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Error Management Theory and biased first impressions: How do people perceive potential mates under conditions of uncertainty?

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ABSTRACT

People must make inferences about a potential mate's desirability based on incomplete information. Under such uncertainty, there are two possible errors: people could overperceive a mate's desirability, which might lead to regrettable mating behavior, or they could underperceive the mate's desirability, which might lead to missing a valuable opportunity. How do people balance the risks of these errors, and do men and women respond differently? Based on an analysis of the relative costs of these two types of error, we generated two new hypotheses about biases in initial person perception: the Male Overperception of Attractiveness Bias (MOAB) and the Female Underperception of Attractive Bias (FUAB). Participants ($N = 398$), who were recruited via social media, an email distribution list, and snowball sampling, rated the attractiveness of unfamiliar opposite-sex targets twice: once from a blurred image, and once from a clear image. By randomizing order of presentation (blurred first vs. clear first), we isolated the unique effects of *uncertainty*—which was only present when the participant saw the blurred image first. As predicted, men *over*perceived women's attractiveness, on average. By contrast, as predicted, women *under*perceived men's attractiveness, on average. Because multiple possible decision rules could produce these effects, the effects do not reveal the algorithm responsible for them. We explicitly addressed this level of analysis by identifying multiple candidate algorithms and testing the divergent predictions they yield. This suggested the existence of more nuanced biases: men overperceived the attractiveness of unattractive (but not attractive) women, whereas women underperceived the attractiveness of attractive (but not unattractive) men. These findings highlight the importance of incorporating algorithm in analyses of cognitive biases.

Imagine you're with your friends in a dimly illuminated bar, and you catch only a brief glimpse of someone as they walk past you. Was that person as attractive as they seemed to be? It's now later in the evening, and your friends want to leave. Do you leave with your friends without giving that person another thought? Or do you feel like you need to approach that person? Can you anticipate the pangs of regret if you don't?

Because people have only incomplete information about potential mates, they must make inferences about potential mates' desirability under conditions of uncertainty. Under these conditions of uncertainty, there are two possible inferential errors. One could infer that the potential mate is more desirable than they actually are, which may lead to a regrettable mating decision. Alternatively, one could underperceive the potential mate's desirability, which could lead to missing out on a valuable opportunity. How do people balance these risks? And do men and women respond differently to this uncertainty?

1. Signal Detection Theory and Error Management Theory

Signal Detection Theory (Green & Swets, 1966) articulates that, when making decisions under uncertainty, two general types of error can occur – false positives and false negatives (Type I and Type II errors, respectively). It is impossible for a decision-making system to concurrently reduce both errors, as decreasing the likelihood of one directly results in an increase in the likelihood of the other (Green & Swets, 1966). When the costs of the two error types within a decision are

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asymmetrical, an engineered system should be designed in such a way that it minimizes the net costs of the errors over the sample space of instances, even if this does not minimize the system's error rate (Green & Swets, 1966). For example, it is costlier for a smoke alarm to fail to detect an actual fire (a "miss", also known as a false negative or Type II error) than it is for a smoke alarm to go off when there is no real fire present (a "false alarm", also known as a false positive or Type I error). For this reason, smoke alarm systems are *designed to be biased* toward false positive errors (Schifiliti & Pucci, 1996). Despite this often leading to us regretting burnt toast, we readily accept this outcome because a false positive is much less costly than a false negative. This design increases error *rates,* but it is superior in terms of the net *costs* incurred over the sample space of instances (Green & Swets, 1966).

Error Management Theory (EMT; Haselton & Buss, 2000) extends this logic from human-engineered information-processing systems to evolved information-processing systems: the psychological mechanisms of the human mind. EMT proposes that, because the outcomes relevant to selection are fitness costs – not error rates – selection should have shaped information-processing adaptations to minimize the net costs of inferential errors, even if this resulted in systems that commit a greater number of errors. This suggests that, when there was a recurrent asymmetry in the fitness costs of the two types of inferential error, selection should have shaped psychological mechanisms that are biased toward committing the less costly error.

2. EMT and evolved biases in person perception

EMT is a "middle-level" evolutionary theory (Buss, 1995) that both (1) can account for known, but previously unexplained, phenomena and (2) has led to the discovery of previously unknown inferential biases. For example, sex differences in perceptions of sexual intent, wherein men perceive greater sexual intent in women than women do in men, were documented at least as early as 1982 (Abbey, 1982). At the time, the causal origins of this phenomenon were not well understood, and attributed variously to proximate explanations such as a general over-sexualization of the world by men, media exposure of women acting shy despite sexual interest, and men projecting their own levels of sexual interest onto women (see Haselton & Buss, 2000).

However, the phenomenon was neatly explained by the EMT framework advanced by Haselton and Buss (2000). Ancestrally, a key limiting factor on men's reproductive success was their access to fertile mates (Symons, 1979). Because of this, missed sexual opportunities were highly costly for men. In estimating women's sexual intent, a false negative – inferring that a woman was uninterested when she actually was interested – could have resulted in the substantial fitness costs of a lost sexual opportunity and decreased reproductive success. By contrast, a false positive – inferring that a woman was sexually interested when she was not – could have included the social embarrassment of rejection and wasted courtship effort, but these have comparatively minor effects on men's fitness (see Abbey, 1987; Perilloux, Easton, & Buss, 2012).

Based on this asymmetry in the two possible inferential errors, Haselton and Buss (2000) hypothesized that men possess intention-reading adaptations that are designed to make the less costly error – to over-infer women's sexual intent – in order to minimize the frequency of missed sexual opportunities. In support of this hypothesis, numerous studies have demonstrated that men overestimate women's sexual intent, a phenomenon now known as the 'sexual overperception bias' (e.g., Haselton & Buss, 2000; Haselton, 2003; Henningsen, 2004; Mongeau & Johnson, 1995; for nuanced analyses and discussion, see Henningsen & Henningsen, 2010; Henningsen, Henningsen, McWorthy, McWorthy, & McWorthy, 2011; Koenig, Kirkpatrick, & Ketelaar, 2007).

EMT has also been used to predict *previously unknown inferential biases*, such as women's systematic tendency to underperceive men's commitment intent: the commitment-skepticism bias (Haselton & Buss, 2000). Due to internal gestation, women's minimum obligatory parental investment is massive: nine months of pregnancy, which is frequently accompanied by multiple years of lactation, breastfeeding, and child-rearing. This results in an unwanted pregnancy being a particularly pronounced problem for women (Goetz & Shackelford, 2009). Although underestimating a man's commitment intent would have carried costs, these would have been dramatically outweighed by the costs of *over*-estimating a man's intention to commit. Being abandoned by a man following sexual relations could have resulted in the woman incurring the costs of an unwanted pregnancy and raising a child without an investing mate (Buss, 1994), which is associated with decreased offspring survival (Hurtado & Hill, 1992). The woman also could have suffered reputational damage (Buss, 1994) and, crucially, reductions in her mate value (Buss, 1994) and future reproductive potential (Hurtado & Hill, 1992). Based on this, Haselton and Buss (2000) hypothesized that that women possess intention-reading adaptations designed to make the less costly error: underestimating men's commitment intent. This hypothesis has received empirical support in several studies (e.g., Cyrus, Schwarz, & Hassebrauck, 2011; Haselton & Buss, 2000).

3. Error Management Theory: prospects and limitations

This previous literature has articulated the logic of EMT and demonstrated the theory's empirical merit. However, as a middle-level theory based on first principles, EMT has tremendous predictive power and broad scope. Some of its strengths remain largely untapped.

First, EMT is a rich fount of a priori hypotheses. Yet, the EMT work that is perhaps best known – Haselton and Buss's (2000) account of men's overperception of women's sexual interest – was (openly) designed to explain known findings rather than predict new ones. Although observation-driven research is a fundamental component of science, the fact that the seminal EMT research was observation-driven may be unfortunate, because evolutionary approaches to psychology have long been subjected to unwarranted accusations of 'just-so' story-telling (e.g., Gould, 1978). This allegation, which reflects a fundamental misunderstanding of the enterprise of evolutionary psychology, has been headed off multiple times in the scholarly literature (see Confer et al., 2010; Lewis, Al-Shawaf, Conroy-Beam, Asao, & Buss, 2017 for recent discussions; see also Al-Shawaf, 2020 for an essay devoted to this issue). Nonetheless, this allegation can be most easily avoided when the phenomenon of interest is discovered after a priori theorizing about its existence, as in the case of the commitment-skepticism bias (see Haselton & Buss, 2000). When such discoveries are made on the basis of a priori hypotheses, it becomes abundantly clear that the just-so charge falls flat. In the current study, we used EMT to generate several novel hypotheses, thereby demonstrating the theory's a priori predictive power.

Second, EMT's principles apply to all domains of inferential procedures, granting it incredibly broad scope (Al-Shawaf, Lewis, & Evans, 2021). EMT can be used to generate hypotheses across diverse domains, from auditory perception (e.g., Neuhoff, 2001) to visual perception (e.g., Jackson & Cormack, 2007) to mating cognition (Haselton & Buss, 2000). Moreover, because there are many inferential procedures *within* each of these domains, EMT may be used to generate numerous hypotheses within each domain. This is certainly true of mating cognition.

In human mating, inferences can occur at numerous stages, from initial person perception through relationship maintenance to breakups and attributions about their causes. Yet, to date, EMT-inspired research on human mating has focused heavily on inferences made post-interaction—thereby neglecting an important component of human mating psychology: the inferences that occur *before* potential mates interact. These pre-interaction inferences are critical; by motivating individuals to engage in approach or avoidance behavior, they may influence the likelihood of interactions occurring at all (Tooby, Cosmides, Sell, Lieberman, & Sznycer, 2008). Because inferential errors can be made in these crucial pre-interaction phases, we might expect selection to have favored psychological mechanisms that are biased toward producing the less costly error in these initial information-processing stages. To our knowledge, this aspect of human mating – inferential errors in pre-interaction decision-making – has never been explored. Here, we advance the overarching hypothesis that selection should have favored inferential biases in initial perceptions of potential mates' desirability, and that these biases should be sex-differentiated.

4. Error Management Theory and sex differences in perceiving attractiveness

Perceptions of attractiveness are powerful determinants of approach and avoidance behavior (Hatfield, Roberts, & Schmidt, 1980). This has implications for the inferential procedures that the mind uses when information about a potential mate is limited, unavailable, or otherwise uncertain. Because perceiving a target as unattractive motivates avoidance behavior, mistakenly inferring that a potential mate is unattractive carries the cost of missing a potentially valuable opportunity. Conversely, erroneously inferring that a target is a desirable mate when they are *not* could lead to negative consequences as well, including (for example) injudicious sexual relations.

To generate predictions about whether humans' psychological mechanisms will be systematically biased toward one of these errors, we must consider the cost asymmetry between the two errors. Moreover, because the costs of these errors may differ for men and women, these cost asymmetries – and the resulting inferential biases – may be sex-differentiated. For example, in the commitment-skepticism bias, the costly investment of pregnancy is not endured by men. This renders overestimation of commitment intent much costlier for women than for men. Consequently, women exhibit the commitment-skepticism bias, but men do not (Haselton & Buss, 2000; Henningsen & Henningsen, 2010).

4.1. Male (over)perceptions of female attractiveness

Because a key limiting factor on ancestral men's reproductive success was their ability to have sexual intercourse with fertile women (Symons, 1979), forgoing potentially valuable mating opportunities would have carried substantial fitness costs for men. Errors of commission also would have carried costs, but these likely would have been comparatively smaller. The exact costs of injudicious mating behavior cannot be known, but they would have been mitigated by the fact that men's minimum obligatory parental investment is substantially lower than women's. Injudicious mating might have resulted in a man producing offspring with a woman that he did not want to commit to or invest in, but this would not necessarily have prevented him from engaging in other mating effort, including mating with and producing offspring with other women. On balance and on average, for men, a missed sexual opportunity likely was costlier than injudicious sexual behavior (Fig. 1, top panel) (Haselton & Buss, 2000; Haselton & Nettle, 2006; Symons, 1979). Consequently, we should expect men's minds to minimize inferential errors that result in forgoing valuable mating opportunities (see Haselton & Buss, 2000). In the current context, if the downstream costs of mistakenly inferring that a woman was *unattractive* were greater than the costs of wrongly inferring that a woman was *attractive*, selection should have favored inferential procedures in the male mind biased toward overperceiving women's attractiveness under conditions of uncertainty.

Hypothesis 1. The Male Overperception of Attractiveness Bias (MOAB): Under conditions of uncertainty, men will overestimate women's attractiveness, on average.

4.2. Female (under)perceptions of male attractiveness

For women, on the other hand, the asymmetry in the cost matrix is different, and may even be reversed. The large metabolic and time investment required from women for successful reproduction (Goetz & Shackelford, 2009) means that engaging in injudicious mating behavior would have been substantially costlier, on average, for women than for men. Additionally, the ability to have intercourse with members of the opposite sex would not have been a limiting factor on women's reproductive success to the same extent that it constrained men's reproductive success (Symons, 1979). The cost matrix is therefore different: forgoing a mating opportunity would have carried greater costs for men than for women, whereas errors of commission would have carried higher costs for women than for men. Although the exact costs of forgoing a mating opportunity and of engaging in injudicious mating behavior cannot be known, this a priori analysis suggests that, for ancestral women, the costs of commission exceeded the costs of omission (Fig. 1, bottom panel) (Haselton & Buss, 2000). If this is true, then we should expect women's minds to have evolved to be biased toward inferential errors that result in forgone mating opportunities rather than errors of commission. In the current context, if the downstream costs of mistakenly inferring that a man was *attractive* were greater than the costs of wrongly inferring that a man was *unattractive*, selection should have favored inferential procedures in the female mind biased toward *under*perceiving men's attractiveness under conditions of uncertainty.

Hypothesis 2. The Female Underperception of Attractiveness Bias (FUAB): Under conditions of uncertainty, women will underestimate men's attractiveness, on average.

5. EMT and decision rules: the integration of heuristics and evolved biases

EMT is a powerful framework for generating a priori hypotheses across diverse domains, but the research it inspires needs further refining (see McKay & Efferson, 2010; see also Al-Shawaf, 2016). Certain content in the seminal work introducing EMT – "Errors may be evidence of evolved adaptive biases, not simplifying heuristics" (Haselton & Buss, 2000, p. 90) – could be construed to mean that evolved biases and heuristics are competing explanations. They are not, and this was not the emphasis of statements such as these. Rather, the focus of these statements was to contrast (1) the EMT view that the

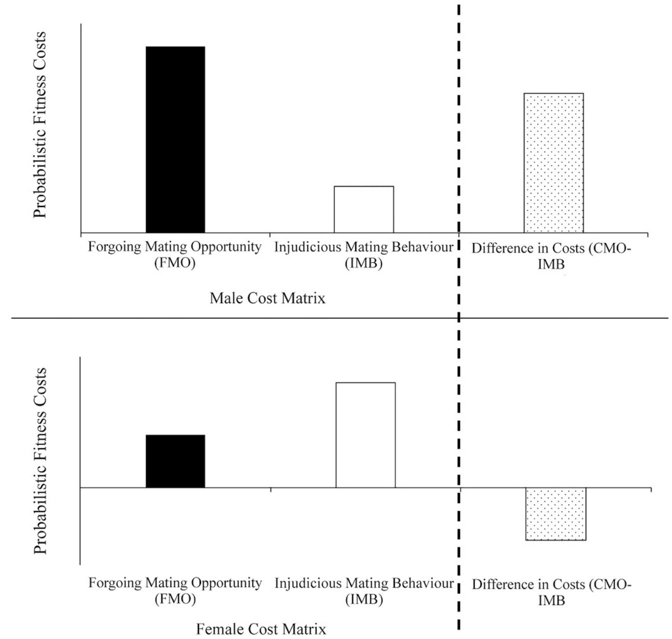

Fig. 1. A conceptual illustration of the relative costs of forgoing a mating opportunity and engaging in injudicious mating behavior among men (top), among women (bottom), and between men and women (top right vs. bottom right).

biases reflected evolved, adaptive design with (2) the prevalent view that dismissed such biases as "illusions" (Piatelli-Palmarini, 1994) or "fallacies" (Tversky & Kahneman, 1974). As a theory about cognition and information processing, heuristics are integral to EMT.

One of the foundations of cognitive science is that a complete analysis of an information-processing system includes the specification of its (1) *function*, as well as the (2) *algorithm* and (3) *implementation* by which it achieves that function (McClamrock, 1991; see also Marr, 1982). By articulating why selection should have favored inferential systems that lead men, on average, to overestimate women's sexual intent, and women, on average, to underestimate men's commitment intent, the seminal EMT work thoroughly addressed *function* – "What is the goal [...], why is it appropriate, and what is the logic of the strategy [...]?" (Marr, 1982, p. 25). However, this and subsequent excellent theoretical work on EMT (e.g., Haselton & Nettle, 2006) has tended not to emphasize these distinct levels of analysis of an information-processing system. Consequently, it has either explicitly conflated these levels of analysis (see McKay & Efferson, 2010 for discussion) or simply neglected one or multiple of them. Here, we focus on the *algorithmic* level (Marr, 1982)—the information-processing decision rules by which the mind may systematically produce biased inferences.

This is a crucial level of analysis for EMT. Because there are multiple possible decision rules that could produce a given bias, we cannot claim to know how "decisions are actually made" (Shafir & Tversky, 1995, p. 77) without knowledge of the specific rule used. The sexual overperception bias illustrates this well. For example, the heuristic of "estimate a woman's sexual intent based on cues detected, and add constant *X* to that estimate in case cues of interest were missed" would yield an on-average overperception of women's sexual intent. But so too would a very different heuristic: "when uncertain about a woman's sexual intent, assume she is sexually interested." That the same effect can be produced by two different algorithms tells us that we cannot resolve the cognitive architecture of the human mind from the effect itself. As McKay and Efferson write, inferences about cognitive architecture based on such effects can be "radically underdetermined" (McKay & Efferson, 2010, p. 313). Ultimately, the issue is that articulating the hypothesized *function* of an information-processing system does not answer questions about *algorithm*. These distinct levels of analysis, and the need to address both as part of a comprehensive analysis of an information-processing system, are foundational concepts in cognitive science (Marr, 1982).

The algorithm level of analysis can be seamlessly integrated into EMT work. First, researchers can identify *candidate algorithms* that could plausibly achieve the proposed *function* of the information-processing system. Second, researchers can specify the quantitative effects predicted by each of these decision rules, with an emphasis on identifying *divergent* predictions generated based on the different candidate algorithms (see Lewis et al., 2017). Third, researchers can then design studies capable of testing for these predicted effects to discriminate between alternative candidate algorithms. We illustrate this approach by applying it to the MOAB hypothesis: the novel hypothesis advanced here that selection favored inferential procedures in the male mind biased toward perceiving women as attractive under conditions of uncertainty.

6. One function, multiple possible algorithms

There are multiple possible algorithms that could serve the same function of preventing men from missing potentially valuable mating opportunities, and which would generate an on-average overperception of women's attractiveness. One possible heuristic would be: "estimate a woman's attractiveness based on available information, but, if available information is limited or other otherwise uncertain, add constant *X* to that estimate" (Algorithm A). Another candidate decision rule would be: "when uncertain whether a woman is attractive, assume that she is attractive" (Algorithm B). We could elaborate many more candidate heuristics, but the point is this: multiple different algorithms could serve the same relevant function. All would produce an on-average overperception of women's attractiveness.

The fact that multiple algorithms would generate an on-average overperception of women's attractiveness tells us that this overall quantitative effect leaves inferences about algorithm underdetermined. To adjudicate between different candidate algorithms, we must specify the unique quantitative effects predicted by each. Algorithm A entails adding a fixed value to the estimate for all women. The quantitative effects of this algorithm do not vary as a function of the women's actual attractiveness (Fig. 2, left panel). By contrast, Algorithm B – "when uncertain whether a woman is attractive, assume that she is attractive" – will produce quantitative effects that vary as a function of the woman's actual attractiveness. This algorithm will generate overestimates of the attractiveness of unattractive women, but (roughly) accurate estimates of the attractiveness of attractive women (Fig. 2, right panel).

To our knowledge, no EMT research to date has sought to identify the actual algorithms underlying the biases. The second goal of our study was therefore to test the distinct effects predicted by different candidate algorithms, alongside the primary goal of testing for previously undiscovered, sex-differentiated biases in the perception of attractiveness.

7. The current study

We tested for these proposed inferential biases in response to uncertainty using a within-subjects, within-target design. We had male and female participants view and rate the attractiveness of unfamiliar opposite-sex targets twice: once from a blurred image, and once from a clear image. By randomizing order of presentation (blurred first vs. clear first), we isolated the unique effects of *uncertainty*—which was only present when the participant saw the blurred image first. That is, when a participant viewed a target's clear image before the target's blurred image, the blurred image did not reflect uncertainty, but *when the participant viewed the blurred image before seeing the clear image*, the participant had to make assessments of the target's attractiveness under uncertainty. If *uncertainty* is the key variable (not merely blurring or order alone), then the effect of blurring should be moderated by order of presentation: if *uncertainty* is the key variable, then blurring should interact with order. Our study design enabled us to test this key idea.

The recording of the participants' ratings of the targets' clear images also enabled us to test the algorithmic structure of the potential bias. If the underlying algorithm uniformly underestimates or overestimates targets' attractiveness under conditions of uncertainty (as in the case of Algorithm A above), then the magnitude of the bias should *not* vary as a function of the targets' "true" attractiveness (i.e., their revealed attractiveness, as indexed by participants' ratings of their clear images). Alternatively, if the decision rule is simply to assume that a target is unattractive or attractive under conditions of uncertainty (as in the case of Algorithm B above), then the magnitude of the bias should vary as a function of the targets' attractiveness. Our design enabled us to test for these different quantitative effects predicted by distinct algorithms, and thereby begin to map the information-processing architecture underlying these hypothesized biases.

8. Method

8.1. Ethics statement

This study was approved by the [REDACTED FOR PEER REVIEW] institutional review board (Approval number: 2018/02).

8.2. Participants

Three hundred and ninety-eight subjects (211 heterosexual women: $M_{age} = 26.1$, $SD_{age} = 4.34$; 187 heterosexual men: $M_{age} = 26.5$, $SD_{age} = 4.77$) participated in the current study between May and November 2018. Participants were recruited by advertising the study to

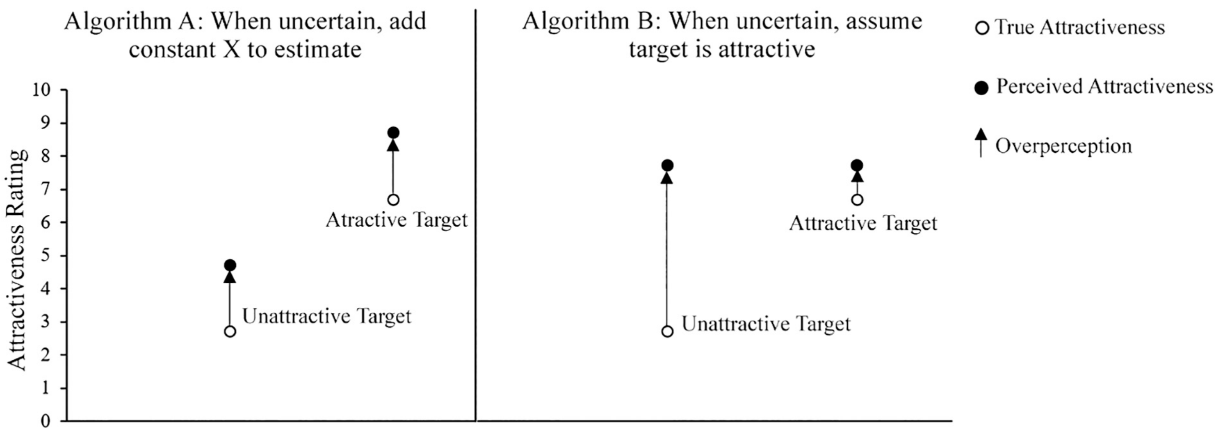

Fig. 2. Different candidate algorithms. The left panel (Algorithm A) depicts a decision rule in which the mind responds to uncertainty by adding a constant value X to its uncertain estimate; this generates an overperception of target attractiveness that does not vary with the target's true attractiveness. The right panel (Algorithm B) depicts a decision rule in which the mind responds to uncertainty by inferring that the target is attractive; this results in the magnitude of the overperception effect varying as a function of the target's true attractiveness.

a distribution list of individuals interested in participating in research. Participants completed the measures described below as part of a longer survey, which was shared via email and completed remotely online via the Qualtrics survey software platform. The sample came from the Czech Republic (86%), Slovakia (10%), Turkey (2%), Russia (1%), and other countries (1%).

8.3. Materials

Forty-eight target images (24 female, 24 male) were drawn from the Chicago Face Database (CFD; Ma, Correll, & Wittenbrink, 2015), a resource developed for scientific research that provides standardized, high-resolution images of both male and female faces. Access to the database along with the references to the faces used can be found at https://osf.io/qw57v/.

To operationalize the construct of uncertainty about a person's physical appearance, we created a second version of each target image by using the Gaussian Blur function in Gimp (open-source raster graphic editor; settings: X = 18, Y = 18; see Fig. 3). This yielded 96 total images: a "clear" image and a "blurred" image of each of the 48 targets.

8.4. Procedure

We employed a within-subjects, within-target design in which participants rated the attractiveness of each opposite-sex target two times. Each participant rated the original, unmodified ("clear") image of the target as well as the Gaussian-blurred version of the target's image.

Participants were presented with one image at a time, and asked to rate the attractiveness of the individual shown on an 11-point scale (0 = Very unattractive, 10 = Very attractive). Each target was presented in a single block (i.e., the target's clear and blurred image appeared on consecutive pages). The order of presentation (clear image first vs. blurred image first) was randomized for each target for each participant.

This design isolated the effect of *uncertainty* from any effects of blurring or order alone. When a participant viewed a target's clear image before the target's blurred image, the blurred image did not reflect uncertainty. However, when the participant viewed the target's blurred image *before* seeing the target's clear image, the participant had to assess the target's attractiveness under conditions of uncertainty.

Order of presentation of targets was randomized across participants.

9. Results

The aim of the current study was to test for inferential biases in the perception of potential mates' attractiveness under conditions of uncertainty. The specific study data capable of testing for these biases were those in which the participant first saw the blurred image of a target (uncertain condition) and then saw the clear image of that target (certain condition). For those data in which the order of presentation was reversed – when the participant viewed the target's blurred image after the clear image – the blurred image no longer reflected uncertainty, as the participant already had clear information about the target (i.e., had already seen the clear image of the target).

For this reason, the specific study data appropriate for testing hypotheses about inferential biases under uncertainty were the "blurred-first" data—those data corresponding to when the participant saw the blurred image of a target before the clear image. The clear-first data were nonetheless a key part of study design because they enabled us to test whether the effects of blur depended on order. If *uncertainty* is the key variable – not order or blurriness per se – then we should expect the effect of blur to be moderated by order: when seen first, the blurred images reflect uncertainty, whereas, when seen second, they do not. This is the core logic of our study design. Our first analyses tested these ideas by assessing (1) whether there was a simple effect of order, (2) whether blurriness influenced perceptions of attractiveness independent of any effect of order and, crucially, (3) whether any effect of blurriness was moderated by order.

Fig. 3. Example study stimuli.

For all analyses, we fit study data (available, along with code, at https://osf.io/qw57v/) to linear mixed-effect models using the *lmerTest* (Version 3.1–2; Kuznetsova, Brockhoff, & Christensen, 2017) package in *R* (R Core Team, 2020). These models enabled us to nest the attractiveness ratings within participants and targets to account for the within-subject, within-target design. Random intercepts for participants were entered to control for differences between participants in their baseline perceptions of attractiveness, and random intercepts were entered for targets to control for baseline differences in attractiveness between targets. This enabled us to better isolate the effects of order, blur, and *uncertainty* (i.e., the unique effect when the blurred image appeared first, captured by the order × blur interaction).

9.1. The effect of uncertainty

To conduct the key test of whether any effect of blurriness was moderated by order – which it should be if *uncertainty* has unique effects – we fit all study data to a linear mixed model in which attractiveness ratings were predicted from the fixed effects of order, blurriness, and, crucially, the interaction between these effects. Precisely as expected if *uncertainty* is the key variable – not order or blurriness alone – the interaction between blurriness and order was significant, $b = -0.16$, $SE = 0.04$, $p < .001$. This indicated that the effect of blurriness on participants' perceptions of targets' attractiveness depended on whether the participant saw the blurred image of the target first – the *uncertainty* condition – or second, after seeing the clear image of the target. This is consistent with the hypothesis that uncertainty exerted unique effects on participants' perceptions. To directly probe these effects, we focused subsequent analyses on the specific subset of study data in which participants made assessments of the targets' attractiveness under uncertainty: when they saw the blurred image of the target first.

9.2. Biases under uncertainty: sex differences

Our next analyses tested for (1) biases under uncertainty and (2) sex differences in any such biases by testing the effects of uncertainty, participant sex, and the interaction between uncertainty and participant sex. If neither men nor women exhibit any inferential bias under uncertainty, then this test should yield no effect of uncertainty *and* no interaction between uncertainty and participant sex. If both sexes possess the same bias, then we should expect to observe an effect of uncertainty, but no interaction between uncertainty and participant sex. However, if at least one sex possesses a bias and the other sex possesses a different bias (or does not possess a bias at all), then we should expect to observe an interaction between uncertainty and participant sex in predicting perceptions of attractiveness. This is precisely what we observed: participant sex interacted with uncertainty to predict perceptions of attractiveness, $b = 0.27$, $SE = 0.06$, $p < .001$. This demonstrated that men and women responded differently to uncertainty.

We therefore conducted separate analyses on the effect of uncertainty among male and female participants. These analyses would tell us whether (1) both sexes had a bias in the same direction, but one sex had a stronger bias, (2) one sex had a bias and the other did not, or (3) both sexes exhibited a bias, but in opposite directions. The study hypotheses predicted that these biases would be in opposite directions: Hypothesis 1 – the male overperception of attractiveness bias (MOAB) – predicted that men would *over*perceive women's attractiveness under uncertainty, and Hypothesis 2 – the female underperception of attractiveness bias (FUAB) – predicted that women would *under*perceive men's attractiveness under uncertainty.

9.2.1. Men's attractiveness overperception bias

In line with the MOAB hypothesis, an analysis of the effect of uncertainty on men's perceptions of the female targets revealed a male tendency to overperceive women's attractiveness under conditions of uncertainty, $b = 0.13$, $SE = 0.04$, $p = .001$ (Fig. 4).

9.2.2. Women's attractiveness underperception bias

In line with the FUAB hypothesis, an analysis of the effect of uncertainty on women's perceptions of the male targets revealed a female tendency to *under*perceive men's attractiveness under conditions of uncertainty, $b = -0.14$, $SE = 0.04$, $p < .001$ (Fig. 4).

9.3. The information-processing architecture of the bias: the algorithm

These findings suggest male and female tendencies to over- and underperceive, respectively, the attractiveness of opposite-sex individuals under conditions of uncertainty. However, these on-average effects leave ambiguity about the structure of the heuristics responsible for these biases. Several different possible decision rules could produce these on-average effects, so further analyses are needed to adjudicate between different algorithms. For example, for men, the algorithm could be: "if uncertain, increase the estimate of the target's attractiveness by constant *X*" (Algorithm A). Alternatively, it could be: "if uncertain, assume the target is attractive" (Algorithm B). Both possibilities would yield the observed average effect of men overperceiving women's attractiveness. However, they lead to different predictions when taking into account variation in the actual attractiveness of the targets. The first algorithm would produce a uniform bias whose magnitude does not vary of a function of the target's actual attractiveness (Fig. 2, left panel). The second algorithm, by contrast, would produce a bias whose magnitude was inversely related to the target's actual attractiveness (Fig. 2, right panel).

If the observed biases are underlain by an information-processing structure like Algorithm A, then the effect of uncertainty should *not* be moderated by the targets' attractiveness. On the other hand, if the information-processing architecture underlying the bias is better described by Algorithm B, then target attractiveness should moderate the effect of uncertainty.

We therefore conducted additional analyses that incorporated the targets' attractiveness in the model. This enabled us to test for different quantitative effects of uncertainty at different levels of target attractiveness, and thereby gain a clearer picture of the information-processing structure of the algorithm responsible for producing the on-average bias. For these analyses, we operationalized each target's attractiveness as their "revealed" attractiveness: the average attractiveness rating given to the target when their clear image was revealed to participants (i.e., after the participants had seen the target's blurred image).

9.3.1. Systematic variation in men's overperception bias

These analyses indicated that the effect of uncertainty on men's perceptions of female targets depended on the targets' attractiveness: uncertainty × target attractiveness interaction $b = -0.12$, $SE = 0.02$, $p < .001$. This meant that the effect of uncertainty on men's perceptions of women's attractiveness varied as a function of the women's actual attractiveness. We therefore conducted follow-up analyses to probe this systematic variation as a function of target attractiveness. For the purpose of these analyses, we categorized female targets as being attractive ($M_{\text{attractiveness}} = 6.12$, $SD_{\text{attractiveness}} = 0.67$) or unattractive ($M_{\text{attractiveness}} = 2.69$, $SD_{\text{attractiveness}} = 1.63$) based on whether the average rating given to the target's clear image by all opposite-sex participants was above or below the midpoint of the response scale for the study (i.e., 5; 0 = Very unattractive, 10 = Very attractive).

Uncertainty had no effect on men's perceptions of attractive women, $b = -0.11$, $SE = 0.07$, *ns*.[1] This indicated that men perceived attractive

[1] Because random intercepts for targets had been included to control for between-target differences in attractiveness, but this analysis pertained to only attractive targets, we removed the random intercept term for targets. We did this for all analyses pertaining to only attractive targets or only unattractive targets.

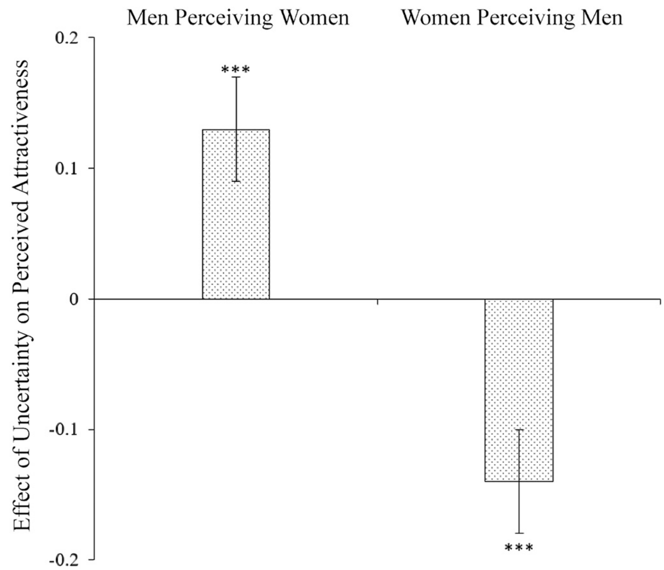

Fig. 4. Sex differences in response to uncertainty. Bars display the mean difference between participants' perceptions of targets' attractiveness under uncertainty versus certainty. Positive values indicate a bias to *over*perceive attractiveness under uncertainty, whereas negative values indicate a bias to *under*estimate attractiveness under uncertainty. Men (left) exhibited a bias to *over*perceive women's attractiveness under uncertainty, whereas women (right) did the opposite: women responded to uncertain information by *under*-estimating men's attractiveness. *Note.* Error bars = ±1*SE*. *** $p < .001$.

women to be attractive, even if they had only incomplete, uncertain information about the women (Fig. 5). Conversely, uncertainty was associated with a positive bias in men's perceptions of unattractive women, $b = 0.33$, $SE = 0.08$, $p < .001$. This indicated that, when men viewed unattractive women but were uncertain about their physical appearance, they exhibited a bias to overperceive their attractiveness (Fig. 5). This finding – that the magnitude of the bias varied as a function of the targets' attractiveness – is less consistent with Algorithm A ("if uncertain, increase the estimate of the target's attractiveness by constant *X*") and more consistent with Algorithm B ("if uncertain, assume the target is attractive"), but future research is needed to tease apart and test the different predictions generated by these and additional candidate algorithms.

9.3.2. *Systematic variation in women's underperception bias*

We conducted parallel analyses on the data from female participants. For women, the algorithm underlying the on-average effect of *under*-perceiving men's attractiveness could be: "if uncertain, decrease the estimate of the target's attractiveness by a constant *X*" (Algorithm C). Alternatively, it could be: "if uncertain, assume the target is unattractive" (Algorithm D). As with men, both heuristics would yield the observed main effect, but they lead to divergent predictions with respect to variation in the attractiveness of the targets. The first algorithm would decrease the attractiveness of *all* targets. The second algorithm, on the other hand, would produce a bias whose magnitude varied with the targets' actual attractiveness. If the observed biases are underlain by an information-processing structure like Algorithm C, then the effect of uncertainty should *not* be moderated by the targets' attractiveness. On the other hand, if Algorithm D better characterizes the relevant information-processing architecture, then target attractiveness should moderate the effect of uncertainty.

These analyses again revealed a significant interaction between the effects of uncertainty and target attractiveness – but in the *opposite* direction to that observed among men: $b = -0.17$, $SE = 0.03$, $p < .001$. This indicated that the effect of uncertainty on women's perceptions of men's attractiveness varied as a function of whether the men were attractive or unattractive. We therefore conducted a subsequent set of analyses in which we tested the effect of uncertainty on women's perceptions of attractive and unattractive men separately. As with the categorization of female targets, we categorized male targets as being attractive ($M_{\text{attractiveness}} = 6.11$, $SD_{\text{attractiveness}} = 0.48$) or unattractive ($M_{\text{attractiveness}} = 2.96$, $SD_{\text{attractiveness}} = 1.04$) based on whether the average rating given to the target's clear image by all opposite-sex participants was above or below the midpoint of the response scale for the study (i.e., 5; 0 = Very unattractive, 10 = Very attractive).

Whereas uncertainty had no effect on men's perceptions of attractive women, uncertainty was associated with a negative bias in women's perceptions of attractive men, $b = -0.67$, $SE = 0.09$, $p < .001$. This indicates that women responded to uncertain information about attractive men by exhibiting a bias to perceive them as less attractive (Fig. 5). On the other hand, uncertainty had no effect on women's perceptions of unattractive men, $b = -0.03$, $SE = 0.05$, $p = .52$. This indicates that

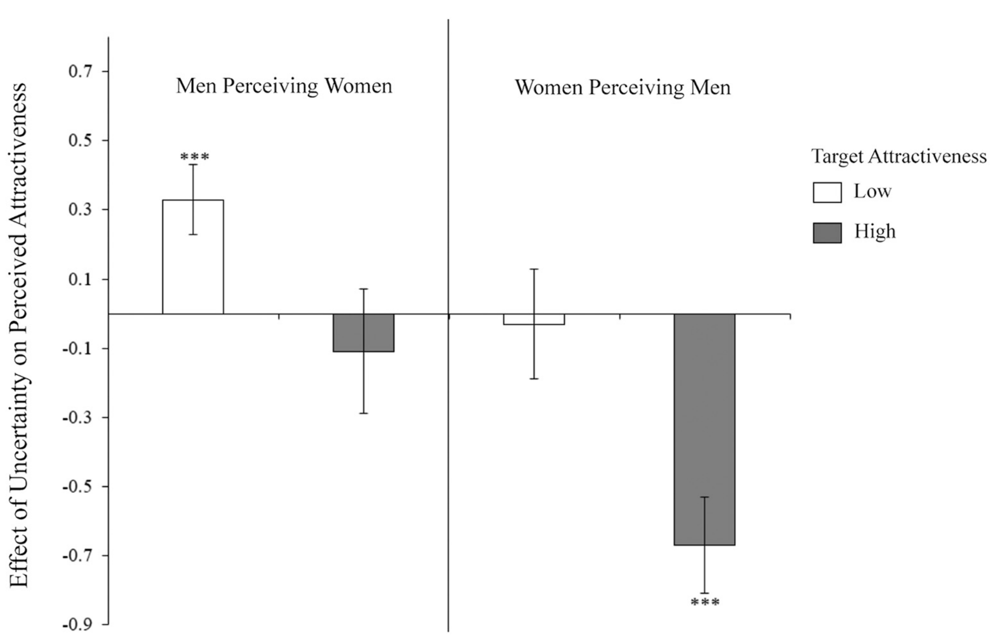

Fig. 5. Investigating the heuristic structure of the inferential biases. Bars display the mean difference between participants' perceptions of targets' attractiveness under uncertainty versus certainty. Positive values indicate a bias to *over*perceive attractiveness under uncertainty, whereas negative values indicate a bias to *under*estimate attractiveness under uncertainty. Men responded to uncertain information about *unattractive* women (left side of left panel) by exhibiting a bias to *over*perceive their attractiveness, whereas there was no effect of uncertainty on men's perceptions of *attractive* women (right side of left panel): men perceived attractive women to be attractive under both certain and uncertain conditions. There was no effect of uncertainty on women's perceptions of *unattractive* men (left side of right panel) – women perceived unattractive men to be unattractive under both certain and uncertain conditions – but women responded to uncertain information about *attractive* men by exhibiting a bias to perceive them as *less* attractive (right side of right panel). *Note.* Error bars = ±1*SE*. *** $p < .001$.

women concluded that unattractive men were unattractive, even if they had only incomplete, uncertain information about the men (Fig. 5). This contrasts with the finding that men overperceived the attractiveness of unattractive women under conditions of uncertainty.

10. Discussion

The current study applied Error Management Theory to a new stage of social perception – initial person perception – to generate hypotheses about two previously unknown cognitive biases. We hypothesized that, on average, men would respond to uncertainty about women's attractiveness by *over*estimating their attractiveness. Second, we hypothesized that women, on average, would respond to uncertainty about men's attractiveness by *under*estimating their attractiveness. Both hypotheses were empirically supported.

We also advanced and tested a new approach for mapping the cognitive architecture responsible for these biases. Previous work on evolved cognitive biases, such as research on men's overperception of women's sexual interest, has heavily emphasized a between-sex difference. This is an important finding, but broad quantitative effects such as these cannot discriminate between multiple candidate decision rules, because multiple different algorithms are capable of producing the same outcome.

In the current paper, we show that identifying the divergent predictions yielded by different candidate algorithms may be useful for charting the cognitive architecture responsible for the bias under investigation. In the current study, we found the predicted on-average sex difference. However, we also probed the observed biases more deeply by testing for specific quantitative effects. These more specific analyses suggested that on-average effects may not reveal the information-processing architecture responsible for the biases. Men, on average, overperceived women's attractiveness, and women, on average, underperceived men's attractiveness. However, further analyses tentatively suggest that men exhibit a bias in the perception of unattractive (but not attractive) women, and women exhibit a bias in the perception of attractive (but not unattractive) men. Had we not directed explicit attention to algorithm, these potential features of the biases might have remained unknown.

This is a first attempt at investigating these biases, and we do not claim to have conclusively revealed their information-processing architecture. Rather, our emphasis here is that work on cognitive biases would benefit by explicitly considering the algorithmic level of analysis. To this end, we have advanced a simple approach and provided an initial demonstration of the value of this approach for discriminating between different candidate algorithms. We hope that research on cognitive biases becomes more explicit about the algorithmic level of analysis, and that the approach we have outlined here might make modest contributions toward mapping the information-processing architecture underlying these biases.

10.1. Sex-differentiated inferential biases or thresholds for activation?

One (ostensible) alternative explanation for the current study's findings is that men might have lower thresholds than women for engaging further with a potential mating opportunity. This threshold hypothesis might also be correct, but is not a *competing* explanation.

The threshold hypothesis generates predictions at a later stage of decision making: the stage of *responding* to a potential mate's perceived attractiveness by motivating (or failing to motivate) further engagement with the potential opportunity, *not* at the stage of *perceiving* attractiveness. In short, the threshold hypothesis does not generate predictions about biases in initial inferences about a potential mate's attractiveness.

Although the current study's findings cannot be readily accounted for by this threshold hypothesis, the threshold hypothesis might simultaneously be true. Sex differences in the relative costs and benefits of forgone mating opportunities and injudicious mating behavior could have selected for *both* (1) sex-differentiated biases at the stage of making inferences about a mate's desirability *and* (2) sex-differentiated thresholds for activation in response to those inferences. These are two distinct and potentially complementary hypothesized design features. Future research is needed to more clearly resolve whether men have different thresholds than women for engaging further with a potential mating opportunity.

10.2. Uncertainty in ancestral conditions

For selection to have favored the inferential biases proposed in the current study, there must have been recurrent scenarios in ancestral mating environments in which a potential mate's physical attractiveness could not have been determined with certainty. Several features of ancestral mating practices and behavior, such as the interaction of exogamy and appearance enhancement behavior, may have prevented perceivers from reliably obtaining *certain*—that is, *complete* and *accurate*—information about a potential mate's physical attractiveness.

Exogamy is the predominant marriage practice among numerous modern populations (e.g., see Marchi et al., 2018) and occurs in over 90% of human groups (Ember, Gonzalez, & McCloskey, 2021). Analyses of ancient DNA from multiple archaeological sites provide evidence of mating patterns predominantly characterized by women reaching reproductive maturity where they were born, but then mating with men from geographically distant groups (Knipper et al., 2017). In short, evidence suggests that ancestral men and women frequently were mated to individuals who were *not* part of their tribe or group (see also Walker, Hill, Flinn, & Ellsworth, 2011). This exogamy-linked reduction in prior interaction could have combined with physical appearance enhancement behavior to constrain individuals' ability to obtain complete and accurate information about potential mates.

Physical appearance enhancement behaviors, which range from cosmetics to clothing to combing hair (see Davis & Arnocky, 2020), are ubiquitous across both time and space: they occur in virtually every known culture (see Davis & Arnocky, 2020) and may date all the way back to the emergence of *Homo sapiens*, or perhaps even earlier (see Tacon, 2006).[2] Although specific appearance-enhancement behaviors may vary across cultures, these behaviors all have the same defining characteristic: they change or conceal the appearance of specific physical features (Lewis & Buss, 2021). In short, physical appearance enhancement behaviors – a human universal whose roots appear to trace back to the emergence of our species – reliably alter one's appearance such that it does *not* provide complete and accurate information about one's true physical phenotype. Indeed, in a sense that is the *purpose* and the point of appearance enhancement behaviors.

This combination of exogamy and physical appearance enhancement behavior may have resulted in ancestral humans frequently *not* having complete and accurate information about the physical phenotype of potential mates. Consequently, in some circumstances they may have had to make inferences about a potential mate's physical phenotype under conditions of uncertainty – in particular in initial stages of person perception.

It is important to note that the male overperception of attractiveness bias (MOAB) hypothesis does not propose that men's initial bias persists after further information acquisition, or that it necessarily forms the basis for men's final decision whether to mate with a woman. Instead, the MOAB hypothesis proposes that selection may have favored a bias in men to overperceive women's attractiveness in initial person perception; if initial perceptions of a mate's desirability are too low, this could

[2] To take just one example, evidence suggests that the application of red ochre, a cosmetic used by ancient Egyptians (see Caton, Lewis, Al-Shawaf, & Evans, 2021) and still used in traditional societies such as the Ovahimba of Namibia (Molefe, 2015), was a cultural practice among both *Homo sapiens* and *Homo neanderthalensis* at least a quarter of a *million* years ago (see Tacon, 2006).

result in disinterest and lack of motivation to gather additional information about them. Future research is needed to more clearly resolve whether men are more likely than women to engage in further information acquisition after being exposed briefly to incomplete information about a potential mate, and whether women more than men experience disinterest following these brief exposures.

10.2.1. An alternative, byproduct hypothesis

Compared to information about attractiveness, reliable information about *other* components of a person's mate value (e.g., intelligence, social status, kindness) may be even more difficult to glean from brief exposures or during early stages of social interaction. Consequently, selection could have shaped inferential procedures to systematically over- or under-infer the levels of these qualities under conditions of uncertainty.

This overarching hypothesis raises an intriguing possibility: the effects observed in the current study may be *byproducts* (see Park, 2007; see also Kurzban, Tooby, & Cosmides, 2001; Al-Shawaf, Lewis, Barbaro, & Wehbe, 2020). To the extent that reliable information about *other* mate value-relevant characteristics may have been difficult to obtain (in particular during initial interactions in the context of exogamy), selection could have shaped psychological mechanisms to make biased inferences about a potential mate's mate value under such conditions of uncertainty. These adaptations may not have evolved to make inferences about a potential mate's physical attractiveness per se. However, in modern dating environments in which unfamiliar individuals frequently interact, there can be a great deal of informational uncertainty surrounding a potential mate's true physical phenotype—whether due to selectively chosen photographs for an online dating profile or dim illumination in a bar or night club. In these modern environments, the activation of mechanisms that evolved to deal with informational uncertainty about a potential mate's mate value – but not *specifically* uncertainty about their physical attractiveness – may result in the biased inferences observed in the current study. In short, the biases observed in the current study may be incidental byproducts of psychological adaptations that evolved to solve a different adaptive problem. We think this byproduct hypothesis is a plausible alternative, and eagerly await future research that pits the adaptation and byproduct hypotheses against each other. More broadly, this highlights the importance and utility of considering both adaptation and byproduct hypotheses in psychological research (Lewis et al., 2017; see also Al-Shawaf et al., 2020).

11. Conclusion

In contrast to the plentiful literature on biases in interpersonal perception that occur *after* two potential mates have interacted, much less EMT-informed work exists on *pre*-interaction biases in initial person perception. The current study addressed the possibility of an EMT bias in first impressions, which, to our knowledge, no work has addressed before. In support of the MOAB hypothesis, we found preliminary evidence of a male tendency to overperceive women's attractiveness, and, in support of the FUAB hypothesis, we observed a female tendency to underperceive men's attractiveness.

We also presented and applied a method for testing different candidate algorithms. These analyses suggested that on-average effects, such as on-average sex differences, may fail to reveal the underlying information-processing architecture. We hope these findings encourage research on other cognitive biases to more explicitly address algorithm, and that the approach we have outlined here might make modest contributions toward the goal of mapping the information-processing architecture underlying these biases.

The findings in the current study provide preliminary evidence of first-impression biases. However, future work is needed to more firmly establish the robustness of these effects and more clearly resolve the information-processing architecture responsible for producing them. We eagerly await future research that discriminatively tests the adaptation and byproduct hypotheses presented here, and that investigates first-impression biases about other components of mate value. More broadly, we hope the current study inspires new EMT research in uncharted domains and promotes greater attention to the algorithmic level of analysis in research on cognitive biases.

Declarations of Competing Interest

None.

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Authors' note

D.M.G.L. generated the hypotheses, designed the study, and wrote the manuscript. A.Y.S. created the study materials and collected, prepared, and analyzed all study data. L.A.S. and K.C.E. contributed to manuscript writing.

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