no; 2 = not sure; 3 = yes
AI thin bodies	4	Perceived algorithmic aesthetic bias (thinness norm)	1 = no; 2 = not sure; 3 = yes
AI improves photos	4	Perceived AI-mediated aesthetic intervention	1 = no; 2 = not sure; 3 = yes
AI body types	4	Perceived body-type composition of AI output	1 = thin or athletic; 2 = diverse; 3 = have not noticed
Training AI with diverse bodies	4	Normative judgement on model training	1 = indifferent; 2 = no; 3 = yes

Block numbers correspond to the four thematic sections of the instrument described in Sect. 3.3: 1 = sociodemographic characteristics; 2 = body self-perception; 3 = digital experiences mediated by artificial intelligence; 4 = perceptions of algorithmic bias and aesthetic discrimination. Codes are those applied in the analysis matrix and are reproduced here so that every rank-based statistic reported in Sect. 4 can be traced to the response options on which it was computed

Authors' contribution All authors contributed to the study conception and design. The individual contributions, following the CRediT (Contributor Roles Taxonomy), were distributed as follows: Angel Torres-Toukoumidis (A.T.-T.): Conceptualization; Methodology; Validation; Supervision; Project administration; Funding acquisition; Writing – review & editing. Tatiana León-Alberca (T.L.-A.): Formal analysis; Data curation; Software; Investigation; Visualization; Writing – original draft. Josue Paul Cale Lituma (J.P.C.L.): Investigation; Resources; Software; Visualization; Writing – original draft.

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Data availability The data supporting the findings of this study consist of the anonymized responses of the 284 participants to the 20-item structured questionnaire (sociodemographic variables and the categorical and ordinal items on body self-perception, AI-mediated digital practices, and perceptions of algorithmic aesthetic bias), together with the corresponding SPSS analysis matrix. These data were collected anonymously and contain no personally identifiable information. The dataset is not currently deposited in a public repository; it is available from the corresponding author (A.T.-T.) upon reasonable request, for non-commercial academic and verification purposes. Peer reviewers may also request access to the underlying data and analysis files during the evaluation of the manuscript.

Declarations

Ethical approval All procedures performed in this study involving human participants were in accordance with the ethical standards of the institution and with the 1964 Declaration of Helsinki and its later amendments. The study, and specifically the survey instrument and its data-collection procedure, were reviewed by the Vice-Rectorate for Research (Vicerrectorado de Investigación) and the Ethics Committee of Universidad Politécnica Salesiana, which approved the administration of the survey.

Informed consent Informed consent was obtained from all individual participants included in the study. Participation was voluntary, anonymous, and confidential, and respondents provided consent through a mandatory digital consent form before accessing the questionnaire.

Conflict of interest The authors declare that they have no financial, personal, academic, institutional, or professional relationships, and no competing interests, that could be perceived as influencing the work reported in this manuscript.

References

Abid, A., Farooqi, M., & Zou, J. (2021). *Persistent anti-Muslim bias in large language models* [Preprint]. arXiv. https://arxiv.org/abs/2101.05783

Adelardi, L. (2022). Bullying, gordofobia y salud mental. *Límbica: Revista de Salud Feminista*, *3*(4), 21–31. https://revistalimbica.com/numero-4-gordura/

Albet-Castillejo, L. (2020). *Repensar el cuerpo gordo desde la filosofía de Michel Foucault: Biopolítica, disciplina y género*. Faber & Sapiens.

Ali, M., Sapiezynski, P., Korolova, A., Mislove, A., & Rieke, A. (2019). *Ad delivery algorithms: The hidden arbiters of digital opportunity* [Preprint]. arXiv. https://arxiv.org/abs/1912.04255

Allen, M. S., Iliescu, D., & Greiff, S. (2022). Single item measures in psychological science: A call to action. *European Journal of Psychological Assessment*, *38*(1), 1–5. https://doi.org/10.1027/1015-5759/a000699

Allende-Allende, I. (2020). Gordofobia, una lectura desde (y para) el trabajo social. *Perspectivas: Revista de Trabajo Social*, *35*, 109–133. https://doi.org/10.29344/07171714.35.23.93

Álvarez-Castillo, C. (2015). *La cerda punk: Ensayos desde un feminismo gorda, lésbiko, antikapitalista y antiespecista*. Trío Editorial. https://www.bibliotecafragmentada.org/cerda-punk/

Anikina, A. (2020). Algorithmic superstructuring: Aesthetic regime of algorithmic governance. *Transformations: Journal of Media Culture and Technology*, *34*, 35–48. https://www.transformationsjournal.org

Aparicio-Martín, E. (2015). Los medios de comunicación en la violencia contra las mujeres: El paradigma de la delgadez. *Historia y Comunicación Social*, *20*(1), 107–119. https://doi.org/10.5209/rev_HICS.2015.v20.n1.49550

Arcila-Calderón, C., Blanco-Herrero, D., & Valdez-Apolo, M. (2020). Rechazo y discurso de odio en Twitter: Análisis de contenido de los tuits sobre migrantes y refugiados en español. *Revista Española de Investigaciones Sociológicas*, *172*, 21–40. https://doi.org/10.5477/cis/reis.172.21

Arcila-Calderón, C., Holgado, S., Gómez, P., Barbosa, J., Qi, M., Matilla, H., Amado, A., Guzmán, P., López-Matías, A., D., & Fernández-Villazala, T. (2024). From online hate speech to offline hate crime: The role of inflammatory language in forecasting violence against migrant and LGBT communities. *Humanities and Social Sciences Communications*, *11*(1). https://doi.org/10.1057/s41599-024-03899-1

Barocas, S., Hardt, M., & Narayanan, A. (2023). *Fairness and machine learning: Limitations and opportunities*. MIT Press.

Bergkvist, L., & Rossiter, J. R. (2007). The predictive validity of multiple-item versus single-item measures of the same constructs. *Journal of Marketing Research*, *44*(2), 175–184. https://doi.org/10.1509/jmkr.44.2.175

Bethlehem, J. (2010). Selection bias in web surveys. *International Statistical Review*, *78*(2), 161–188. https://doi.org/10.1111/j.1751-5823.2010.00112.x

Bianchi, F., Kalluri, P., Durmus, E., Ladhak, F., Cheng, M., Nozza, D., Hashimoto, T., Jurafsky, D., Zou, J., & Caliskan, A. (2023). Easily accessible text-to-image generation amplifies demographic stereotypes at large scale. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency* (pp. 1493–1504). Association for Computing Machinery. https://doi.org/10.1145/3593013.3594095

Birhane, A. (2021). Algorithmic injustice: A relational ethics approach. *Patterns*, *2*(2). https://pubmed.ncbi.nlm.nih.gov/33659914/

Bucher, T. (2017). The algorithmic imaginary: Exploring the ordinary affects of Facebook algorithms. *Information Communication & Society*, *20*(1), 30–44. https://doi.org/10.1080/1369118X.2016.1154086

Buolamwini, J. (2023). Unmasking AI: My mission to protect what is human. *Critical AI*, *2*(2). https://doi.org/10.1215/2834703X-11556092

Buolamwini, J., & Gebru, T. (2018). Gender shades: Intersectional accuracy disparities in commercial gender classification. *Proceedings of Machine Learning Research*, *81*, 77–91.

Clay, S., & Brickell, C. (2022). The dad bod: An impossible body? *The Journal of Men's Studies*, *30*(1), 70–86. https://doi.org/10.1177/10608265211035790

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.

Cohen, R., Fardouly, J., Newton-John, T., & Slater, A. (2019). #BoPo on Instagram: An experimental investigation of the effects of viewing body positive content on young women's mood and body image. *New Media & Society*, *21*(7), 1546–1564. https://doi.org/10.1177/1461444819826530

Cohen, R., Newton-John, T., & Slater, A. (2021). The case for body positivity on social media: Perspectives on current advances and future directions. *Journal of Health Psychology*, *26*(13). https://pubmed.ncbi.nlm.nih.gov/32191132/

Costanza-Chock, S. (2020). *Design justice*. MIT Press. https://designjustice.mitpress.mit.edu

Cronbach, L. J., & Meehl, P. E. (1955). Construct validity in psychological tests. *Psychological Bulletin*, *52*(4), 281–302. https://doi.org/10.1037/h0040957

Del Mar, M., Vargas, Y., & Marauri, I. (2025). The treatment of fatphobia on the social networks YouTube and TikTok: The case of Itziar Castro. *Icono 14*, *23*(1). https://icono14.net/ojs/index.php/icono14/article/view/2219

Díaz Barahona, J., & Marín Liébana, P. (2025). Representaciones del cuerpo en imágenes generadas por IA en el ámbito físico-deportivo: Sesgos, estereotipos y reflexiones para su uso. *Retos*, *71*, 716–729. https://doi.org/10.47197/retos.v71.116433

Ellison, J. (2020). *Being fat: Women, weight, and feminist activism in Canada*. University of Toronto.

Eslami, M., Rickman, A., Vaccaro, K., Aleyasen, A., Vuong, A., Karahalios, K., Hamilton, K., & Sandvig, C. (2015). I always assumed that I wasn't really that close to [her]: Reasoning about invisible algorithms in news feeds. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems* (pp. 153–162). Association for Computing Machinery. https://doi.org/10.1145/2702123.2702556

Fardouly, J., Diedrichs, P. C., Vartanian, L. R., & Halliwell, E. (2015). Social comparisons on social media: The impact of Facebook on young women's body image concerns and mood. *Body Image*, *13*, 38–45. https://doi.org/10.1016/j.bodyim.2014.12.002

Festinger, L. (1954). A theory of social comparison processes. *Human Relations*, *7*(2), 117–140. https://doi.org/10.1177/001872675400700202

Flake, J. K., & Fried, E. I. (2020). Measurement schmeasurement: Questionable measurement practices and how to avoid them. *Advances in Methods and Practices in Psychological Science*, *3*(4), 456–465. https://doi.org/10.1177/2515245920952393

Fredrickson, B. L., & Roberts, T. A. (1997). Objectification theory: Toward understanding women's lived experiences and mental health risks. *Psychology of Women Quarterly*, *21*(2), 173–206. https://doi.org/10.1111/j.1471-6402.1997.tb00108.x

Funder, D. C., & Ozer, D. J. (2019). Evaluating effect size in psychological research: Sense and nonsense. *Advances in Methods and Practices in Psychological Science*, *2*(2), 156–168. https://doi.org/10.1177/2515245919847202

García-Díaz, J., Pan, R., Jiménez-Zafra, S., & Valencia-García, R. (2024). Spanish FatPhoCorpus 2023: Combating fatphobia in social media in Spanish using transformers. In *CEUR workshop proceedings*. CEUR-WS.

Gibson, G. (2022). Health(ism) at every size: The duties of the 'good fatty'. *Fat Studies: An Interdisciplinary Journal of Body Weight and Society*, *11*, 22–35. https://doi.org/10.1080/21604851.2021.1906526

Gillespie, T. (2014). The relevance of algorithms. In T. Gillespie, P. J. Boczkowski, & K. A. Foot (Eds.), *Media technologies: Essays on communication, materiality, and society* (pp. 167–194). MIT Press.

Gordon, A. (2020). *What we don't talk about when we talk about fat*. Beacon Press.

Guerrero-Salazar, S. (2020). Léxico e ideología sobre la gordofobia en la comunicación digital. *Círculo de Lingüística Aplicada a la Comunicación*, *83*, 93–107. https://doi.org/10.5209/clac.70566

Henrich, J., Heine, S. J., & Norenzayan, A. (2010). The weirdest people in the world? *Behavioral and Brain Sciences*, *33*(2–3), 61–83. https://doi.org/10.1017/S0140525X0999152X

Hernández-Ávila, C. E., & Escobar, N. A. C. (2019). Introducción a los tipos de muestreo. *Alerta: Revista Científica del Instituto Nacional de Salud*, *2*(1), 75–79. https://doi.org/10.5377/alerta.v2i1.7535

Javornik, A., Marder, B., Barhorst, J. B., McLean, G., Rogers, Y., Marshall, P., & Warlop, L. (2022). What lies behind the filter?' Uncovering the motivations for using augmented reality (AR) face filters on social media and their effect on well-being. *Computers in Human Behavior*, *128*, 107126. https://doi.org/10.1016/j.chb.2021.107126

Kleemans, M., Daalmans, S., Carbaat, I., & Anschütz, D. (2018). Picture perfect: The direct effect of manipulated Instagram photos on body image in adolescent girls. *Media Psychology*, *21*(1), 93–110. https://doi.org/10.1080/15213269.2016.1257392

Lind, E. (2020). Queering fat activism: A study in whiteness. In M. Friedman, C. Rice, & J. Rinaldi (Eds.), *Thickening fat: Fat bodies, intersectionality, and social justice*. Routledge. https://doi.org/10.4324/9780429507540-16

Lobaton, R. (2022). *Infancias y adolescencias gordas*. Raquel Lobatón Nutrición Incluyente. https://raquel-lobaton.com/infancias-y-adolescencias-gordas/

Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes*, *151*, 90–103. https://doi.org/10.1016/j.obhdp.2018.12.005

Luccioni, A., Akiki, C., Mitchell, M., & Jernite, Y. (2023). *Stable bias: Analyzing societal representations in diffusion models* [Preprint]. arXiv. https://arxiv.org/abs/2303.11408

Manjarrés, P. E. M. (2024). Afectaciones en la autopercepción asociadas al uso de la inteligencia artificial. *Uru: Revista de Comunicación y Cultura*, (10), 30–46. https://doi.org/10.32719/26312514.2024.10.2

Maxwell, S. E., & Cole, D. A. (2007). Bias in cross-sectional analyses of longitudinal mediation. *Psychological Methods*, *12*(1), 23–44. https://doi.org/10.1037/1082-989X.12.1.23

Meadows, A., & Daníelsdóttir, S. (2016). What's in a word? On weight stigma and terminology. *Frontiers in Psychology*, *7*., Article 1527. https://doi.org/10.3389/fpsyg.2016.01527

Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., & Galstyan, A. (2021). A survey on bias and fairness in machine learning. *ACM Computing Surveys*, *54*(6), 1–35. https://doi.org/10.1145/3457607

Noble, S. U. (2018). *Algorithms of oppression*. NYU. https://nyupress.org/9781479837243/algorithms-of-oppression/

Palomino-Flores, P., Berckholtz-Benavides, K., & Díaz-Hernández, C. (2026). Virtual soul': The aesthetics of the disembodied being. A conceptual and visual analysis of an artificial influencer. *Visual Review: International Visual Culture Review*, *18*(1), 191–209. https://doi.org/10.62161/revvisual.v18.5976

Papaioannou, T., & Monaghan, L. F. (2023). Affect as community connectedness: Re-framing weight-related stigma and disordered eating online. *Journal of Communication Inquiry*. https://doi.org/10.1177/01968599231210794. Advance online publication.

Perloff, R. M. (2014). Social media effects on young women's body image concerns: Theoretical perspectives and an agenda for research. *Sex Roles*, *71*(11–12), 363–377. https://doi.org/10.1007/s11199-014-0384-6

Piñeyro, M. (2016). *Stop gordofobia y las panzas subversas*. Zambra.

Piñeyro, M. (2019). *10 gritos contra la gordofobia*. Vergara.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Raji, I. D., & Buolamwini, J. (2019). Actionable auditing: Investigating the impact of publicly naming biased performance results of commercial AI products. In *Proceedings of the 2019 AAAI/*

ACM Conference on AI, Ethics, and Society (pp. 429–435). Association for Computing Machinery. https://doi.org/10.1145/3306618.3314244

Ring Carlson, C. (2022). *El discurso del odio*. Cátedra.

Rodgers, R. F., McLean, S. A., & Paxton, S. J. (2015). Longitudinal relationships among internalization of the media ideal, peer social comparison, and body dissatisfaction: Implications for the tripartite influence model. *Developmental Psychology*, *51*(5), 706–713. https://doi.org/10.1037/dev0000013

Ronconi, M., Zemaitis, S., Alessi, D., & Barrena, M. (2024). La mirada social sobre los cuerpos: El mandato de la delgadez y el gordo-odio. In D. V. Alessi (Coord.), *ESI en la secundaria: Hacia una educación sexualmente justa y placentera* (pp. 62–65). EDULP. https://www.memoria.fahce.unlp.edu.ar/libros/pm.6507/pm.6507.pdf

Rosenthal, R. (1991). *Meta-analytic procedures for social research* (Rev. ed.). Sage. https://doi.org/10.4135/9781412984997

Selbst, A. D., Boyd, D., Friedler, S. A., Venkatasubramanian, S., & Vertesi, J. (2019). Fairness and abstraction in sociotechnical systems. In *Proceedings of the Conference on Fairness, Accountability, and Transparency* (pp. 59–68). Association for Computing Machinery. https://doi.org/10.1145/3287560.3287598

Strings, S. (2019). *Fearing the Black body*. NYU. https://nyupress.org/9781479819805/fearing-the-black-body/

Sundar, S. S. (2008). The MAIN model: A heuristic approach to understanding technology effects on credibility. In M. J. Metzger, & A. J. Flanagin (Eds.), *Digital media, youth, and credibility* (pp. 73–100). MIT Press.

Sundar, S. S. (2020). Rise of machine agency: A framework for studying the psychology of human–AI interaction (HAII). *Journal of Computer-Mediated Communication*, *25*(1), 74–88. https://doi.org/10.1093/jcmc/zmz026

Taylor, A., Mitchell, A., & Rice, C. (2023). Performing fat liberation: Pretty Porky and Pissed Off's affective politics and archive. *Social Sciences*, *12*(5), 270. https://doi.org/10.3390/socsci12050270

Thompson, J. K., Heinberg, L. J., Altabe, M., & Tantleff-Dunn, S. (1999). *Exacting beauty: Theory, assessment, and treatment of body image disturbance*. American Psychological Association. https://doi.org/10.1037/10312-000

Tiggemann, M., & Slater, A. (2013). NetGirls: The Internet, Facebook, and body image concern in adolescent girls. *International Journal of Eating Disorders*, *46*(6), 630–633. https://doi.org/10.1002/eat.22141

Tomczak, M., & Tomczak, E. (2014). The need to report effect size estimates revisited: An overview of some recommended measures of effect size. *Trends in Sport Sciences*, *21*(1), 19–25.

Ugarte, N. (2021, June 15). Estudio de autoestima política: ¿Cuál es la primera palabra que se te viene a la cabeza cuando te miras al espejo? *El Mostrador*. https://www.elmostrador.cl/braga/2021/06/15/estudio-de-autoestima-politica-cual-es-la-primera-palabra-que-se-te-viene-a-la-cabeza-cuando-te-miras-al-espejo/

Vandenbosch, L., Fardouly, J., & Tiggemann, M. (2022). Social media and body image: Recent trends and future directions. *Current Opinion in Psychology*, *45*, 101289. https://doi.org/10.1016/j.copsyc.2021.12.002

Wanniarachchi, V. U., Mathrani, A., Susnjak, T., & Scogings, C. (2022). Methodological aspects in study of fat stigma in social media contexts: A systematic literature review. *Applied Sciences*, *12*(10). https://doi.org/10.3390/app12105045

Wanniarachchi, V. U., Scogings, C., Susnjak, T., & Mathrani, A. (2023). Hate speech patterns in social media: A methodological framework and fat stigma investigation incorporating sentiment analysis, topic modelling and discourse analysis. *Australasian Journal of Information Systems*, *27*. https://doi.org/10.3127/ajis.v27i0.3929

Wherry, R. J. (2014). *Contributions to correlational analysis*. Academic.

Wood, J. V. (1989). Theory and research concerning social comparisons of personal attributes. *Psychological Bulletin*, *106*(2), 231–248. https://doi.org/10.1037/0033-2909.106.2.231

Wright, K. B. (2005). Researching internet-based populations: Advantages and disadvantages of online survey research, online questionnaire authoring software packages, and web survey services. *Journal of Computer-Mediated Communication*, *10*(3). https://doi.org/10.1111/j.1083-6101.2005.tb00259.x

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