She wants me, she wants me not: Integration of signal detection theory and error management theory to study sexual communication

by

Jordann Leigh Brandner

B.A., North Dakota State University, 2014
M.S., Kansas State University, 2019

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Psychological Sciences
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Abstract

Decades of previous research has found support for a male sexual overperception effect, where men misperceive a woman's friendliness as sexual interest. This overperception effect is thought to be a leading cause of sexual harassment and assault. However, recent research using Signal Detection Theory failed to find this effect, instead finding that both men and women had high sensitivity when evaluating interest and disinterest. In the present research, videos showing an opposite sex dyad talking were used as stimuli to examine the male sexual overperception effect using Signal Detection Theory. Study 1 (N = 121) attempted to replicate previous research, but failed to replicate sensitivity effects, suggesting that participants were not particularly sensitive or biased in their responses, regardless of sex. Study 2 (N = 124) manipulated the signal-to-noise ratio in an attempt to manipulate bias. Participants who saw more disinterested opposite-sex individuals had a slightly conservative "no"-bias. However, participants who saw more interested opposite-sex individuals did not have a more liberal bias. Study 3 (N = 119) tested competing hypotheses about whether sex ratio manipulations alter bias via signal-to-noise ratio or decision outcomes. Results showed mild support for manipulated sex ratios altering decision outcomes, but only for male participants. Finally, Study 4 (N = 118) tested four interventions that aimed to manipulate bias and/or sensitivity. The pre-/posttest biases and sensitivities were not significantly different depending on the manipulation condition, however results did trend in the hypothesized directions. Across the studies, Mate Value, Short-Term Mating Orientation, Long-Term Mating Orientation, Life History Strategy, and Sexual Aggression showed minimal effects on sensitivity or bias. Additionally, across the studies, the traditional male sexual overperception bias was not found, suggesting that the male sexual overperception effect could be mitigated by recent cultural pressures or previous analytical methods could be flawed.

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Major Professor
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Chapter 1 - Introduction

Communications about sexual interest have always been complicated. Recently, these communications have garnered media attention as they become legal and societal issues. This is of particular importance as misinterpretations of sexual intent are important factors in understanding why sexual assault is committed. There is a need to understand how the men and women communicate about sex in order to make more informed decisions regarding Title IX laws, sexual harassment in the work environment, and the #MeToo movement. A more complete understanding of how individuals communicate about sex is necessary, especially when 25.9% of undergraduate women experience sexual assault (Cantor et al., 2019).

Sexual Overperception Effect

A variety of research has established that men tend to overperceive a woman's friendliness as sexual interest, known as the male sexual overperception effect. In opposite sex conversations, male observers and male conversation partners both overperceived the female conversation partner's sexual interest, indicating that the sexual overperception effect occurs both when perceiving cues directed at the individual or directed at another (Abbey, 1982; Saal et al., 1989; Shotland & Craig, 1988). This effect also persists when positions of power of the people in the conversation are manipulated, such as that of a manager and employee or professor and student (Saal et al., 1989). Additional manipulations on behaviors ranging from non-sexual offers to lend a book to more sexual offers of wine at the person's house also showed a consistent effect of male viewers perceiving women's behaviors are sexier (Johnson et al. 1991). Moreover, in other face-to-face situations, male participants also overperceive the female conversation partner's sexual interest (Henningsen & Henningsen, 2010; Perilloux et al., 2012).

Similarly, male sexual overperception has been observed in situations without any dynamic behaviors, such as through photographs (Abbey & Melby, 1986), descriptions of behaviors (Kowalski, 1993; Haselton & Buss, 2000), vignettes describing a situation (Abbey & Harnish, 1995; DeSouza et al., 1992; Fisher & Walters, 2003; Brandner et al., 2021), and surveys of past behaviors and relationships (Abbey, 1987; Bendixen, 2014; Haselton, 2003; Hiraishi et al., 2016; Koenig et al., 2007). This effect has also been confirmed in a meta-analysis of these studies, showing a consistent, albeit somewhat small, male sexual overperception effect (La France et al., 2009).

However, there is also some evidence for an absence of the male sexual overperception effect. For example, when examining specifically Brazilian participants, men and women did not have a sex difference in perceptions of sexual interest communicated (DeSouza et al., 1992). Additionally, men who are in relationships tend to underperceive their partner's sexual interest, rather than overperceive it (Muise et al., 2016) and women tend to overperceive their partner's interest (Dobson et al., 2018). Samara and colleagues (2021) found that sex did not predict accuracy when perceiving interest, but a sex and own-interest interaction did, such that men who were not attracted to their conversation partner were more accurate in perceiving her interest than women who were unattracted to their partner. Moreover, some research finds that women perceive more sexual interest than men (e.g., Terrett & Anderson, 2021). Finally, some researchers have found mixed results between studies, where one study finds the male sexual overperception effect and another does not (Bendixen et al., 2019).

Individual Differences and Sexual Overperception

Sociosexual Orientation

One possible individual difference that may affect the perception of sexual interest is sociosexual orientation. Sociosexual orientation is a measure of how comfortable an individual is with sex without commitment (Simpson & Gangestad, 1991). Those with more restricted sociosexual orientations are less comfortable with sexual activity without commitment whereas those with more unrestricted sociosexual orientations are more comfortable with sexual activity without commitment. Unrestricted sociosexual orientation is associated with valuing attractiveness highly in potential partners, whereas more restricted sociosexual orientation is associated with valuing personality traits such as loyalty and responsibility and preference for emotional closeness prior to sexual activity (Simpson & Gangestad, 1992; 1991).

Sociosexual orientation derives from Sexual Strategies Theory (Buss & Schmitt, 1993) and parental investment theory (Trivers, 1972). Parental investment theory states that due to the difference between male and female mammals in required biological investment into offspring, men tend to pursue shorter-term relationships and women tend to pursue longer-term relationships. To make up for an energetic deficit created by bearing children, women tend to seek resources from families and mates, making it advantageous to secure longer-term investments through longer-term relationships. Men, who do not have the same required energetic investments, are advantaged by greater number of offspring and providing lower investment for each, and thus shorter-term relationships. However, as pointed out in Sexual Strategies Theory, there are also evolutionary benefits to women in shorter-term relationships and men in longer-term relationships. Women who can secure resources quickly can maximize those resources by seeking short-term relationships, as there are likely to be many men seeking that form of relationship and she can seek higher quality mates. Conversely, if men can identify high quality mates, it can be beneficial to pursue a long-term relationship, as the offspring may be higher quality and more likely to survive. The psychological effect of these different mating strategies is sociosexual orientation (Gangestad & Simpson, 1990). Given the origin of this trait, there are unsurprisingly some sex differences found in sociosexual orientation, such that women are more likely to have more restricted sociosexual orientations (Simpson & Gangestad, 1991; Gangestad & Simpson, 2000), however there is still variability within each sex (Schmitt, 2005). Additionally, short- and long-term orientations appear to be independent and can be altered by proximate influences (Arnocky et al., 2016; Thomas & Stewart-Williams, 2018; Jackson & Kirkpatrick, 2007).

Individuals with more unrestricted sociosexual orientations should prioritize correctly perceiving interest over avoiding overperceiving disinterest since it is more beneficial to them to maximize the number of mating opportunities over the quality of their mate, resulting in a bias to perceive sexual interest. Those with more restricted sociosexual orientations should desire higher quality mates rather than greater numbers of sexual partners. Correctly detecting an interested partner is still important to these individuals (particularly if that mate is of high quality) but avoiding pursuit of an uninterested partner is also quite important, as it can communicate promiscuity and lower their own mate value. This should lead to a more conservative bias than those with unrestricted sociosexual orientations.

Previous research has provided mixed evidence for this, however. Some research has found that those with more unrestricted sociosexual orientations are more likely to perceive a face as more flirtatious than those with more restricted sociosexual orientations (Howell et al., 2012). Additionally, other research finds that sex differences in overperception can be explained through a mediator of sociosexual orientation (Lee et al., 2020). Other research finds that unrestricted sociosexual orientation is associated with finding sexual advances to be less harmful (Klümper & Schwarz, 2020). However, other research provides conflicting results: Perilloux and colleagues (2012) found that men with more unrestricted sociosexual orientations may be more likely to overperceive sexual interest based on one subscale, but not women, and Brandner et al. (2021) found no evidence that those with more unrestricted sociosexual orientations had more liberal biases to perceive sexual interest.

Mate Value

Another potential individual difference that may affect sexual communication is the self-perceived mate value of the observer. Mate value is the overall valuation of a potential partner, including physical, psychological, and personality traits which correspond to mate quality and predicts the quality of mates one can attract (Buss & Barnes, 1986). As such, self-perceived mate value is an individual's perception of their own valuation as a potential partner. Individuals with higher mate values are higher quality partners and thus are more attractive as potential mates whereas those with lower mate values are lower quality partners and thus less attractive as potential mates. Regarding sexual communication, perceivers with higher mate values should experience more communication of sexual interest (as they should commonly attract potential partners), and thus should have a more liberal bias to perceive sexual interest more often due to the high signal/noise ratio they experience. Perceivers with lower mate values should attract fewer interested parties, and thus experience lower signal/noise ratios, resulting in a conservative bias.

However, the majority of research on overperception and mate value focuses on the attractiveness of the target (Hill, 2007; Treat, Hinkel, Smith & Viken, 2016; Treat, Viken, Farris, & Smith, 2016; Yndo & Zawacki, 2020; Lewis et al., 2022). However, some studies have looked at the attractiveness of the perceiver and found mixed evidence for the hypothesized effects. Perilloux and colleagues (2012) found that men's self-ratings of attractiveness were associated with overperception, but women's ratings of the men's attractiveness were not. Additionally, Brandner et al. (2021) also failed to find evidence that self-assessed mate value is predictive of bias. However, other research does, in fact, find that men with higher mate values are more likely to overperceive sexual interest (Kohl & Robertson, 2014).

Life History Strategy

Another individual difference which may affect sexual communication is life history strategy (Figueredo et al., 2006; Del Guidice, 2009). Life history strategy as a trait is a measure of the fundamental tradeoff in energy expenditure in which an individual engages. Those with faster life history strategies tend to live shorter lives, spend more energy in finding high quantities of mates, and have greater numbers of offspring with lower levels of parental investment. However, those with slower life history strategies tend to live longer, spend more energy finding a high-quality mate, and have fewer offspring in which they invest heavily. Slower life history strategies are associated with traits that would benefit parenting and long-term relationships, such as being considerate, kind, hard-working and reliable, whereas faster life history strategies are associated with traits that assist with social situations and mating, such as being charming, socially skilled, talkative, and dominant (Sherman et al., 2013). Additionally, faster life histories are associated with sexual assault and breakups (Gladden et al., 2008; Olderbak & Figueredo, 2010).

Those with faster life history strategies should have a more liberal bias when perceiving sexual intent, as they should prioritize correctly perceiving interest over correctly perceiving disinterest and minimize underperceiving interest overperceiving disinterest as a way to maximize their number of mating opportunities. Those with slower life history strategies could have no bias when perceiving sexual intent as they should value correct perceptions equally (as correctly perceiving disinterest prevents unnecessary energy expenditure) and they should avoid overperception as well as underperception, as pursuing an uninterested person can signal promiscuity. Previous research has found no evidence for an effect of life history strategy on bias, however (Brandner et al., 2021).

Chapter 2 - Theoretical Explanations for Sexual Overperception

Error Management Theory

From a theoretical standpoint, much of the research on sexual overperception has been conducted through the lens of Error Management Theory (EMT; Haselton & Buss, 2000). EMT is a broad theory used to explain many biases (e.g., Haselton & Nettle, 2006; Johnson et al., 2013), which states that decisions repeatedly made under uncertainty lead to evolutionarily biased behavior patterns that reduce costs, maximize benefits, or both, even if it results in more errors overall. In cases of unequal costs, there will be a bias that favors high rates of lower-cost errors and low rates of higher-cost errors. In cases of unequal benefits, the bias will favor greater benefits over lesser benefits. EMT has been used to study a variety of biases, including female commitment skepticism (Haselton & Buss, 2000; Henningsen & Henningsen, 2010; Cyrus et al., 2011; Brown & Olkhov, 2015), perceptions of rival attractiveness (Hill, 2007), perceptions of intrasexual attractiveness under uncertainty (Lewis et al., 2022), forgiveness of sexual infidelity (Bendixen et al., 2018), beliefs in conspiracy theories (van Prooijen & van Vugt, 2018), disgust (Al-Shawaf et al., 2018), and many others (see Haselton & Nettle, 2006 and Johnson et al, 2013 for reframing of cognitive biases using EMT).

In the specific case of sexual overperception, males are less physically obligated to invest in offspring, and thus they tend to be more willing to engage in sexual activity. Meanwhile, females are more selective about potentially costly sexual activity. This differential parental investment (Trivers, 1972) makes it more costly for males to incorrectly perceive female sexual disinterest from an interested female than it is to incorrectly perceive female sexual interest from a disinterested female. Differential parental investment also makes it more beneficial for males to perceive true interest than it is to perceive true disinterest. This results in a strategic, sex differentiated bias that favors perceiving interest to reduce possible costs and maximize possible benefits (Figure 1).

		Male Perception	
		Interest	**Disinterest**
Reality	**Interest**	**Hit/Correct Detection** Highly beneficial to male • Mating opportunity	**Type II Error/Miss** Higher cost to male • Missed mating opportunity
	Disinterest	**Type I Error/False Alarm** Lower cost to male • Wasted energy/rejected courtship	**Correct Rejection** Lower benefit to male • Friendship/no relationship

Figure 1. Decision outcomes and values for EMT and SDT.

EMT has been used to describe sexual overperception and has generated unique hypotheses. Women report being misperceived more frequently than men, and importantly, these results showed overperception happening more often than underperception (Haselton, 2003). Additionally, this has been replicated in numerous cultures, where despite differing levels of gender equality, the same pattern persists (Bendixen, 2014; Hiraishi et al., 2016; Perilloux et al., 2015).

EMT has also generated hypotheses of situations where male overperception *should not* occur, such as men's judgements about their sisters' sexual interest in another man (Haselton & Buss, 2000). Other EMT applications have hypothesized situations where female overperception *should* occur, specifically, when judging a woman's interest in their sons, which has not yet been tested (Al Shawaf, 2016). In these instances, due to kin relationships, it is expected that the bias should be altered in an effort to improve genetic fitness, despite typical sex-differences in behaviors.

Finally, non-evolutionary research is also consistent with the EMT explanation of sexual overperception. Individuals report higher levels of regret for missed relationship opportunities than for being rejected in hypothetical scenarios, and they believed missed relationship opportunities were more impactful on their lives (Joel et al., 2017). Relatedly, men were more likely to post "missed connections" ads on websites such as Craigslist than women, confirming an EMT-predicted sex difference in regret for missed relationship opportunities (Webster et al., 2020).

Signal Detection Theory

Signal Detection Theory (SDT; Green & Swets, 1966; Macmillan & Creelman, 2005) is a theory to explain how humans make categorical decisions about the presence or absence of a signal when confronted with ambiguous stimuli which includes both the signal and noise. In SDT, there are four outcomes for the observer: 1) a hit (or correct detection) is when the observer judges the signal to be present when it is present; 2) a miss is when the observer judges the signal to be absent when it is present; 3) a false alarm is when the observer judges the signal to be present when it is absent; and 4) a correct rejection is when the observer judges the signal to be absent when it is absent.

Previous researchers have stated that EMT is an applied instance of SDT, using evolutionary theory to drive cost/benefit analyses (Nettle, 2012; p. 70-73). However, SDT goes further than EMT by identifying more of the factors that go into deciding if a stimulus is a signal, including 1) the perceived similarity of stimuli, 2) the value of decision outcomes, and 3) the base rate of signals compared to noise. Finally, SDT can provide standardized measures, avoids problematic difference scores (Cronbach & Furby, 1970; Griffin et al., 1999), and allows for precise examination of individual differences through analysis of repeated measures data. Additionally, other research on romantic relationships have used quasi-Signal Detection methods to research topics such as rejection from a romantic partner (Dobson et al., 2022).

Perceived Similarity of Stimuli

The more similar the stimuli are perceived to be, the more ambiguity is introduced when the observer classifies the incoming information. SDT includes a measure of sensitivity (*d'*) which is how distinct signals and noise are from one another to the individual. Low sensitivity means that the signals and noise are similar and therefore more difficult to classify correctly (Figure 2a); high sensitivity means that the signals and noise are very distinct and therefore easy to classify correctly (Figure 2b). Differences in sensitivity can be reflective of the individual's unique ability to distinguish signals and noise, but also can reflect the relative difference between different signals and noise.

Sensitivity is measured through *d'*, a standardized measure that allows comparison of sensitivity across different studies, researchers, methods, and topics. A *d'* of 0 indicates chance responding and positive values indicate better ability to distinguish between signals and noise. Negative *d'* values are possible but would indicate that the participants are responding opposite to reality – in other words, classifying signals as noise and noise as signals (Stanislaw &

Todorov, 1999).

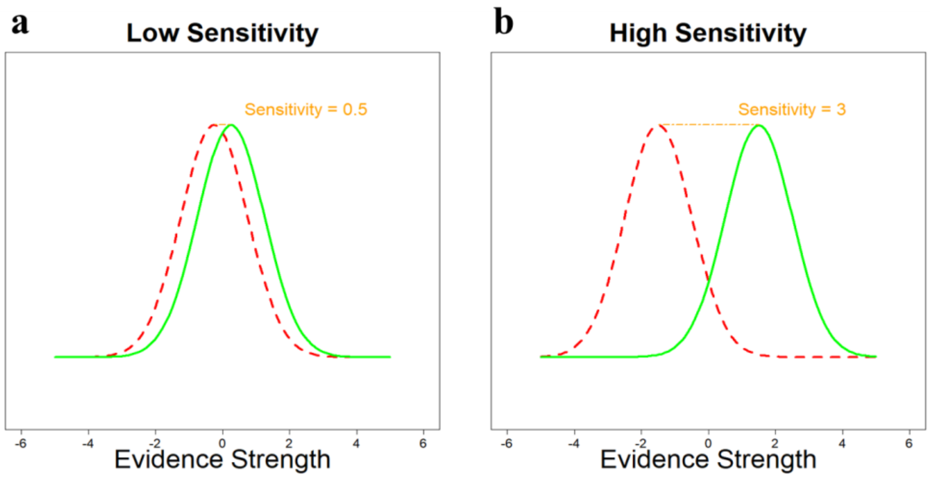

Figure 2. Visualization of low and high sensitivities from Brandner (2019). Sensitivity is indicated by the distance between the dashed red noise distribution and the solid green signal distribution.

Value of Decision Outcomes

Similarly to EMT, each decision outcome is associated with costs and benefits to the observer. Because of this, the value of the decision outcomes using SDT predicts sexual overperception for the same reasons as EMT (Figure 1). SDT also includes a measure of bias, quantified by the decision criterion (*c*) which is how much evidence is required for the observer to switch from responding that the signal is absent to responding that the signal is present (Figure 3). Conservative biases, or having a tendency to respond that there is not a signal present, are represented by positive *c* values; liberal biases (tendency to respond that there is a signal present) are represented by negative *c* values. The absolute distance from 0 represents the strength of the conservative or liberal bias, such that *c* values closer to 0 represent weaker biases (Lynn & Barrett, 2014).

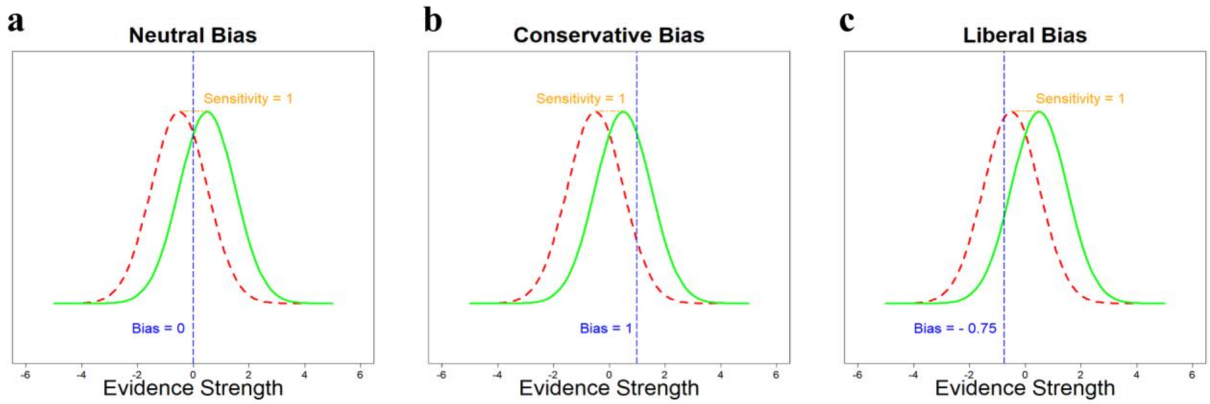

Figure 3. Visualization of neutral, conservative, and liberal biases from Brandner (2019). Blue vertical lines indicated the decision criterion for each panel. The dashed red curve represents the noise distribution, and the solid green curve represents the signal distribution.

Sex Ratios

However, unlike EMT, SDT also can incorporate more proximate causes of biases, rather than focusing solely on ultimate evolutionary causes. One possible environmental factor that could affect decision outcomes are sex ratios. The sex ratio of an environment is the relative ratio of men to women. Different forms of sex ratio exist, including overall sex ratio (i.e., all males to all females), adult sex ratio (i.e., all adult males to all adult females), and operational sex ratio (i.e., all available adult males of reproductive ability to all available adult females of reproductive ability; Hamilton, 1967; Marlowe & Beresque, 2012; Székely et al., 2014). While human sex ratios tend to normalize close to 50/50 ratios, biased ratios can and do occur (Schmitt, 2005; Del Guidice, 2012) due to environmental or cultural influences that affect one sex more strongly, such as wars or China's one-child policy. Moreover, there is evidence that sex ratios are perceived relatively automatically and accurately (Brandner et al., 2020), suggesting that sex ratios can alter behaviors either consciously or subconsciously.

In unequal sex ratio conditions, members of the scarcer sex have more opportunities and less competition, which results in more choosiness. In contrast, members of the more populous sex have fewer opportunities and more competition, resulting in increased mate attraction and retention behaviors (Hahn et al., 2014; Kvarnemo & Ahnesjo, 1996; Moss & Maner, 2016; Uecker & Regnerus, 2010; see Dillon et al., 2015 for a review). When males are the more populous sex, men have increased spending habits, discount future events more, and make more of an effort to gain resources and status (Griskevicius et al., 2012; Chang & Zhang, 2012; Schacht et al., 2016; Wei & Zhang, 2011; Xing et al., 2016; Kirsner et al., 2003; Buss, 1989). Individuals also exhibit relationship behaviors that align with female mating preferences such as higher levels of monogamy, prolonged courtship, and emotional investment (Hassinger & Kruger, 2013; Kruger & Vanas, 2012; Schmitt, 2005; Pedersen, 1991). Moreover, women in male-heavy sex ratios have stronger preference for higher socioeconomic status and more symmetrical faces in potential mates (Pollet & Nettle, 2008; Watkins et al., 2012).

When females are the more populous sex, women have a larger number of sexual partners (Hassinger & Kruger, 2013) and exhibit relationship behaviors that align with male mating preferences, such as lower emotional investment and common short-term relationships (Simpson & Gangestad, 1991). Additionally, single-mother households are more common, and women tend to be pursue careers rather than childbearing (Kruger & Schelmmer, 2009; Durante et al., 2012).

A member of the more populous sex should place even more importance on hits rather than correct rejections and should more strongly avoid misses rather than false alarms due to scarcity of potential partners which generates harsher consequences. Meanwhile, a member of the scarcer sex should be less affected by the decision outcomes than the more populous sex due to an abundance of potential partners, resulting in less severe consequences. This should result in the more populous sex having a more liberal bias and the scarcer sex having a more conservative bias, even if that conflicts with the evolutionary causes for sex differences.

Base Rate of Signals Compared to Noise

Another factor that enables the actor to decide if a stimulus is a signal or a noise is the frequency with which signals and noise occur in the environment (Green & Swets, 1966; Lynn & Barrett, 2014). If true signals are common whereas non-signals are rare, the high signal base rate will encourage signal-present judgments in ambiguous situations (a liberal bias). Conversely, a low signal base rate will encourage no-signal judgments in ambiguous situations (a conservative bias).

In regard to sexual overperception, these rates could be altered experimentally through either manipulation of sex ratios or manipulations of stimuli. A member of the more populous sex should encounter fewer signals overall due to fewer signalers (i.e., potential partners) present in the environment and due to the increased choosiness of the scarcer sex, resulting in the more populous sex having a more conservative bias. A member of the scarcer sex should encounter more signals overall due to more signalers present and due to decreased choosiness of the more populous sex, resulting in the scarcer sex having a more liberal bias than the more populous sex. Alternatively, the rates of signal-to-noise could be directly manipulated through adjusting the rates of true signals shown to participants. As pointed out by McKay and Efferson (2010), it is unlikely that in a true scenario that the rates of signals and noise would be equal. This should lead to Bayesian updating of priors, which should then result in biases based on the unequal signal-to-noise ratio.

Optimality

While sensitivity and bias are independent measurements, these concepts interact to affect individuals' decisions, known as optimality (Lynn & Barrett, 2014). Optimality refers to the balance of sensitivity and bias required to fit the environment best, by maximizing bias, maximizing sensitivity, or balancing both. Low levels of sensitivity can be compensated for by higher levels of bias (either conservative or liberal biases, whichever best fits the cost/benefit analysis). Additionally, little to no bias can be compensated for by increasing sensitivity, so that errors are reduced to minimal levels. Finally, sensitivity and bias can be balanced, if a maximization of one of these factors is detrimental or difficult.

In regard to evolutionary fitness and male sexual overperception, maximization of sensitivity would evolutionarily be difficult to achieve, as sexual communication from women may have evolved to be purposefully ambiguous to conceal sexual interest to allow evaluation of potential partners (e.g., parental investment theory; Trivers, 1972). While EMT hypothesizes that optimality is reached through only a maximization of bias (due to the consideration of only bias in this theory), previous research has suggested that sensitivity is playing more of a role than bias in predicting individuals' assessments. Even when ambiguity is increased, sensitivity still appears to drive responses (Brandner et al., 2021). This indicates that evolutionary optimality in sexual perception could be reached by consistent accuracy along with any level of bias (including none at all).

Synthesis of Error Management Theory and Signal Detection Theory

Brandner et al. (2021) built upon the similarity between EMT and SDT to compare these two theories. Vignettes of behaviors were used to explore male sexual overperception using both

EMT and SDT analyses. SDT analyses revealed that high sensitivity drove participants' perceptions more than bias did (and with no difference in sensitivity between the sexes; Figure 4). In fact, overall interest was *under*perceived compared to sex-specific pre-ratings of the vignettes, and women perceived slightly more interest than men (although a non-significant difference). Moreover, SDT analyses showed no effect of life history strategy, sociosexual orientation, or mate value on sensitivity or bias. However, the EMT analyses contradicted these results, finding overall underperception, but with mixed evidence for sex differences between the two studies. Further exploration of the results revealed that this was due to EMT's use of difference scores, which could not account for the initial difference in communication of intent for male vs female vignettes. Even when the vignettes were chosen to communicate similar levels of sexual interest between the sexes, the EMT analysis relied on difference scores, which resulted in negative misperception scores as vignettes were underperceived. This led to the conclusion that men were overperceiving compared to women, despite showing more accurate perceptions than women.

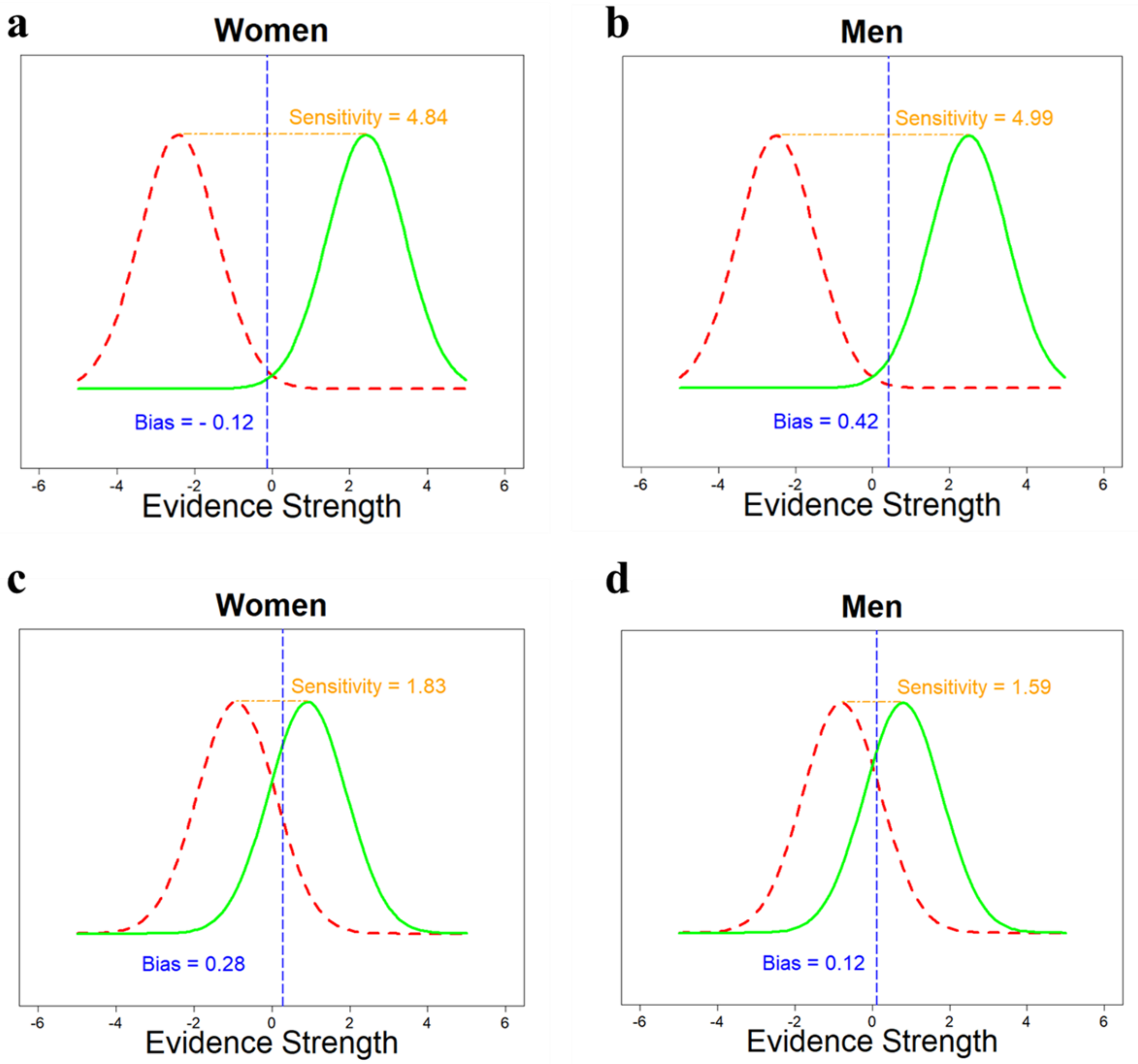

Figure 4. Visualization of SDT results from Brandner et al. (2021). Panel a shows women's results and panel b shows men's results from Study 1. Panel c shows women's results and panel d shows men's results from Study 2 using ambivalent vignettes. The dashed red curve represents the noise distribution, and the solid green curve represents the signal distribution.

However, there are some methodological limitations with these studies. Previous research has shown that the method in which stimuli are presented (e.g., video, audio, photograph, etc.) affects overperception, such that modes with less information result in more overperception (Edmondson & Conger, 1995; Tomich & Schuster, 1996). Additionally, in order to complete SDT analyses, a "true" answer of whether or not a vignette communicated sexual intent was necessary, resulting in extremely ambiguous vignettes being removed from the stimuli (Brandner et al., 2021). While Study 2 reintroduced some ambiguity back into the stimuli, EMT specifically hypothesizes the bias to be from decisions made under uncertainty, and thus this necessary reduction of ambiguity could be the reason EMT performed less well than SDT.

Additional research that is SDT-inspired also has methodological limitations. For instance, Farris and colleagues (2008) used a model that separated sensitivity and bias to find that men did not have a liberal “yes”-bias, and instead, men had less sensitivity than women, resulting in less accuracy. However, this research did not use true signal detection methods; instead, participants were asked to classify photos of women as portraying one of four emotions: friendly, sexually interested, sad, or rejecting. This limited the SDT analyses possible, as positive-affect and negative-affect judgements were used rather than interest/disinterest. It is possible that accuracy and bias were influenced by judgments of friendliness or sadness, and moreover, the central thesis of the sexual overperception effect is that friendliness is mistaken for sexual interest. By including both friendliness and sexual interest in the same category, it becomes difficult to assess if there is an overperception effect. That said, this research does have merit, as it separates bias from sensitivity and attempts to de-confound these variables.

Chapter 3 - Sexual Overperception and Nonconsensual Sexual Behavior

Prevalence of Nonconsensual Sexual Behavior

Sexual harassment and assault are pervasive issues in the United States. Roughly 65% of U.S. women report experiencing street harassment (Kearl, 2014). When asked about workplace sexual harassment, ~22-25% of U.S. women report experiencing sexual harassment and ~40% report experiencing gender-based discrimination (Parker & Funk, 2017; Feldblum & Lipnic, 2016). An estimated ~20-25% of U.S. women are sexually assaulted during their undergraduate education (Muehlenhard et al., 2017; Cantor et al., 2019). A 2018 study found that 81% of U.S. women reported sexual harassment across a variety of verbal, physical, or cyber situations and 27% of women reported experiencing sexual assault (Raj et al., 2019).

Men also experience sexual harassment and assault, but at greatly reduced numbers compared to women. Roughly 25% of U.S. men reported experiencing street harassment (Kearl, 2014), ~7% reported workplace sexual harassment (Parker & Funk, 2017), and ~9% reported experiencing online sexual harassment (Duggan, 2017). Across all situations, ~43% of U.S. men reported sexual harassment and ~6% reported sexual assault (Raj et al., 2019). Approximately 6% of U.S. men have experienced rape or attempted rape or have been forced to penetrate someone (Smith et al., 2017). One possible cause of this sex difference is that different behaviors are considered harmful and negative based on sex. For example, in a study of sexual advances from a coworker, Klümper and Schwarz (2020) found that sexual advances were perceived less negatively by men, in particular when the advances were made by a physically attractive woman. Additionally, in workplace sexual harassment scenarios, women were more likely than men to perceive a woman as a harasser, although men and women were equally likely to perceive harassment from a man (Hehman et al., 2022).

There is also a sex difference in the perpetration of sexual harassment and assault, where males are more likely to perpetrate sexual harassment and assault, to both male and female targets (Espelage et al., 2016; Berkowitz, 1992). While only ~5% of men self-report perpetrating rape (e.g., Kolivas & Gross, 2007; Spitzberg, 1999), ~32% of college men reported being willing to engage in forced intercourse if they would not be caught (Edwards et al., 2014). Moreover, there is evidence that men underreport sexually aggressive behavior. Strang and Peterson (2016) found using a Bogus Pipeline technique that ~38-53% of men who believed they would be caught lying admitted that they had previously used either force or drugs and alcohol to intoxicate a woman to have sexual intercourse with her. Additionally, between ~41-67% admitted to verbally coercing women to have sexual intercourse.

Overperception and Nonconsensual Sexual Behavior

It has been suggested that sexual overperception may influence the perpetration of sexual harassment and assault (Stockdale, 1993; Abbey et al., 1998). Research using vignettes found that overperceiving interest was associated with willingness to force a woman into having sexual intercourse (Willan & Pollard, 2003). Similar research using video stimuli found that overperception of interest was correlated with tolerance for sexual harassment (Mazer & Percival, 1989). Additional research using vignettes shows that more attractive targets are more often overperceived and an increase in overperception is associated with decreases in identifying rape as sexual assault (Yndo & Zawaki, 2020).

Outside of lab conditions, frequency of past misperceptions is correlated with frequency of sexual aggression (Abbey & McAuslan, 2004; Abbey et al., 1998). Abbey and colleagues (2011) confirmed that previous experiences overperceiving a woman's sexual interest were associated with rape-supportive attitudes and self-reported sexual aggression in men. Additionally, men who have perpetrated sexual aggression on dates (including those that involved forced sexual intercourse) were more likely to report misperceiving the woman's sexual interest compared to those who have not perpetrated sexual aggression on dates (Abbey et al., 2001).

The mechanism for this relationship has been suggested to be high-risk men's inattention to relevant cues and attention to irrelevant cues (Treat et al., 2016; Farris et al., 2006; Farris et al., 2010; Treat et al., 2001; Treat et al., 2011). The irrelevant cues could include anything from clothing choices (Farris et al., 2006; Farris et al., 2010) to the physical attractiveness of the target individual (Treat et al., 2015) instead of more relevant emotional cues.

Reduction of Nonconsensual Sexual Behavior Resulting from Overperception

Previous research has used an approach informed by Signal Detection Theory to try to reduce reliance on irrelevant cues. In this research (Treat et al., 2015), participants viewed photos of women and determined their sexual interest. Half of the participants received feedback that was based on the sexual interest perceived by the authors when viewing the photos. They found that those who received this "expert" feedback used sexual interest cues more often than irrelevant judgments.

However, the use of these "expert judgments" of interest is flawed, despite high interrater reliability. Given that the authors themselves can carry bias, it is not clear how accurate feedback (i.e., that which is based in real ratings of target sexual interest) will affect perceptions of sexual interest. Additionally, these photos were highly staged images – the individuals pictured were told to act as if they were sexually interested or rejecting with no one to perceive the cues other than a photographer who guided them into stronger affective poses, resulting in a caricature of interest or disinterest. Finally, this research changed reliance on different cues, but did not measure how reliance on those cues influenced accuracy in perceptions – it is unclear from this research if expert feedback increased the likelihood of a correct detection of sexual interest/disinterest. That said, this type of research is particularly important, as efforts to reduce sexual assault have been met with resistance when using traditional power-dynamic interventions, which may do more harm than good for those at risk of perpetrating sexual assault (Malamuth et al., 2018).

Chapter 4 - Research Objectives

The purpose of the following studies is to synthesize SDT and EMT approaches to better understand sexual overperception, this time using more realistic stimuli: videos of opposite sex conversations to provide real cues of sexual interest or disinterest rather than depictions. Study 1 attempted to replicate the results of Brandner et al. (2021) using different stimuli and establish a baseline of comparison for experimental manipulations. Study 2 examined the effects of skewed signal-to-noise ratios on sexual overperception. Study 3 examined the effects of skewed sex ratios on sexual overperception. Finally, Study 4 determined if sensitivity and bias regarding sexual interest can be changed through specific interventions.

Goals of the Current Studies

- Provide a comparison and synthesis of EMT practices and SDT practices.
- Use realistic video stimuli to study Sexual Overperception.
- Calculate sensitivities and biases for men and women to provide a richer comparison of sex differences.
- Evaluate the effects of sex ratios in perceiving sexual interest.
- Evaluate the effects of signal-to-noise ratios in perceiving sexual interest.
- Determine if sensitivity and bias to sexual interest can be trained via intervention.

Chapter 5 - Stimuli and Stimuli Creation

Stimuli

Videos of a man and woman conversing were collected between 2016-2020. The individuals were seated across from each other at a table and given a list of conversation topics (Figure 5). Each video was 15 minutes long but has subsequently been turned into 30s clips (taken at the 5-minute mark into their conversation). Literature on thin slices suggests this should be sufficient to judge expressive behaviors (Ambady & Rosenthal, 1992). Each clip is muted to ensure that topic of conversation does not affect perceptions of sexual interest. After their conversation, each participant answered questions about their conversation partner and themselves, including binary (yes/no to the question "Are you sexually attracted to your conversation partner" and scale (1 corresponding to "Not at all" sexually attracted to their partner and 7 corresponding to "Extremely" sexually attracted to their partner) sexual interest in their conversation partner. Binary self-reported interest is used to determine whether an individual is interested in their partner. An example video can be viewed at https://bit.ly/3cG8DLy.

Figure 5. Example video screenshot.

Participants

Participants (*N* = 260) were recruited from a large Midwestern university between 2016-2020 and paid $10 for their participation. Because the goal of the study was to collect videos of opposite-sex dyads conversing, if a participant was a no-show, the other participant was dismissed for the day and invited to sign up again to participate. There were equal numbers of male and female participants (*n* = 130 respectively), and participants were pre-screened to be heterosexually attracted (i.e., heterosexual, bisexual/pansexual).

Videos featuring non-heterosexual individuals (*n* = 4) were removed, as were videos featuring underage participants (*n* = 1) and videos where participants did not answer sexual orientation or attraction items (*n* = 6) resulting in 120 total videos featuring 240 total participants. The final sample participants were primarily White, non-Hispanic (*n* = 156), followed by Hispanic (*n* = 21), African American (*n* = 8), Asian-American (*n* = 4), American

Indian or Alaska Native (n = 1), or identified as another ethnicity (n = 15).

Initially, participants were only recruited if they were single, however, after checking the ratio of participants who were sexually interested in their partner to those not sexually interested in their partner, participation was opened to pre-established friendships and relationships to increase the number of videos where at least one person was sexually interested in their conversation partner. Therefore, participants were primarily single (n = 148), followed by those in an exclusive relationship (n = 63), in a casual/non-committed relationship (n =22), engaged/married (n = 3), and divorced/separated (n = 2).

Video Collection Procedure and Measures

After indicating informed consent and signing a video release form, participants were instructed to talk with their partner for 15 minutes while being video recorded. Directions stated:

"The first task I'll have you do is talk with your partner. I will give you a topic list, but please feel free to talk naturally with your partner, including about topics not on the list. This is the portion of the study which will be recorded, but please ignore the camera and interact naturally with your partner and get to know them. You will have 15 minutes to talk with your partner before the next portion of the study. Do you have any questions?"

After the 15 minutes were up, participants were taken to another room and seated apart from each other in locations where they could not see another's screen to take a series of questionnaires through Qualtrics.

First, participants were asked questions about their conversation, including whether they knew their conversation partner and how, and binary and scale measures of whether they were sexually attracted to their conversation partner. The binary measure asked, "Are you sexually attracted to your conversation partner?" with response options of yes and no. The scale measure asked, “How sexually attracted are you to your conversation partner?” on a scale of 1 (Not sexually attracted at all) to 7 (Extremely sexually attracted). Additionally, participants were asked binary and scale measures of whether their conversation partner was attracted to them. The binary measure asked, “Is your conversation partner sexually attracted to you?” with response options of yes and no. The scale measure asked, “How sexually attracted is your conversation partner to you?” on a scale of 1 (Not sexually attracted at all) to 7 (Extremely sexual attracted). Before answering the sexual attraction questions, participants were reminded that their answers are private and would not be shared with their conversation partner.

Following the conversation questions, participants took a variety of personality and individual differences measures in random order, including measures of basic demographics questions (e.g. age, sex, sexual orientation, relationship status, etc.); mate value (Self-Perceived Mate Value Inventory; Fisher et al., 2008 and the Mate Value Scale; Edlund & Sagarin, 2014); sociosexual orientation (Revised Sociosexual Orientation Inventory; SOI-R; Penke & Asendorpf, 2008); HEXACO personality traits (HEXACO-60; Ashton & Lee, 2009); dark triad traits (Dirty Dozen; Jonason & Webster, 2010); sexual narcissism (Hurlbert Index of Sexual Narcissism; HISN; Hurlbert et al., 1994); life history strategy (K-SF-42; Figueredo et al., 2017); ambivalent sexism (Ambivalent Sexism Inventory; Glick & Fiske, 1996); sex roles (Bem Sex Roles Inventory; Bem, 1974); and social dominance (Social Dominance Orientation; Pratto et al., 1994). These personality and individual differences measures were included for future studies using these stimuli, however, as they will not be used for these studies, information about each scale is not included here.

Finally, participants answered questions regarding if they had ever participated in a study like this and received debriefing information.

Video Stimuli Editing and Classification

Following collection, videos were edited into 30s clips taken at the 5-minute mark into the conversation. Clips were muted to ensure that the topic of conversation does not affect perceptions of sexual interest. Each clip was classified into whether it shows male sexual interest/disinterest and female sexual interest/disinterest based on the binary sexual attraction questions answered by each participant in the videos (Table 1).

Table 1. Number of videos broken down by target gender and sexual interest in their conversation partner.

Gender	Interest	Disinterest
Male	47	70
Female	35	82
Overall	*82*	*152*

Chapter 6 - Present Studies

Study 1 – Extend Brandner et al. (2021) and Establish a Baseline

Study 1 aimed to alleviate some of the methodological concerns associated with written vignettes by using video stimuli, specifically by providing true answers of whether an individual is interested in their conversation partner. This reintroduced ambiguity to the stimuli, which had been removed to produce a categorical yes/no interest variable in the vignettes, while still providing binary categorizations of whether an individual is sexually interested. Additionally, to determine if sensitivity and bias are associated with sexual aggression, a sexual aggression scale was included.

Participants

Study 1 recruited 251 participants from Amazon Mechanical Turk through Cloud Research (Litman et al., 2017). Of these, 108 participants' work was rejected for failure of one or more attention checks, resulting in 143 participants who were paid $0.50 for successfully completing the study. Sample size was informed by general statistical guidelines due to little precedent for a study of this nature; 150 participants was chosen as the goal number of participants because the effect was predicted to be smaller than Study 1 from Brandner et al. (2021). Data collection stopped when close to this goal. Participation was limited to those located in the United Stated with at least 100 completed HITs and a 95% past approval rating. Participants were excluded from participating if they did not pass a captcha or an English competency test that requires a minimum of university level English understanding.

Participants' data were excluded from analysis if they did not accept payment for their participation (*n* = 2), if their gender and sexual orientation did not match the gender in which they were sexually interested (e.g., a heterosexual man identifying as being sexually interested in men; *n* = 16), if they identified as transgender or intersex (*n* = 3), or if they indicated in the open-ended comments item that they had technical issues that prevented accurate participation (*n* = 1). This resulted in 121 total participants with an average age of 44 (*SD* = 15). Most participants were women (n_{woman} = 83; n_{man} = 38), which is not abnormal for research on relationships. Most participants were straight (*n* = 102), followed by bisexual/pansexual (*n* = 14), gay or lesbian (*n* = 3), and asexual (*n* = 2).

Measures and Procedure

After indicating informed consent and passing a captcha and English proficiency question, participants were instructed:

"You will now see a series of 30-second videos of two people talking. Please watch each video and answer the questions following each video. Please note that these videos intentionally do not have sound. You will not be able to move to the next page until the video has finished."

Then, participants were presented with a random selection of 40 clips (described above) chosen from a pool with 50% female-interested clips and 50% female-disinterested clips. After viewing each clip, participants were asked binary and scale measures of the female conversation partner's sexual interest in the male conversation partner. The binary measure asked, *"Is the woman in this clip sexually attracted to in the man in this clip?"* with response options of yes and no. The scale measure asked, *"How sexually attracted is this woman to this man?"* on a scale of 1 (Not sexually attracted at all) to 7 (Extremely sexual attracted). For concealment of the study design and purpose, the same questions were asked about the male conversant, although these items were not analyzed (although they may be used for future exploratory research).

Following this, participants answered the individual differences measures. The Self-Rated Mate Value Scale (Edlund & Sagarin, 2014) was used to measure mate value. This short scale has 4 items measuring self-reported desirability as a partner. Higher values on this scale indicate higher mate values. Items are measured on a 1 to 7 scale, with endpoints corresponding to each item. Example items and end points include *"Overall, how would you rate your level of desirability as a partner on the following scale"* with endpoints of 1 (Extremely undesirable) to 7 (Extremely desirable). Cronbach's alpha for this scale was 0.90, indicating very good reliability. Participants had an average score of 4.60 (*SD* = 1.27).

The Multidimensional Model of Sociosexual Orientation Inventory (Jackson & Kirkpatrick, 2007) was used to measure mating strategy. This scale has three subscales: long-term mating orientation (LTMO), short-term mating orientation (STMO), and a behavioral measure. The behavioral measure was collected but was not used in analyses. The LTMO subscale includes 7 items measured on a scale of 1 (Strongly disagree) to 7 (Strongly agree) with items such as *"I hope to have a romantic relationship that lasts the rest of my life."* Higher values on this scale indicate a more long-term mating orientation. Participants had an average score of 5.91 (*SD* = 1.45).The STMO subscale includes 10 items, measured on the same scale, with items such as "I could enjoy sex with someone I find highly desirable even if that person does not have long-term potential." Higher values on this scale indicate a more short-term mating orientation. Participants had an average score of 3.36 (*SD* = 1.88).Reliability of these scales were very good (Cronbach's alphas of 0.96 for both LTMO and STMO).

The K-SF-42 (Figueredo et al., 2017) was used to measure life history strategy. The K-

SF-42 is a shorter version of the Arizona Life History Battery (ALHB; Figueredo et al., 2007) which retains the original subscales from the long form of this measure (i.e., Insight, Planning, & Control; Parental Relationship Quality; Family Contact & Support; Friends Contact & Support; Romantic Partner Attachment; General Altruism; and Religiosity). Each subscale uses an average of the z-scores for each scale, and the average of theses averages is used to estimate K-value. Lower values on this scale indicate faster life history strategies. Participants had an average score of 0 (*SD* = 0.57; indicating near average responses due to z-transformation).Cronbach's alphas for each subscale ranged between 0.73 and 0.96, indicating very good reliability for analyses.

A portion of the Attraction to Sexual Aggression Scale (as used in Edwards et al., 2014; adapted from Malamuth, 1989a, b) was included to measure sexual aggression. The portion of this scale that was used asks how likely the individual would be on a scale of 1(Not at all likely) to 5 (Very likely) to engage in a variety sexual acts if no one would know and no punishment would happen. The sexual acts asked about in this study were *heterosexual intercourse*, *forcing a person to do something sexual that they didn't want to do*, and *rape*, but the heterosexual intercourse item was only included as a decoy item, not for analysis. Cronbach's alpha for this scale was 0.97, indicating very good reliability for analysis. Participants had an average score of 1.12 (*SD* = 0.63).

These individual differences measures were presented in the same order for each participant. First, participants saw the Mate Value scale, then the Sociosexual Orientation scale, then the K-SF-42, then the Sexual Aggression scale. Finally, participants answered demographics questions (e.g., age, sex, gender, sexual orientation) and attention check questions, then were presented with debriefing information.

Hypotheses

It was predicted that results from Brandner et al. (2021) would be replicated:

a) EMT analyses would show traditional sex differences with men perceiving more sexual interest than women (Figure 6).

b) SDT analyses would show an overall conservative (rather than liberal) bias (Figure 6).

c) There would be no effects of Sociosexual Orientation, Mate Value, or Life History on bias or sensitivity (Figure 7a-d).

d) Sexual aggression would be associated with a more liberal bias; it is unclear how sexual aggression will affect sensitivity (Figure 7e).

e) Sensitivity overall would be high (Figure 6).

f) Sensitivity would show a greater role than bias (Figure 6).

However, since the reintroduction of ambiguity in vignettes reduced the effect of sensitivity in Brandner et al. (2021), additional ambiguity introduced through the use of video stimuli could result in sensitivity and bias playing similar roles in predicting participants' perceptions.

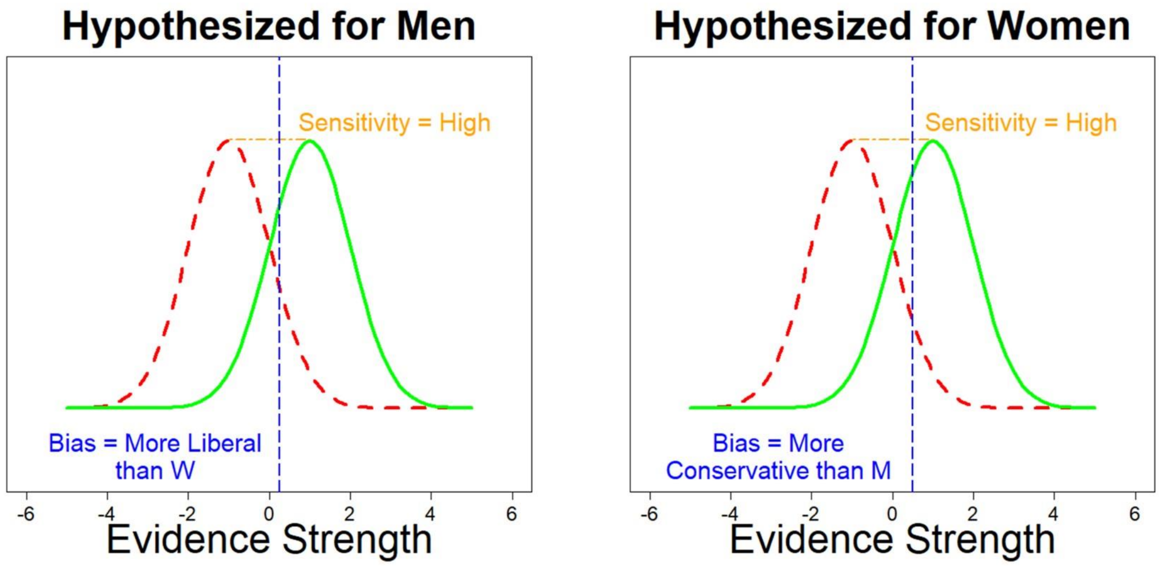

Figure 6. Hypothesized Study 1 bias (*c*) and sensitivity (*d′*) for both men and women.

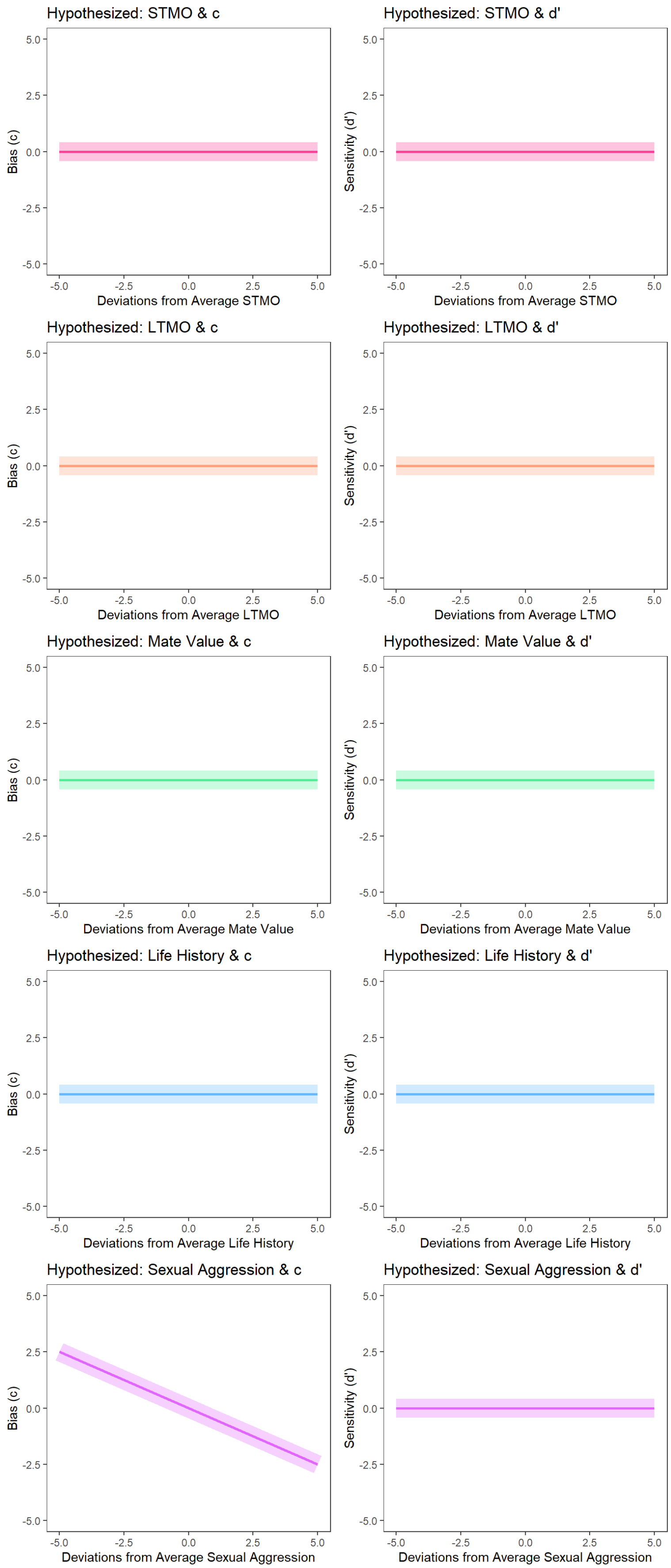
Hypothesized: STMO & c
Hypothesized: STMO & d'
Hypothesized: LTMO & c
Hypothesized: LTMO & d'
Hypothesized: Mate Value & c
Hypothesized: Mate Value & d'
Hypothesized: Life History & c
Hypothesized: Life History & d'
Hypothesized: Sexual Aggression & c
Hypothesized: Sexual Aggression & d'
Bias (c)
Sensitivity (d')
5.0
2.5
0.0
-2.5
-5.0
Deviations from Average STMO
Deviations from Average LTMO
Deviations from Average Mate Value
Deviations from Average Life History
Deviations from Average Sexual Aggression

Figure 7. Hypothesized Study 1 bias (*c*) and sensitivity (*d'*) for each mating-relevant trait. The first panel shows hypothesized relationship with STMO in red (higher values indicate more short-term orientation), the second panel shows hypothesized relationship with LTMO in orange (higher values indicate more long-term orientation), the third panel shows hypothesized relationship with Mate Value in green (higher values indicate greater mate value), the fourth panel shows hypothesized relationship with Life History in blue (higher values indicate slower life history strategies), and the fifth panel shows hypothesized relationship with Sexual Aggression in purple (higher values indicate higher sexual aggression). Negative *c* values indicate liberal yes-biases. Sensitivities (*d'*) closer to 0 indicate chance responding.

Analyses

For SDT, results were analyzed using multilevel probit regression to determine *c* and *d'* (DeCarlo, 1998; Wright & London, 2009). This model predicted participants' binary perceptions using female binary sexual interest for each video, participant sex, STMO, LTMO, Mate Value, Life History Strategy, and Sexual Aggression as main effects. Additionally, interactions between each individual difference and the binary sexual interest for each video were included to determine the effect of each individual difference on sensitivity. Bias was allowed to vary for each participant, and intercept was allowed to vary for each video. Initial plans had included sensitivity being allowed to vary for each participant, however, the random effect structure was determined empirically through model comparison (i.e., the random effect structure with the lowest AIC value without fixed effects added to the model was selected for the final analysis model, see Appendix A for all model comparisons). Additional model specifications are available in the R code in Appendix B.

For EMT, an average misperception score was calculated for each participant (i.e., mean of participant scale perception – female scale sexual interest) and was predicted using a general linear model with participant sex, STMO, LTMO, Mate Value, Life History Strategy, and Sexual Aggression as predictors.

Results

The SDT analysis showed that overall, participants had no bias when responding to the videos (c = 0.05, SE = 0.14, p = .699), and were not sensitive to women's sexual interest (d' = 0.25, SE = 0.26, p = .321; Figure 8). There were no main effects of sex on bias (b = 0, SE = 0.07, p = .979) or sensitivity (b = -0.06, SE = 0.05, p = .211), suggesting that men and women did not differ in their perceptions of women's sexual interest. However, due to the nature of the hypotheses, biases and sensitivities for both men and women were calculated. Marginal means showed that men (c = 0.06, SE = 0.17) and women (c = 0.05, SE = 0.15) had very similar neutral biases. Men and women had similar sensitivities as well, although men's sensitivity was slightly higher than women's sensitivity, however not significantly so (d'_{Men} = 0.32, SE_{Men} = 0.26, d'_{Women} = 0.19, SE_{Women} = 0.26, Figure 9). The overall low sensitivities for both men and women are reflected in the overall low accuracy and rates of hits, misses, false alarms, and correct rejections displayed in Table 2 and in Figure 10.

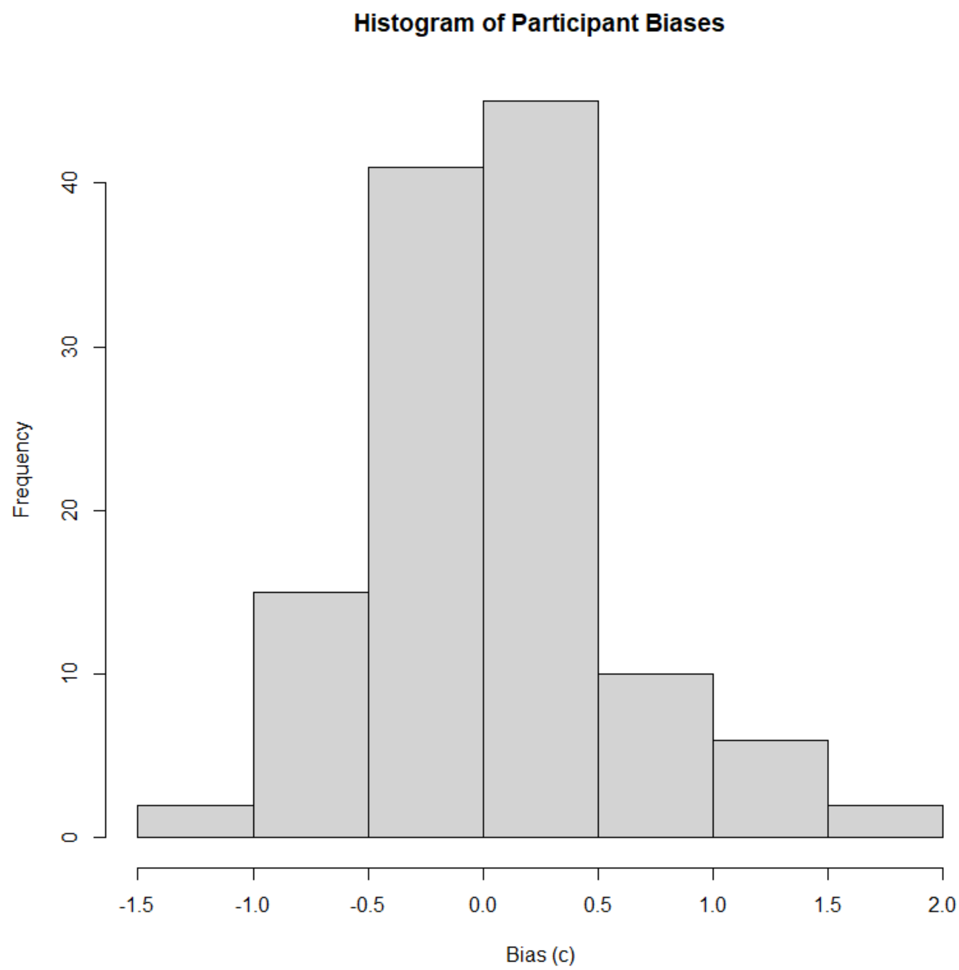

Figure 8. Study 1 histogram of participant biases.

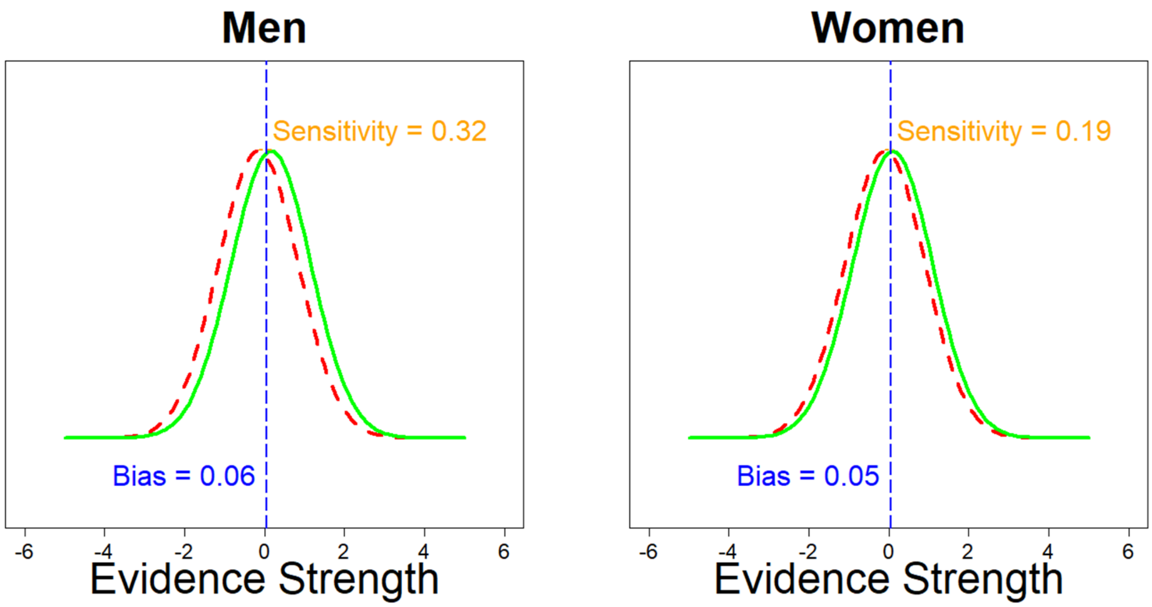

Figure 9. Study 1 bias (*c*) and sensitivity (*d′*) for both men and women.

Table 2. Rates and percentages of hits, correct rejections, misses, and false alarms by participant gender.

Gender	Hits	Correct Rejections	Misses	False Alarms
Men	402 (26.4%)	432 (28.4%)	358 (23.6%)	328 (21.6%)
Women	839 (25.3%)	912 (27.5%)	821 (24.7%)	748 (22.5%)
Overall	1241 (25.6%)	1344 (27.8%)	1179 (24.4%)	1076 (22.2%)

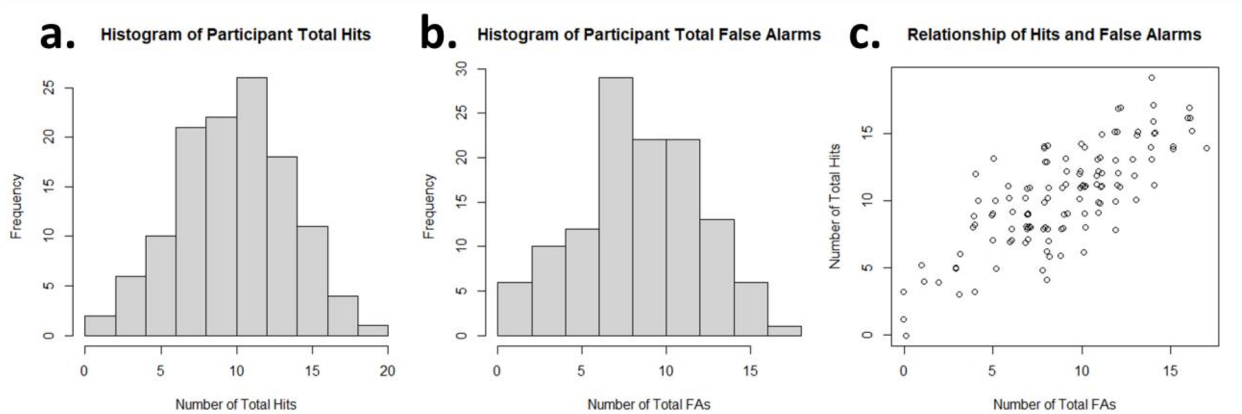

Figure 10. Study 1 number and relationship of total hits and false alarms for each participant. Panel a is a histogram of the total hits of each participant. Panel b is a histogram of the total false alarms of each participant. Panel c shows the relationship between hits and false alarms.

Additionally, individual differences did not affect participants' perceptions. Short-term mating orientation, long-term mating orientation, mate value, life history strategy, and sexual aggression did not significantly affect sensitivity or bias (Table 3, Figure 11). These individual differences showed minimal multicollinearity (VIF_{STMO} = 1.24, VIF_{LTMO} = 1.07, VIF_{MV} = 1.29, VIF_{LH} = 1.25, VIF_{SA} = 1.08). Pearson correlations were run between the individual differences measures due to previous research that suggests mating-relevant individual differences may be correlated (Strouts et al., 2017). Short-term mating orientation was significantly correlated with sexual aggression (r = 0.23, p = .012). Mate value was correlated with both LTMO (r = 0.23, p = .012) and life history strategy (r = 0.42, p < .001). The remaining individual differences were not significantly correlated with one another, which fails to replicate previous research that found significant correlations between life history strategy and STMO and LTMO and between STMO and LTMO.

These results support the hypothesis generated from Brandner (2021) showing minimal effects of sociosexual orientation, mate value, or life history on bias or sensitivity. Moreover, sexual aggression also did not affect bias or sensitivity, contrary to hypotheses, but consistent with the other mating-relevant individual differences tested here.

Table 3. Parameter estimates and standard errors of mating-relevant individual differences on bias and sensitivity.

	STMO (a)	LTMO (b)	Mate Value (c)	Life History (d)	Sexual Aggression (e)
Bias	-0.03 (0.03)	0.03 (0.04)	0.01 (0.05)	-0.14 (0.11)	0.13 (0.10)
Sensitivity	0.02 (0.02)	0.04 (0.03)	-0.02 (0.04)	0.01 (0.08)	0.04 (0.07)

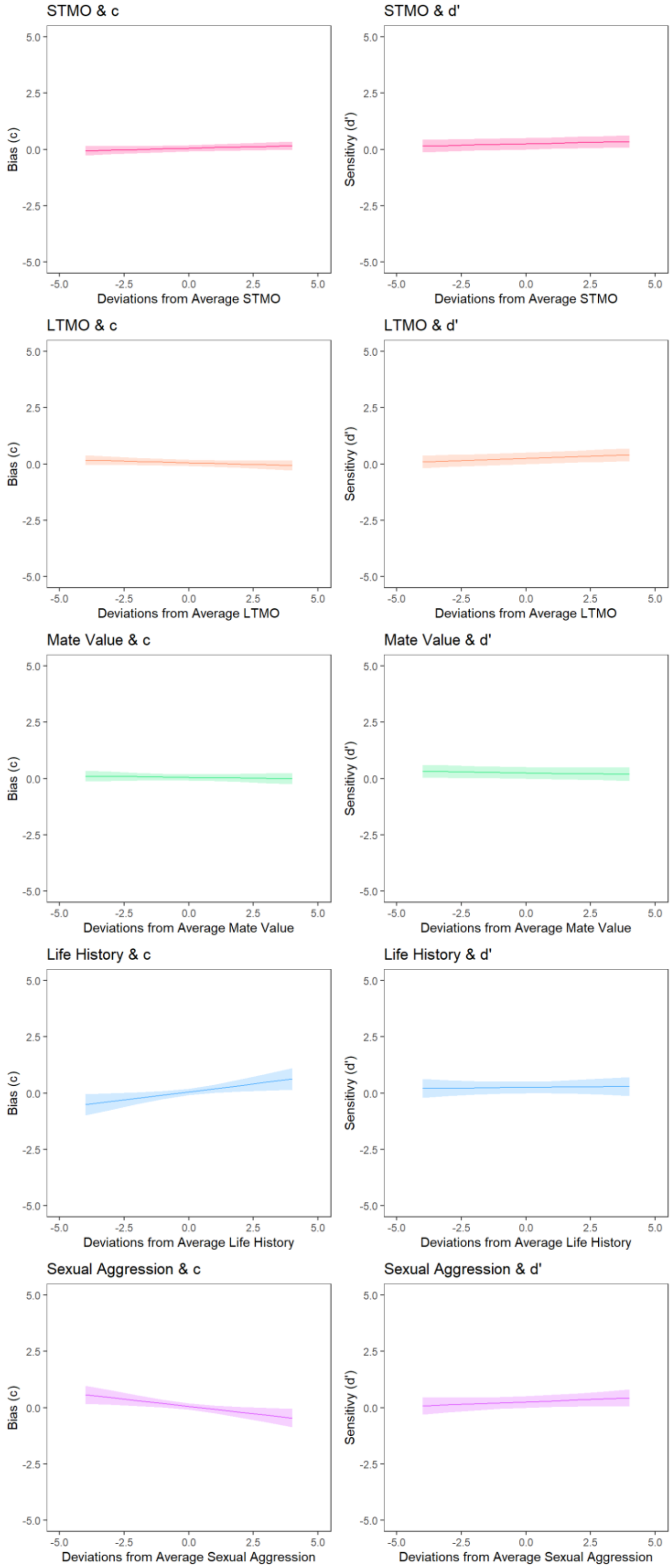
STMO & c
STMO & d'
Bias (c)
Sensitivy (d')
Deviations from Average STMO
LTMO & c
LTMO & d'
Deviations from Average LTMO
Mate Value & c
Mate Value & d'
Deviations from Average Mate Value
Life History & c
Life History & d'
Deviations from Average Life History
Sexual Aggression & c
Sexual Aggression & d'
Deviations from Average Sexual Aggression
5.0
2.5
0.0
-2.5
-5.0

Figure 11. Study 1 bias (*c*) and sensitivity (*d'*) for each mating-relevant trait. The first panel shows hypothesized relationship with STMO in red (higher values indicate more short-term orientation), the second panel shows hypothesized relationship with LTMO in orange (higher values indicate more long-term orientation), the third panel shows hypothesized relationship with Mate Value in green (higher values indicate greater mate value), the fourth panel shows hypothesized relationship with Life History in blue (higher values indicate slower life history strategies), and the fifth panel shows hypothesized relationship with Sexual Aggression in purple (higher values indicate higher sexual aggression). Negative *c* values indicate liberal yes-biases. Sensitivities (*d'*) closer to 0 indicate chance responding.

The EMT analysis showed that overall, participants were underperceiving sexual interest (b = -0.31, SE = 0.09, p < .001). Men's misperception scores (M = -0.37, SE = 0.16) were slightly lower than women's (M = -0.25, SE = 0.10), indicating that men are perceiving interest slightly less often than women are, although the effect was not significant (t(59.52) = 0.55, p = .582). This indicates that men and women are not perceiving sexual interest differently, and moreover, men are not overperceiving sexual interest compared to women or compared to the amount of interest communicated, contrary to previous EMT literature but consistent with Brandner et al. (2021). The EMT analysis also did not show significant effects of mating-relevant traits (b_{MV} = 0.06, SE = 0.07, p = .444; b_{STMO} = 0, SE = 0.05, p = .973; b_{LTMO} = 0.06, SE = 0.06, p = .333; $b_{LifeHistory}$ = -0.10, SE = 0.16, p = .529; $b_{SexualAggression}$ = 0.04, SE = 0.14, p = .772).

Discussion

These results indicate that people are primarily guessing when determining a woman's sexual interest and may not be relying on either sensitivity or bias to optimize their behaviors. This floor effect of accuracy could be concealing effects of individual differences including sex, mate value, sociosexual orientation, life history strategy, or sexual aggression. Men and women both had a neutral bias, indicating that men were not overperceiving interest compared to women or compared to interest communicated.

This study failed to replicate the results of Brandner et al. (2021). It was predicted that there would be an overall conservative “no”-bias; this hypothesis was not supported as there was minimal bias for men or women. Sensitivity was predicted to be high and have a greater effect on responses than bias. This was not supported; sensitivities were low for both men and women. It is possible however, that this lower sensitivity was caused by additional ambiguity through the use of video stimuli rather than vignettes. It was also predicted that EMT analyses would show male sexual overperception. This hypothesis was not supported. Instead, EMT analysis found no sex difference and overall underperception of interest.

Finally, it was predicted that mating-relevant individual differences such as Sociosexual Orientation, Mate Value, and Life History strategy would have no effect on bias or sensitivity; this hypothesis was supported as no effects were found. However, it was also predicted that higher sexual aggression would be associated with a liberal bias, when in fact, the opposite (but non-significant) trend was found.

Study 2 – Effects of Skewed Signal-to-Noise Ratios

Study 2 aimed to experimentally alter the signal-to-noise ratio involved in sexual overperception by altering the numbers of videos showing sexually interested and sexually disinterested people. This study helps determine how flexible sexual overperception is by comparing proximate and ultimate causes. Additionally, this study tests if SDT is a better theoretical framework for evaluating sexual perception by testing if an effect not predicted by EMT can affect sexual perception. Finally, this study will help determine how quickly participants adjust their responses to different signal-to-noise ratios.

Participants

Study 2 recruited 245 participants from Amazon Mechanical Turk through Cloud Research (Litman et al., 2017). Of these, 99 participants' work was rejected for failure of one or more attention checks, resulting in 146 participants who were paid $0.50 for successfully completing the study. Sample size was estimated at 150 participants but aimed to meet similar participant numbers as in Study 1. Data collection was stopped when close to this goal. Participation was limited to those located in the United Stated with at least 100 completed HITs and a 95% past approval rating. Participants were excluded from participating if they did not pass a captcha or an English competency test that requires a minimum of university level English understanding.

Participants' data were excluded from analysis if they did not accept payment for their participation (n = 8), if their gender and sexual orientation did not match the gender they were sexually interested in (n = 5), if they identified as something other than male or female (n = 1), if they self-identified as primarily same-sex attracted (n = 7), or if they did not complete the personality measures (n = 1). This resulted in 124 total participants with an average age of 45 (SD = 14). Most participants were women (n_{woman} = 78; n_{man} = 46), which is not abnormal for research on relationships.

Measures and Procedure

After indicating informed consent and passing a captcha and English proficiency question, participants answered demographic questions (e.g., age, sex, gender, sexual orientation) and were presented with a randomly assigned selection of 40 video clips (described above). Participants then were instructed that they would see a series of 30-second videos and answer questions regarding the videos after each. They were informed that videos intentionally did not include sound and that they wouldn't be able to move to the next page until each video was finished. Participants were assigned one of three sex-specific conditions: Interested (75% clips with the opposite sex reporting interest in their partner), Disinterested (75% clips with the opposite sex reporting no interest in their partner), or Even (50% clips with opposite sex reporting interest, 50% with opposite sex reporting no interest).

After viewing each clip, participants were asked binary and scale measures of the opposite sex conversation partner's sexual interest in their conversation partner. The binary measure asked, *"Is the [wo]man in this clip sexually attracted to in the [wo]man in this clip?"* with response options of yes and no. The scale measure asked, *"How sexually attracted is this [wo]man to this [wo]man?"* on a scale of 1 (Not sexually attracted at all) to 7 (Extremely sexual attracted). For concealment of the study design and purpose, the same questions were asked about the same-sex conversant.

Following the video task, participants answered the individual differences measures of Sociosexual Orientation (M_{STMO} = 3.86, SD_{STMO} = 1.71, STMO Cronbach's alpha = 0.96; M_{LTMO} = 6.00, SD_{STMO} = 1.09, LTMO Cronbach's alpha = 0.93), Mate Value (*M* = 4.80, *SD* = 1.20, Cronbach's alpha = 0.91), Life History Strategy (*M* = 0.01, *SD* = 0.60, subscale Cronbach's alphas ranged between 0.60 and 0.93), and Sexual Aggression (*M* = 1.07, *SD* = 0.43, Cronbach's alpha = 0.85) in the same order from Study 1 for replication purposes. Finally, participants answered attention check questions and were presented debriefing information.

Analyses

Results were analyzed using multilevel probit regression to determine *c* and *d'*. This model predicted participants' binary perceptions using the opposite sex binary sexual interest for each video, participant sex, STMO, LTMO, Mate Value, Life History Strategy, Sexual Aggression, their video condition, and log of trial order as main effects. Additionally, interactions between each predictor and the binary sexual interest for each video were included to determine the effect of each predictor on sensitivity. Bias was allowed to vary for each participant (sensitivity was not), and intercept was allowed to vary for each video. As in Study 1, the random effect structure was determined through model comparison, and the random effect structure with the lowest AIC value was selected for analysis (see Appendix A for all model comparisons). Additional model specifications are available in the R code in Appendix B. Results were not analyzed using traditional EMT methods.

Hypotheses

a) Those in the Interested condition will have a more liberal bias compared to the baseline established in Study 1 (Figure 12).
b) Those in the Disinterested condition will have a more conservative bias compared to the baseline established in Study 1 (Figure 12).
c) Those in the Even condition will have a similar bias to the baseline established in Study 1 (Figure 12).
d) Trial order will affect bias, such that those in the Interested (75%) condition will have a bias that becomes more liberal, those in the Disinterested (25%) condition will have a bias that becomes more conservative, and those in the Even (50%) condition will have a bias that becomes more neutral (Figure 13).
e) Individual differences effects from Study 1 will be replicated.

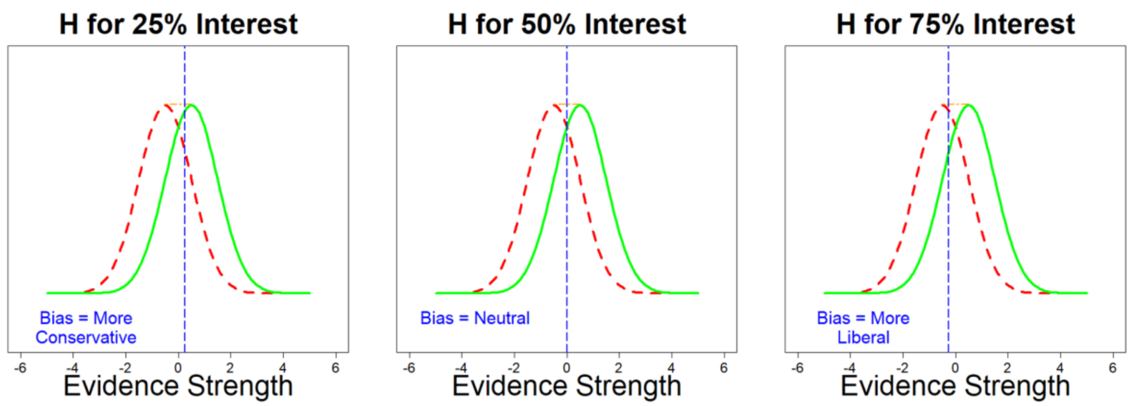

Figure 12. Hypothesized Study 2 bias (c) and sensitivity (d') for each interest condition.

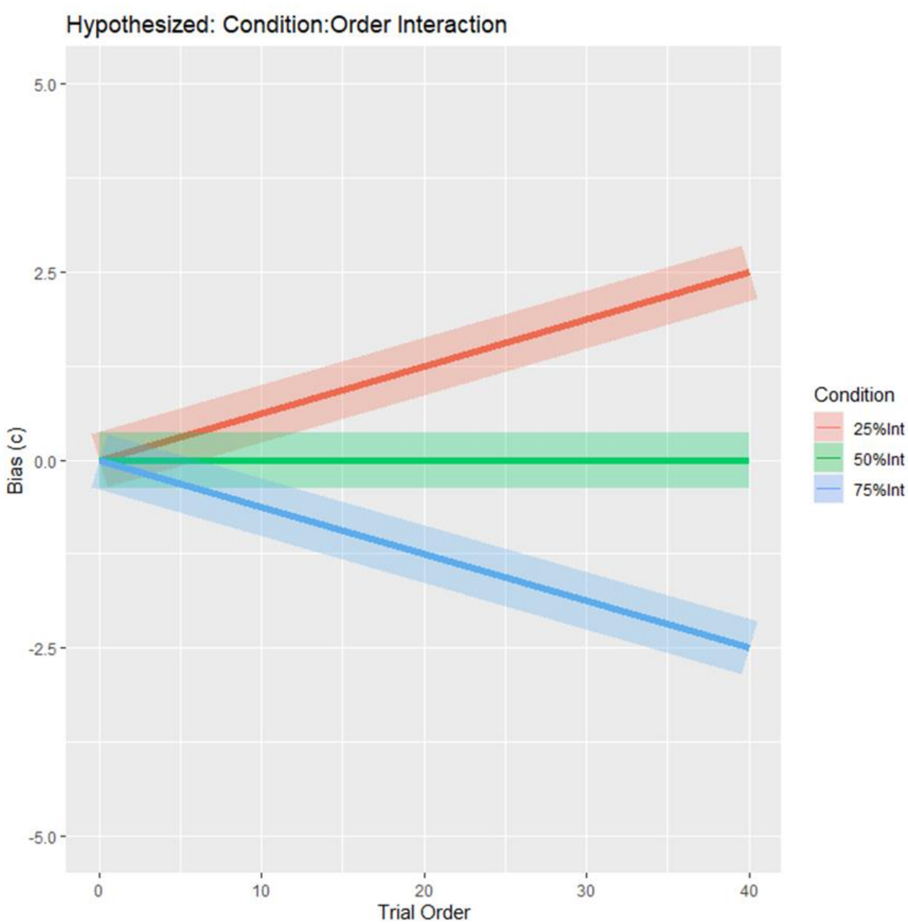

Figure 13. Hypothesized Study 2 interaction between interest condition and trial order. The Interested condition (75% interest) is shown in blue. The Disinterested condition (25% interest)

is shown in red. The Even condition (50% interest) is shown in green. Negative *c* values indicate liberal yes-biases**.**

Results

The SDT analysis showed that overall, participants had a conservative no-bias when responding to the videos (c = 0.26, SE = 0.12, p = .034). However, as in Study 1, participants were not sensitive to the opposite-sex conversation partner's sexual interest (d' = 0.18, SE = 0.17, p = .275). There were no main effects of sex on bias (b = 0.13, SE = 0.07, p = .060) or sensitivity (b = 0.01, SE = 0.07, p = .874), suggesting that men and women did not differ in their perceptions of sexual interest. However, due to the nature of the hypotheses, biases and sensitivities for both men and women were calculated. Marginal means showed that men had a conservative bias (c = 0.21, SE = 0.13) while women (c = -0.05, SE = 0.11) had almost no bias. Men and women had similar sensitivities as well (d'_{Men} = 0.09, SE_{Men} = 0.11, d'_{Women} = 0.11, SE_{Women} = 0.10, Figure 14). The overall low sensitivities for both men and women are reflected in the overall low accuracy and rates of hits, misses, false alarms, and correct rejections displayed in Table 4.

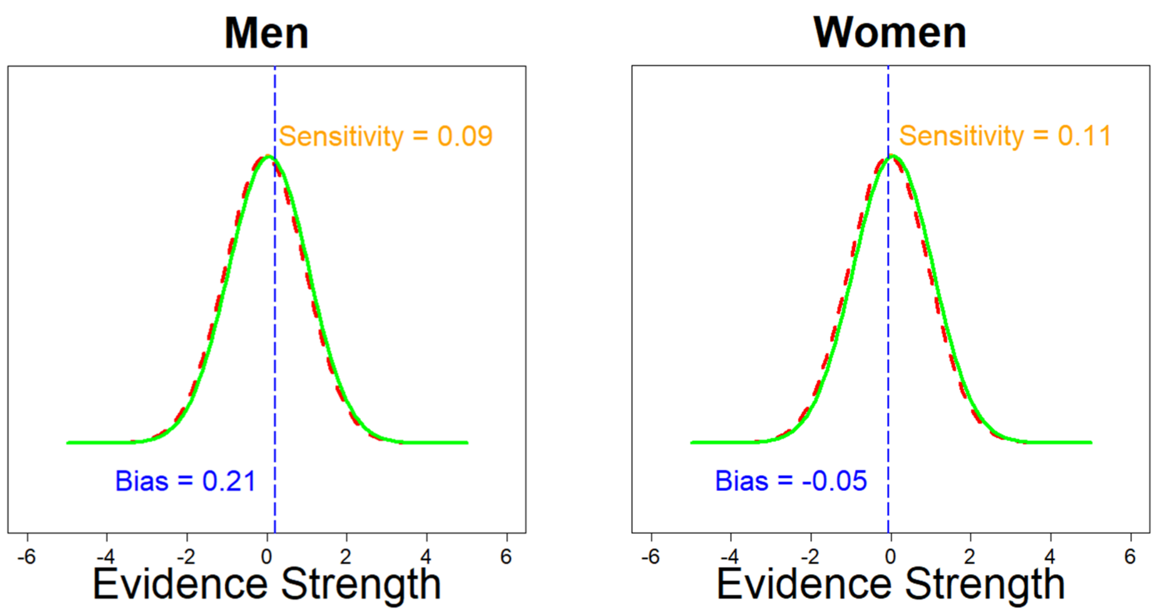

Figure 14. Study 2 bias (*c*) and sensitivity (*d′*) for both men and women.

Table 4. Rates and percentages of hits, correct rejections, misses, and false alarms by participant gender.

Gender	Hits	Correct Rejections	Misses	False Alarms
Men	422 (22.9%)	571 (31.0%)	458 (24.9%)	389 (21.1%)
Women	869 (27.9%)	743 (23.8%)	731 (23.4%)	777 (24.9%)
Overall	1291 (26.0%)	1314 (26.5%)	1189 (24.0%)	1166 (23.5%)

Condition did significantly affect bias (X^2 (2, N = 124) = 8.33, p = .016) but did not affect sensitivity (X^2 (2, N = 124) = 3.33, p = .189). Specifically, those in the 25% Interest (i.e., Disinterested) condition had a slight conservative bias (c = 0.23, SE = 0.14), those in the 50% Interest (i.e., Even) condition (c = -0.08, SE = 0.13) and those in the 75% Interest (i.e., Interested) condition (c = 0.08, SE = 0.14) had fairly neutral (but opposite) biases. Fisher's LSD post hoc tests of the largest difference in mean biases revealed that the 25% Interest condition was not significantly different from the 50% Interest condition (*LSD* = -0.31, *SE* = 0.16, *p* = .055; Figure 15), indicating that while there was a significant effect of condition on bias, this could be due to chance or possibly that there is not sufficient power to detect an effect.

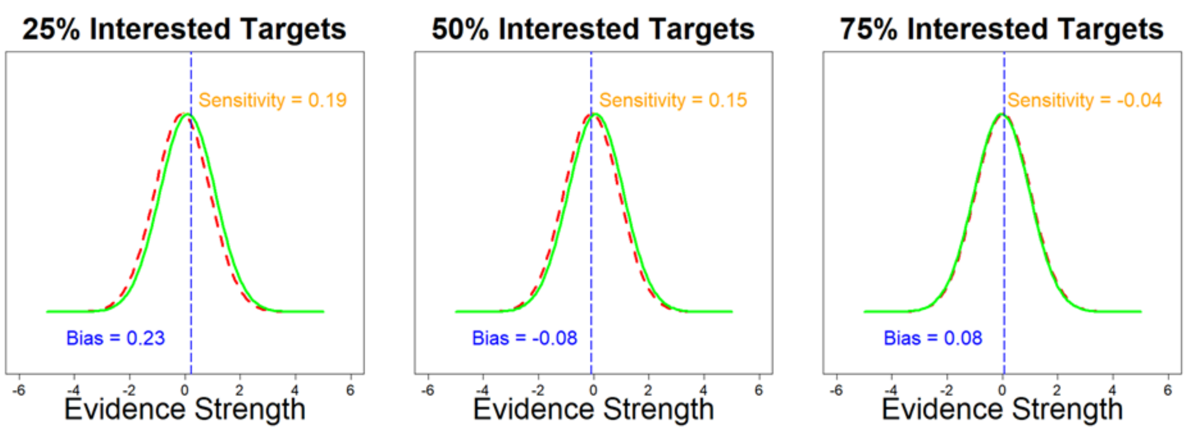

Figure 15. Study 2 bias (*c*) and sensitivity (*d'*) for each interest condition.

Item order did significantly affect bias (*b* = 0.06, *SE* = 0.03, *p* = .015), such that as participants continued in the study, their bias became more liberal. However, there was not a significant interaction between condition and order on bias (X^2 (2, *N* = 124) = 4.68, *p* = .096), indicating that participants biases did not significantly change as they progressed further and experienced more of the altered signal-to-noise base rate in their condition. Figure 16a shows the overall tendency of each condition to get more liberal as the trials increase, including the 25% Interested condition, which was hypothesized to become more conservative over time. Item order did not affect sensitivity (*b* = -0.03, *SE* = 0.05, *p* = .566) and there was no significant interaction between condition and order on sensitivity (X^2 (2, *N* = 124) = 2.38, *p* = .305), indicating that participants' sensitivity did not change as they experienced more of the altered signal-to-noise ratio. Figure 16b shows the sensitivity change of each condition as the trials increase.

While those in the 25% Interested and 75% Interested conditions get a little better over time (but ultimately stay around chance performance), those in the 50% Interested condition actually get slightly worse as the trials continue, such that by the end of the trials, they are consistently responding opposite to the true interest (i.e., answering “no” when the opposite sex conversation partner is interested and answering “yes” when the opposite sex conversation partner is not interested).

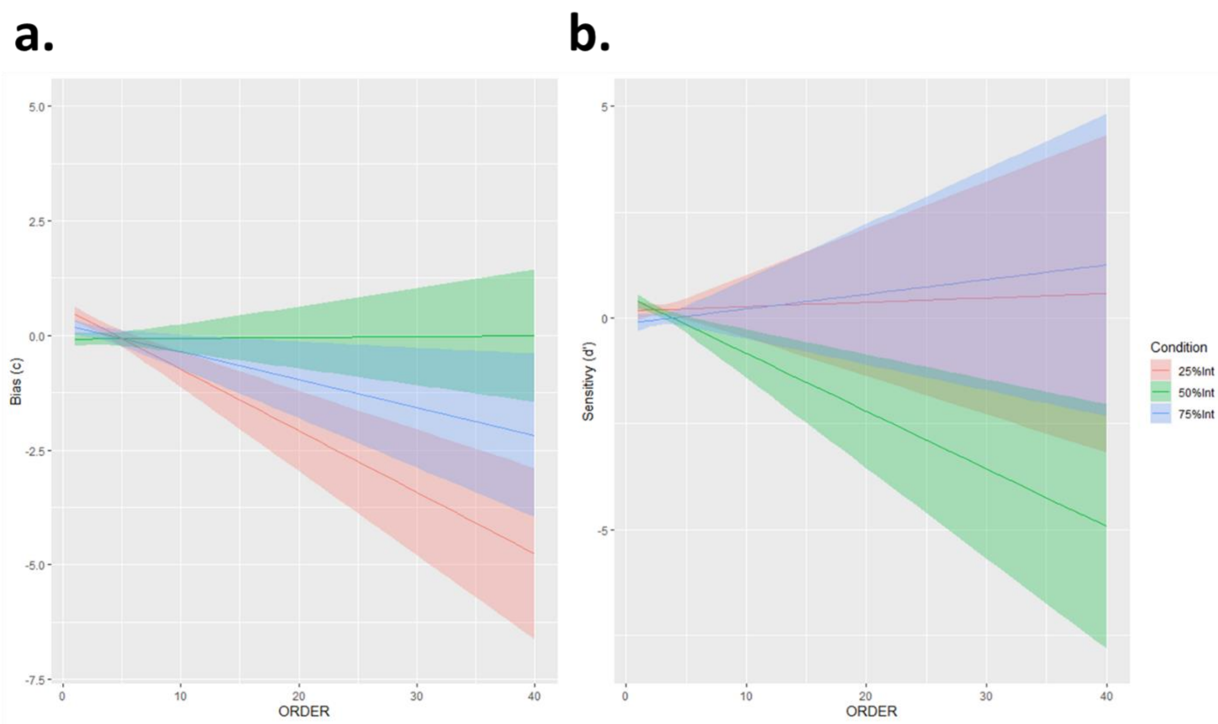

Figure 16. Study 2 interaction between interest condition and trial order. The Interested condition (75% interest) is shown in blue. The Disinterested condition (25% interest) is shown in red. The Even condition (50% interest) is shown in green. Negative *c* values indicate liberal yes-biases. Sensitivities (*d'*) closer to 0 indicate chance responding. Shading indicates +/-1 standard error.

Finally, individual differences were examined to see if they affected participants' perceptions. Long-term mating orientation affected bias ($b = 0.17$, $SE = 0.06$, $p = .006$; Figure 15b), such that those with more long-term mating orientations had more liberal biases and those with less long-term mating orientations had more conservative biases. This is contradictory to the null results in Study 1 which found no effect of LTMO on bias. LTMO did not affect sensitivity. Additionally, STMO, mate value, life history strategy, and sexual aggression did not significantly affect sensitivity or bias (Table 5). These individual differences showed minimal multicollinearity ($VIF_{STMO} = 1.38$, $VIF_{LTMO} = 1.21$, $VIF_{MV} = 1.20$, $VIF_{LH} = 1.42$, $VIF_{SA} = 1.07$). Pearson correlations were run between the individual differences measures. Short-term mating orientation was significantly correlated with life history strategy ($r = -0.39$, $p < .001$) and LTMO ($r = -0.26$, $p = .003$). Mate value was correlated with both LTMO ($r = 0.23$, $p = .010$) and life history strategy ($r = 0.32$, $p < .001$). These results somewhat replicated previous research (e.g., Strouts et al., 2017). Sexual aggression was not significantly correlated with any other individual difference, unlike in Study 1 where it was found to be correlated with STMO.

Despite the bias effect found for LTMO, overall, these results support what was found in Study 1: mating-relevant individual differences minimally effect bias and sensitivity (Figure 17).

Table 5. Parameter estimates and standard errors of mating-relevant individual differences on bias and sensitivity.

	STMO (a)	LTMO (b)	Mate Value (c)	Life History (d)	Sexual Aggression (e)
Bias	0.07 (0.04)	0.17 (0.06)*	0.01 (0.06)	0.09 (0.12)	0.05 (0.15)

Sensitivity	-0.03 (0.03)	-0.09 (0.04)	-0.01 (0.04)	-0.08 (0.09)	0 (0.10)

* indicates statistical significance at the *p* < .05 level.

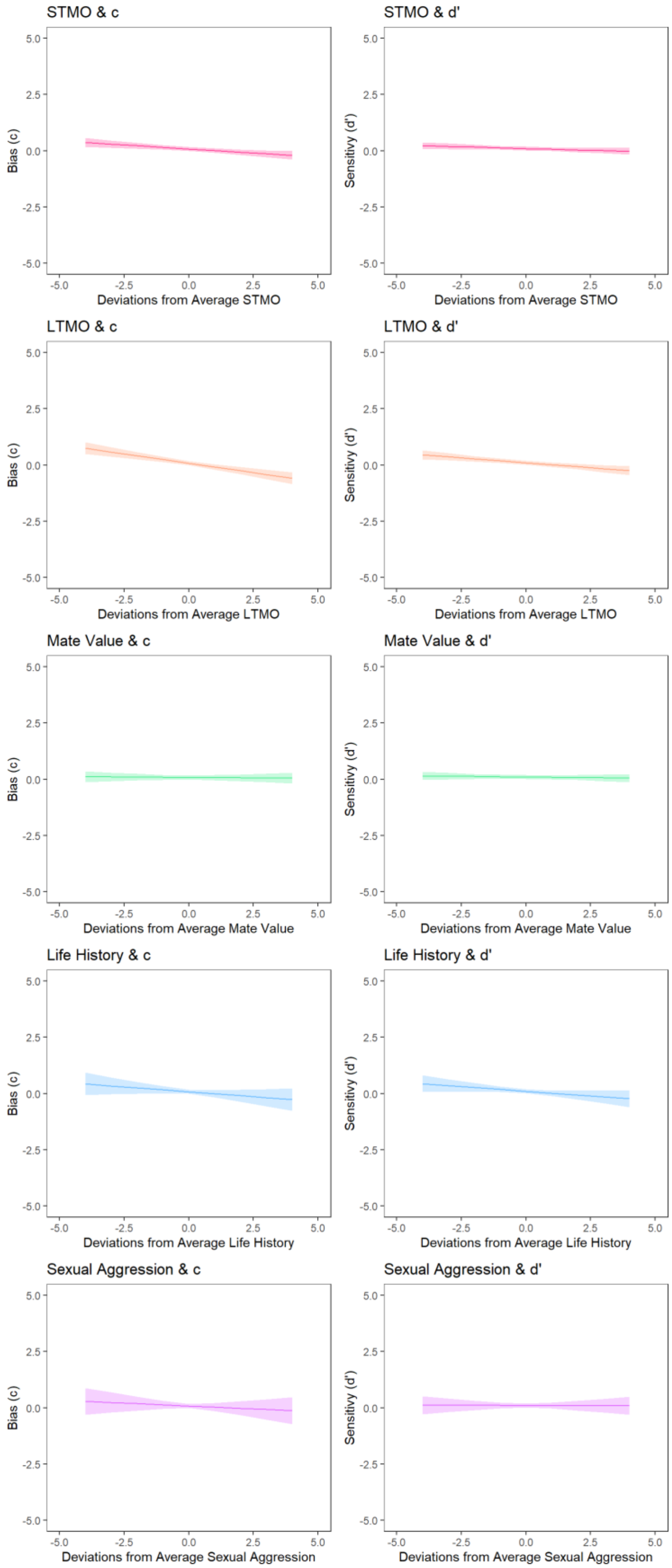
STMO & c
Bias (c)
Deviations from Average STMO
STMO & d'
Sensitivy (d')
Deviations from Average STMO
LTMO & c
Bias (c)
Deviations from Average LTMO
LTMO & d'
Sensitivy (d')
Deviations from Average LTMO
Mate Value & c
Bias (c)
Deviations from Average Mate Value
Mate Value & d'
Sensitivy (d')
Deviations from Average Mate Value
Life History & c
Bias (c)
Deviations from Average Life History
Life History & d'
Sensitivy (d')
Deviations from Average Life History
Sexual Aggression & c
Bias (c)
Deviations from Average Sexual Aggression
Sexual Aggression & d'
Sensitivy (d')
Deviations from Average Sexual Aggression

Figure 17. Study 2 bias (*c*) and sensitivity (*d'*) for each mating-relevant trait. The first panel shows hypothesized relationship with STMO in red (higher values indicate more short-term orientation), the second panel shows hypothesized relationship with LTMO in orange (higher values indicate more long-term orientation), the third panel shows hypothesized relationship with Mate Value in green (higher values indicate greater mate value), the fourth panel shows hypothesized relationship with Life History in blue (higher values indicate slower life history strategies), and the fifth panel shows hypothesized relationship with Sexual Aggression in purple (higher values indicate higher sexual aggression). Negative *c* values indicate liberal yes-biases. Sensitivities (*d'*) closer to 0 indicate chance responding.

Discussion

Once again, these results indicate that people are primarily guessing when determining a woman's sexual interest but may be relying on bias to optimize their behaviors. Unlike in Study 1, participants had a slightly conservative bias, but like Study 1, there was no effect of sensitivity. As in Study 1, there was no sex difference in bias, indicating that men were not overperceiving interest compared to women or compared to actual interest communicated (as men had a slightly conservative bias).

It was hypothesized that the Interested condition would have a more liberal bias, that the Disinterested condition would have a more conservative bias, and that the Even condition would have a similar bias to Study 1. This hypothesis was somewhat supported. The Disinterested condition did have a slight conservative bias; however, the Interested condition did not result in a more liberal bias. In fact, the Interested condition had nearly the same bias as the original bias found in Study 1, whereas the Even condition was slightly more liberal. Moreover, these differences between conditions appear to be minimal, as post hoc tests did not reveal a significant difference, despite a significant effect being found. This indicates that these differences may be statistical artifacts or that power is not high enough in this study to detect the effects that are there.

It was also hypothesized that as participants continued in their interest conditions, their biases would change in the direction of the hypothesized changes. While item order did have an effect, with participants getting more liberal as the study went on, it did not interact with conditions, suggesting that participants were not learning the differing signal-to-noise ratios. Interestingly, those in the Even condition had negative sensitivity by the end of the study, indicating that they were consistently responding opposite to true interest. This is highly unusual and unexpected, and indicates that they are picking up the interest/disinterest cues, but interpreting them opposite to reality. Typically, in SDT studies, this indicates an experimenter error (e.g., switching the response keys, incorrect instructions, etc.). However, data and experimental procedures were checked post-hoc and no errors were found. This could be caused by individuals who perceive interest cues to be mere friendliness and disinterest cues to be "playing hard to get", however this explanation does not explain why this effect was only found for the even condition.

Finally, it was hypothesized that individual differences effects would replicate from Study 1, which did find general support as individual differences minimally affected bias and sensitivity.

Study 3 – Effects of Skewed Sex Ratios

Study 3 aimed to experimentally determine how the environment might adjust either signal-to-noise ratio or decision outcomes using exposure to skewed sex ratio primes. Sex ratio was primed rather than adjusted in the stimuli because opposite-sex conversation pairs were required for this research, resulting in an even 50% male, 50% female sex ratio in the stimuli themselves. In regard to sexual overperception, sex ratios could be adjusting the signal-to-noise ratio (resulting in members of the populous sex having a more conservative bias) or the decision outcomes (resulting in members of the populous sex having a more liberal bias). These competing hypotheses address a question that is rarely considered in SDT research and can help elucidate whether the signal/noise ratio or values of the decision outcomes has a stronger effect on bias.

Participants

Study 3 recruited 254 participants from Amazon Mechanical Turk through Cloud Research (Litman et al., 2017). Of these, 113 participants' work was rejected for failure or non-answer of one or more attention checks, resulting in 141 participants who were paid $0.75 for successfully completing the study. Sample size was estimated at 150 participants but aimed to meet similar participant numbers as in Studies 1 and 2. Data collection was stopped when close to this goal. Participation was limited to those located in the United Stated with at least 100 completed HITs and a 95% past approval rating. Participants were excluded from participating if they did not pass a captcha or an English competency test that requires a minimum of university level English understanding.

Participants' data were excluded from analysis if they did not accept payment for their participation (n = 1), if their gender and sexual orientation did not match the gender they were sexually interested in (n = 6), if they identified as transgender (n = 1), if they self-identified as primarily same-sex attracted (n = 11), or if they indicated in the open-ended comments item that they had technical issues that prevented accurate participation (n = 3). This resulted in 119 total participants with an average age of 42 (SD = 16). Most participants were once again women

(n_{woman} = 77; n_{man} = 42).

Measures and Procedure

After indicating informed consent and passing a captcha and English proficiency question, participants answered demographic questions (e.g., age, sex, gender, sexual orientation) and were randomly assigned one of three sex ratio conditions: Skewed male (75% Male faces), Skewed female (75% female faces), or Even (50% male and 50% female faces). Each ratio condition presented participants with a series of 60 sequential male and female faces and participants were asked to report sex ratio as a prime.

These ratio manipulations were considered effective as expected from previous research (Brandner et al., 2020). There were 41 participants assigned to the skewed male condition; of these, 35 reported seeing more male faces and the remaining 6 reported seeing an equal balance of male and female faces. When asked to estimate the percentage of female faces seen (a proxy for sex ratio), participants on average reported 32% female faces (*SD* = 16). There were 49 participants assigned to the even condition; of these, 26 reported seeing an equal balance of male and female faces, 15 reported seeing more female faces, and the remaining 8 reported seeing more male faces. When asked to estimate the percentage of female faces seen, participants on average reported 54% female faces (*SD* = 12). Finally, there were 29 participants assigned to the skewed female condition; of these, 26 reported seeing more female faces and the remaining 3 reported seeing an equal balance of male and female faces. When asked to estimate the percentage of female faces seen, participants on average reported 71% female faces (*SD* = 11).

Following the sex ratio prime, participants were presented with 40 video clips (as described above) and asked binary and scale measures of the opposite sex conversation partner's sexual interest. The binary measure asked, *"Is the [wo]man in this clip sexually attracted to in the [wo]man in this clip?"* with response options of yes and no. The scale measure asked, *"How sexually attracted is this [wo]man to this [wo]man?"* on a scale of 1 (Not sexually attracted at all) to 7 (Extremely sexual attracted). For concealment of the study design and purpose, the same questions were asked about the same-sex conversant.

Individual differences measures from Study 1 and Study 2, Sociosexual Orientation (M_{STMO} = 3.75, SD_{STMO} = 1.70, STMO Cronbach's alpha = 0.95; M_{LTMO} = 5.92, SD_{LTMO} = 1.15, LTMO Cronbach's alpha = 0.93), Mate Value (*M* = 4.80, *SD* = 1.14, Cronbach's alpha = 0.92), Life History Strategy (*M* = 0.10, *SD* = 0.65, subscale Cronbach's alphas ranged between 0.68 and 0.94), and Sexual Aggression (*M* = 1.09, *SD* = 0.36, Cronbach's alpha = 0.79), were included for replication. Finally, participants answered attention check questions and were presented debriefing information.

Analyses

Results were analyzed using multilevel probit regression to determine *c* and *d'*. This model predicted participants' binary perceptions using the opposite sex binary sexual interest for each video, STMO, LTMO, Mate Value, Life History Strategy, and Sexual Aggression, their sex ratio condition, and the sex ratio × participant sex interaction as main effects. Additionally, interactions between each predictor/interaction and the binary sexual interest for each video were included to determine the effect of each predictor on sensitivity. Bias was allowed to vary for each participant (sensitivity was not), and intercept was allowed to vary for each video. As in the previous studies, the random effect structure was determined through model comparison, and the random effect structure with the lowest AIC value was selected for analysis (see Appendix A for all model comparisons). Additional model specifications are available in the R code in Appendix B. Results were not analyzed using traditional EMT methods.

Competing Hypotheses

Sex Ratios Alter Signal-To-Noise Ratios

There will be an interaction between Sex and Sex Ratio Condition, such that:

a) Disadvantaged participants (i.e., men in the skewed male condition and women in the skewed female conditions) will have a more *conservative* bias compared to the baselines established for their sex in Study 1 (Figure 18, in pink).
b) Advantaged participants (i.e., women in the skewed male condition and men in the skewed female conditions) will have a more *liberal* bias compared to the baselines established for their sex in Study 1 (Figure 18, in pink).
c) Neutral participants (i.e., men and women in the even conditions) will have a similar bias to the baselines established for their sex in Study 1 (Figure 18, in gray).

Sex Ratios Alter Decision Outcomes

There will be an interaction between Sex and Sex Ratio Condition, such that:

a) Disadvantaged participants (i.e., men in the skewed male condition and women in the skewed female conditions) will have a more *liberal* bias compared to the baselines established for their sex in Study 1 (Figure 18, in purple).
b) Advantaged participants (i.e., women in the skewed male condition and men in the skewed female conditions) will have a more *conservative* bias compared to the baselines

established for their sex in Study 1 (Figure 18, in purple).

c) Neutral participants (i.e., men and women in the even conditions) will have a similar bias to the baselines established for their sex in Study 1 (Figure 18, in gray).

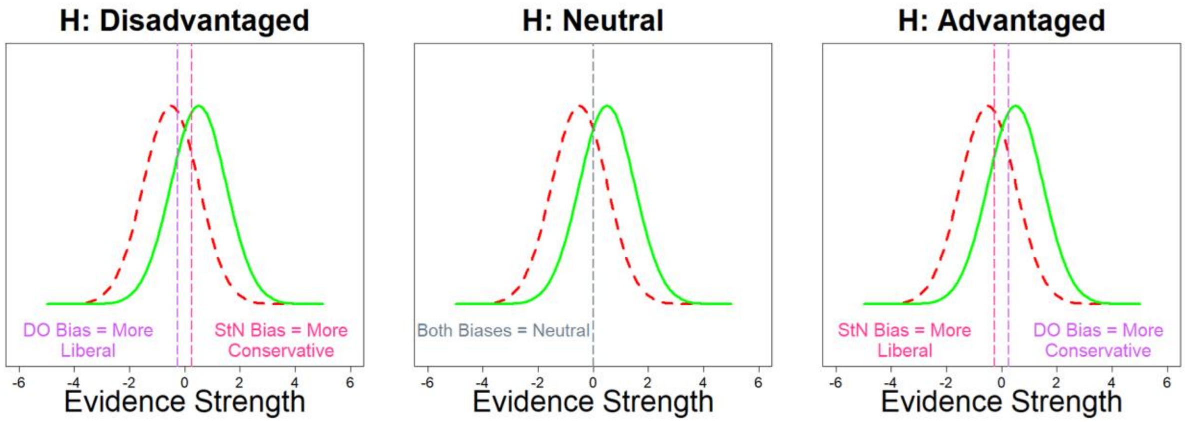

Figure 18. Hypothesized Study 3 bias (*c*) and sensitivity (*d'*) for the sex and sex ratio interaction.

Results

The SDT analysis showed that overall, participants had no strong bias when responding to the videos ($c = 0.08$, $SE = 0.12$, $p = .532$). However, unlike in the previous studies, participants were sensitive to the opposite-sex conversation partner's sexual interest ($d' = 0.22$, $SE = 0.06$, $p < .001$). There was no main effect of sex on bias ($b = 0.01$, $SE = 0.07$, $p = .846$), suggesting that men ($c = -0.06$, $SE = 0.15$) and women ($c = -0.09$, $SE = 0.13$) did not differ in their response biases. Unlike the previous studies, there was a main effect of sex on sensitivity ($b = -0.13$, $SE = 0.06$, $p = .046$), such that men ($d' = 0.35$, $SE = 0.09$) were significantly more sensitive than women ($d' = 0.09$, $SE = 0.09$, Figure 19). The different sensitivities for both men and women are reflected in the rates of hits, misses, false alarms, and correct rejections displayed in Table 6.

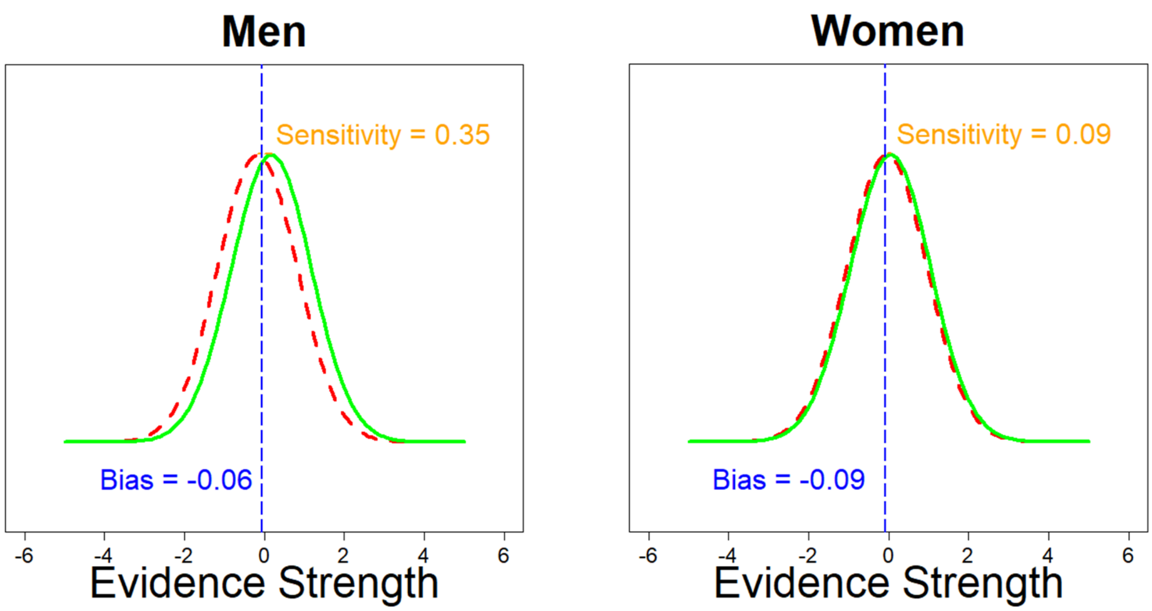

Figure 19. Study 3 bias (*c*) and sensitivity (*d'*) for both men and women.

Table 6. Rates and percentages of hits, correct rejections, misses, and false alarms by participant gender.

Gender	Hits	Correct Rejections	Misses	False Alarms
Men	481 (28.6%)	404 (24.0%)	359 (21.4%)	436 (26.0%)
Women	957 (31.1%)	883 (28.7%)	583 (18.9%)	657 (21.3%)
Overall	1438 (30.2%)	1287 (27.0%)	942 (19.8%)	1093 (23.0%)

Sex ratio condition did not significantly affect bias (X^2 (2, N = 119) = 3.35, p = .187) or sensitivity (X^2 (2, N = 119) = 1.56, p = .460). Specifically, those in the skewed male condition (c = -0.15, SE = 0.14) and the even condition (c = -0.17, SE = 0.15) had weak liberal biases and those in the skewed female condition (*c* = 0.09, *SE* = 0.14) had an even weaker conservative bias. For sensitivity, those in the skewed male condition had the weakest sensitivity (*d'* = 0.16, *SE* = 0.08), followed by the even condition (*d'* = 0.20, *SE* = 0.09) and the skewed female condition (*d'* = 0.30, *SE* = 0.10; Figure 20).

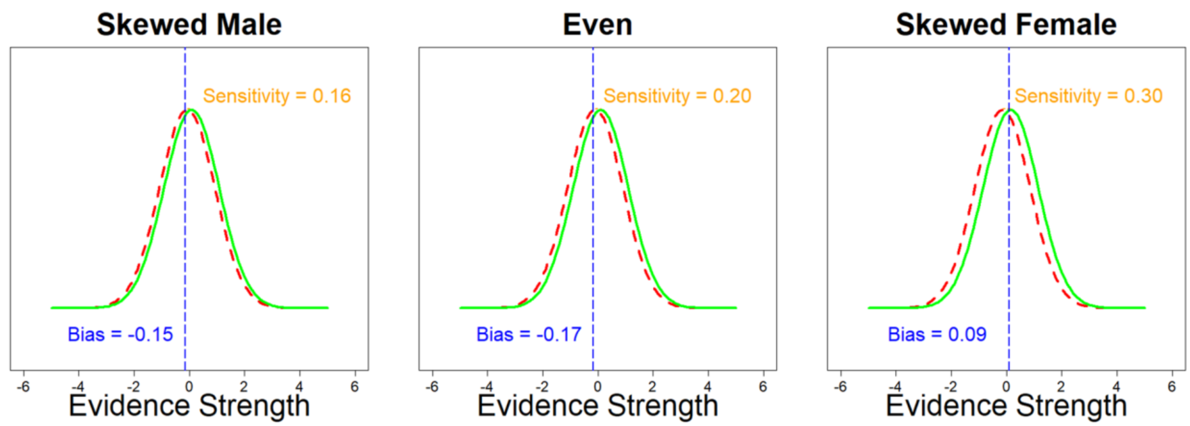

Figure 20. Study 3 bias (*c*) and sensitivity (*d'*) for each sex ratio condition.

The interaction between condition and sex did not significantly affect bias (X^2 (2, *N* = 119) = 2.53, *p* = .282) or sensitivity (X^2 (2, *N* = 119) = 1.21, *p* = .545), contrary to hypotheses. Since this was a hypothesized interaction, biases and sensitivities were examined for each sex in each of the sex ratio conditions (see Table 7, Figure 21).

Table 7. Sensitivities and biases for each gender based on the sex ratio condition they were assigned. Standard error for each estimate in parentheses. Negative biases indicate liberal “yes”-biases; positive biases indicate conservative “no”-biases.

Gender	Skewed Male	Even	Skewed Female
Men			

Bias	-0.24 (0.18)	-0.20 (0.20)	0.25 (0.23)
Sensitivity	0.27 (0.12)	0.28 (0.14)	0.51 (0.16)
Women			
Bias	-0.07 (0.17)	-0.14 (0.15)	-0.06 (0.18)
Sensitivity	0.05 (0.12)	0.13 (0.10)	0.10 (0.13)

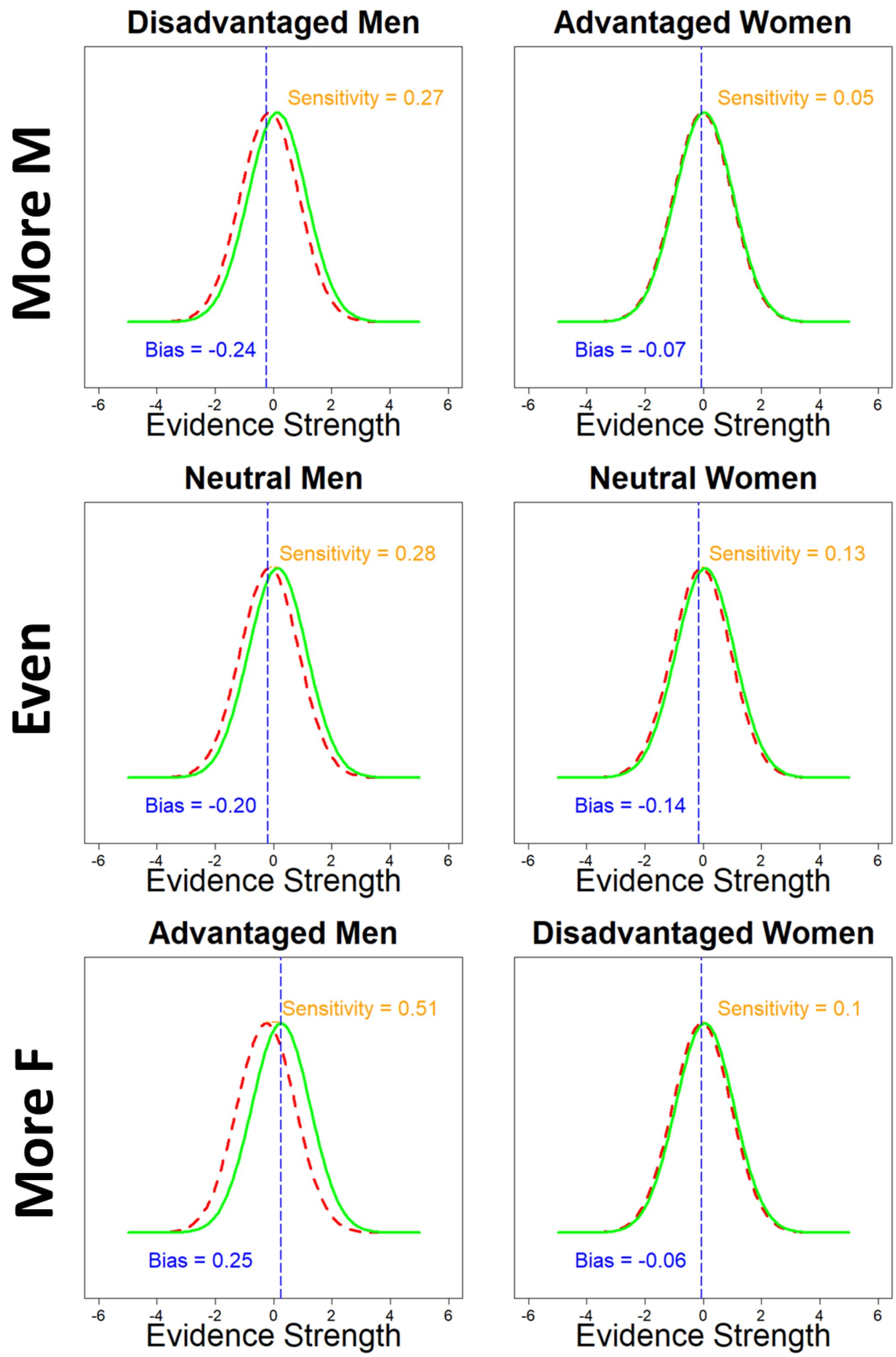

Figure 21. Study 3 bias (*c*) and sensitivity (*d'*) for the sex and sex ratio interaction.

Finally, individual differences were examined to see if they affected participants' perceptions. Short-term mating orientation significantly affected bias (b = 0.08, SE = 0.04, p = .027, Figure 22 top panel), such that those with more short-term mating orientations had more liberal biases. This is contradictory to the null results in Studies 1 and 2 which found no effect of STMO on bias. STMO did not affect sensitivity. Additionally, LTMO, mate value, life history strategy, and sexual aggression did not significantly affect sensitivity or bias (Table 8). These individual differences showed minimal multicollinearity (VIF_{STMO} = 1.40, VIF_{LTMO} = 1.17, VIF_{MV} = 1.07, VIF_{LH} = 1.20, VIF_{SA} = 1.26). Despite the bias effect found for STMO, overall, these results support what was found in the previous studies: mating-relevant individual differences minimally effect bias and sensitivity (Figure 22).

Pearson correlations were run between the individual differences measures. Short-term mating orientation was significantly correlated with life history strategy (r = -0.26, p = .005), LTMO (r = -0.29, p = .002) and sexual aggression (r = 0.22, p = .016). Mate value was not significantly correlated with any other individual difference variable unlike in previous research and in Studies 1 & 2. Long-term mating orientation was significantly correlated with life history strategy (r = 0.24, p = .009).

Table 8. Parameter estimates and standard errors of mating-relevant individual differences on bias and sensitivity.

	STMO (a)	LTMO (b)	Mate Value (c)	Life History (d)	Sexual Aggression (e)
Bias	0.08 (0.04)*	0.04 (0.05)	0.02 (0.05)	0.08 (0.09)	-0.09 (0.17)
Sensitivity	0.03 (0.03)	-0.03 (0.04)	0 (0.04)	0 (0.07)	-0.11 (0.13)

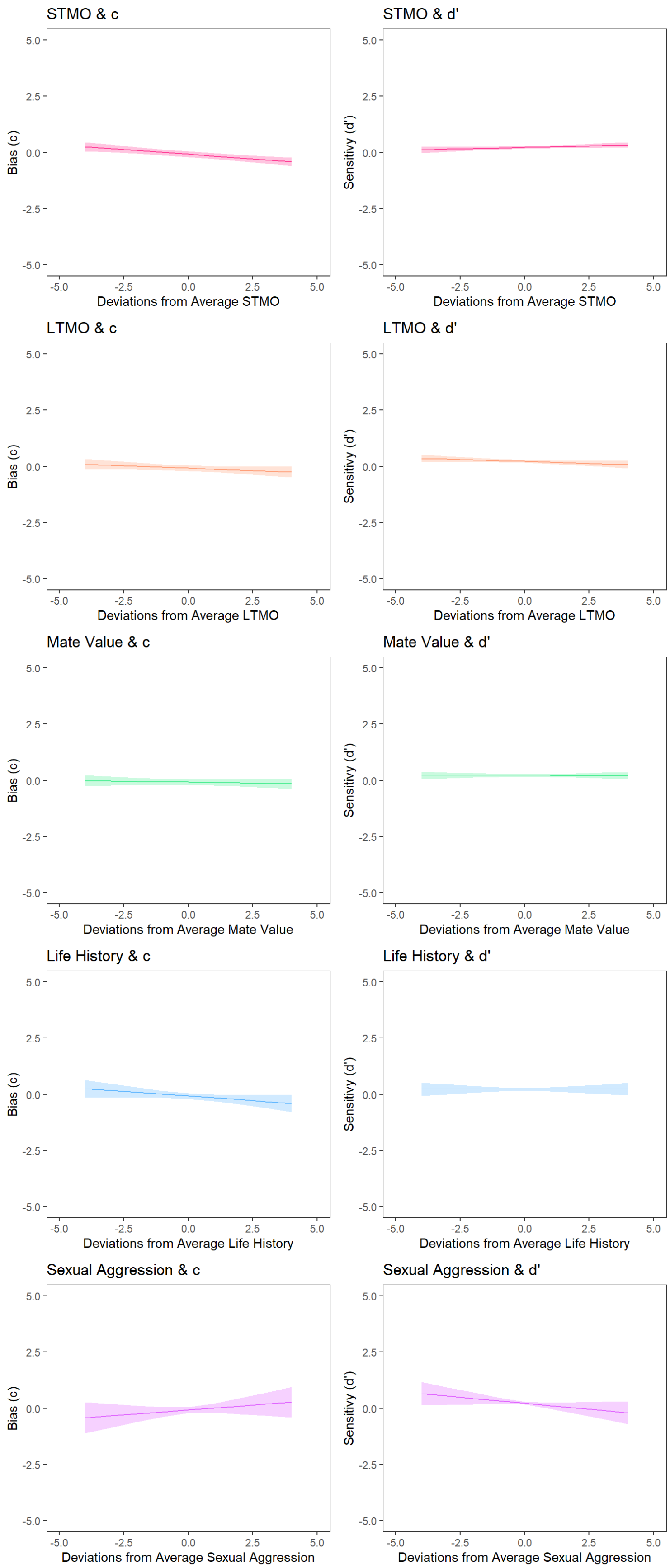
STMO & c
STMO & d'
Bias (c)
Sensitivy (d')
Deviations from Average STMO
LTMO & c
LTMO & d'
Deviations from Average LTMO
Mate Value & c
Mate Value & d'
Deviations from Average Mate Value
Life History & c
Life History & d'
Deviations from Average Life History
Sexual Aggression & c
Sexual Aggression & d'
Deviations from Average Sexual Aggression
5.0
2.5
0.0
-2.5
-5.0

Figure 22. Study 3 bias (*c*) and sensitivity (*d'*) for each mating-relevant trait. The first panel shows hypothesized relationship with STMO in red (higher values indicate more short-term orientation), the second panel shows hypothesized relationship with LTMO in orange (higher values indicate more long-term orientation), the third panel shows hypothesized relationship with Mate Value in green (higher values indicate greater mate value), the fourth panel shows hypothesized relationship with Life History in blue (higher values indicate slower life history strategies), and the fifth panel shows hypothesized relationship with Sexual Aggression in purple (higher values indicate higher sexual aggression). Negative *c* values indicate liberal yes-biases. Sensitivities (*d'*) closer to 0 indicate chance responding.

Discussion

Like in Study 1, participants had no bias, but unlike Studies 1 and 2, there was an effect of sensitivity. This suggests the opposite of Study 2; participants in Study 3 may be relying on sensitivity, not bias, to optimize responses. In particular, men appeared to be more sensitive to interest cues than women were, contradicting previous research (e.g., Farris, 2008). As in the previous studies, there was no evidence that men were overperceiving interest.

As expected, sex ratio condition did not affect biases alone, as the sex ratio effect is theoretically dependent on participant sex. However, there also was not a significant interaction between the sex ratio conditions and participant sex, contrary to the competing hypotheses. Disdvantaged men had a slightly liberal bias, whereas disadvantaged women had a neutral bias. Advantaged men had a slightly conservative bias, whereas advantaged women had a neutral bias. This provides slight support for the hypothesis that sex ratios alter decision outcomes, but in the case of this data, only for men.

This result is particularly interesting, as the sex ratio prime appeared to be effective, with most participants accurately reporting the sex ratio. However, sex ratio manipulations have not been strongly examined themselves, and thus it is unknown how strong a sex ratio needs to be to affect behavior, how many faces need to be viewed to affect behavior, or the longevity and strength of sex ratio manipulations may have on behavior. In fact, only a few research studies exist that have tested the limits and processing of sex ratio manipulations (e.g., Brandner et al., 2020; Brase & Brandner, in press). It is possible that the sex ratio manipulation in this study was not strong enough (either due to too few faces shown or too weak of sex ratios) or that the sex ratios were tracked but did not have the longevity to last throughout the study. Finally, it is possible that as participants were shown videos with equitable sex ratios, the sex ratio prime became less strong as the study went on, potentially limiting the effect. However, these potential reasons do not explain why the sex ratio effect seemed to work somewhat for male participants but not female participants.

As in the previous studies, mating-relevant individual differences minimally affected bias and sensitivity.

Study 4 – Training Sensitivity and Bias

Study 4 aimed to experimentally determine if sensitivity and bias can be trained in regard to the perception of sexual interest. SDT provides methods to alter sensitivity and bias, such as changing the consequences of the decision outcomes and training on whether a signal is present or absent (Green & Swets, 1966; Macmillan & Creelman, 2005). Specifically, sensitivity can be increased through training which offers feedback as it reduces the effort needed to process cues, and bias can be altered to be more liberal or more conservative by directly imposing penalties for specific incorrect responses or offering rewards for specific correct responses (e.g., Wickens et al., 2015). Exploring different interventions to increase sensitivity to sexual interest cues or alter bias helps show that SDT methods integrate with EMT methods, in addition to having real-world uses in reducing sexual assault.

Participants

Study 4 recruited 395 participants from Amazon Mechanical Turk through Cloud Research (Litman et al., 2017). Of these, 226 participants did not complete the study and 20 participants' work was rejected for failure of one or more attention checks, resulting in 149 participants who were paid $1 for successfully completing the study. Sample size was estimated at 150 participants but aimed to meet similar participant numbers as in Studies 1 -3. Data collection was stopped when close to this goal. Participation was only open to those who identified as men[1] (see data exclusion below) and limited to those located in the United Stated with at least 100 completed HITs and a 95% past approval rating. Participants were excluded from participating if they did not pass a captcha or an English competency test that requires a minimum of university level English understanding.

Participants' data were excluded from analysis if they did not accept payment for their participation (*n* = 2), if they identified as transgender (*n* = 2) or cisgender women (*n* = 5)[2], if their gender and sexual orientation did not match the gender they were sexually interested in (*n* = 6), if they self-identified as primarily same-sex attracted (*n* = 15), or if they indicated in the

[1] Initial plans for this study included both men and women participants. However, due to technical constraints on study coding in the feedback condition, it was determined that only heterosexual men would be the primary participant pool. This was done to ensure accurate feedback was given for each video in the Feedback and Combined conditions, based on the true target answers. Limiting gender and sexual orientation of the participants ensured that the feedback would only need to be generated for the female target.

[2] While participation was only open to men, this done by self-identification on a previous Cloud Research qualifying study. Therefore, those who previously identified as men and have since transitioned to women and those who did not correctly identify their gender (either in this study or in the data collected by Cloud Research) could still qualify for this study, resulting in gender-based exclusion criteria.

open-ended comments item that they had technical issues that prevented accurate participation (*n* = 1). This resulted in 118 total participants with an average age of 43 (*SD* = 12).

Measures and Procedure

After indicating informed consent and passing a captcha and English proficiency question, participants were instructed that they would see a series of 30-second videos and answer questions regarding the videos after each. They were informed that videos intentionally did not include sound and that they wouldn't be able to move to the next page until each video was finished. Then, they were presented with a pretest of 20 video clips[3] (as described above; 50% interested targets and 50% disinterested targets) and asked binary and scale measures of the female conversation partner's sexual interest. The binary measure asked, *"Is the woman in this clip sexually attracted to in the man in this clip?"* with response options of yes and no. The scale measure asked, *"How sexually attracted is this woman to this man?"* on a scale of 1 (Not sexually attracted at all) to 7 (Extremely sexual attracted).

Following this, participants was randomly assigned to one of four intervention conditions. Each intervention condition had the participant view 20 additional videos (with 50% interested targets and 50% disinterested targets) and answer binary perceptions of intent as before, but with different feedback or consequences:

1. **Control Condition:** Participants received no feedback or delays, and instead simply viewed videos and answered perceptions of interest

[3] Initial plans for this study included 25 videos in the pre- and posttests. However, due to some video quality issues, this was changed to 20 videos in both the pre- and posttests to ensure that videos were high quality, functional, and maintained a similar ratio of female interest/disinterest.

2. **Delay Condition**: Participants who indicated a false alarm (i.e., perceiving interest when the female conversation partner indicated no interest) received a 30 second delay before moving on to the next video, altering the immediate consequences of the decision outcomes, and therefore biases.
3. **Feedback Condition:** Participants answered and received feedback indicating they were correct or incorrect and whether the female conversation partner indicated interest or no interest, providing training on specific interest/disinterest cues, and therefore altering sensitivity.
4. **Combined Condition:** Participants experienced the consequences from both the delay and the feedback conditions, therefore altering both bias and sensitivity.

Following the intervention, participants were presented with a post-test of 20 video clips and asked binary and scale measures of the female conversation partner's sexual interest, as in the pretest. Individual differences measures were not included in this study as to reduce the time to completion for this study. Finally, participants answered demographic and attention check questions and were presented debriefing information. Figure 23 shows the Study 4 procedure.

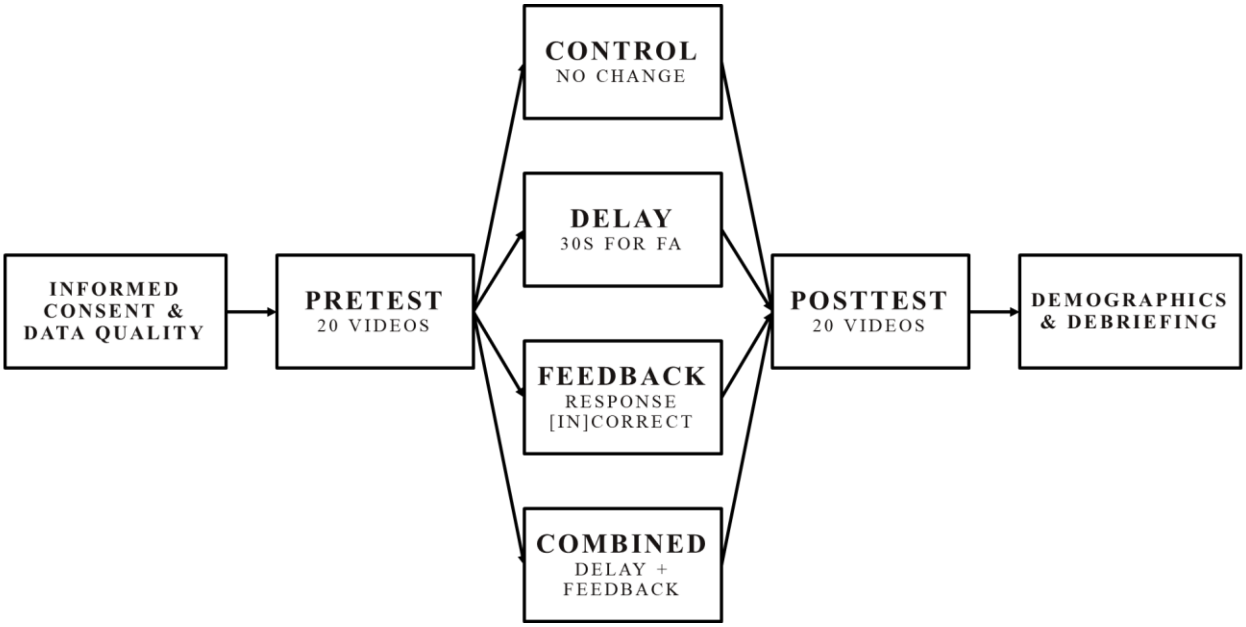

Figure 23. Study 4 procedure order.

Analyses

Results were analyzed using multilevel probit regression to determine *c*s and *d'*s for both pre- and post-tests. This model predicted participants' binary perceptions using the female binary sexual interest for each video, time of measurement (i.e., pre- or post-test), intervention condition, and the interaction of time of measurement × intervention condition as main effects. Additionally, interactions between each predictor/interaction and the binary sexual interest for each video were included to determine the effect of each individual difference on sensitivity. Bias was allowed to vary for each participant (sensitivity was not), and intercept was allowed to vary for each video. As in the previous studies, the random effect structure was determined through model comparison, and the random effect structure with the lowest AIC value was selected for analysis (see Appendix A for all model comparisons). Additional model specifications are available in the R code in Appendix B. Results were not analyzed using traditional EMT methods.

Hypotheses

a) Participants in the Control condition will have similar pre- and post-test sensitivities and biases and will have similar sensitivities and biases as the baseline established for their sex in Study 1 (Figure 24a).

b) Participants in the Delay condition will have a more conservative bias after the intervention and in comparison to the baseline established for their sex in Study 1 and the control condition (Figure 24b).

c) Participants in the Feedback condition will have a higher sensitivity after the intervention and in comparison to the baseline established for their sex in Study 1 and the control condition (Figure 24c).

d) Participants in the Combined condition will have a more conservative bias and a higher sensitivity after the intervention and in comparison to the baseline established for their sex in Study 1 and the control condition (Figure 24d).

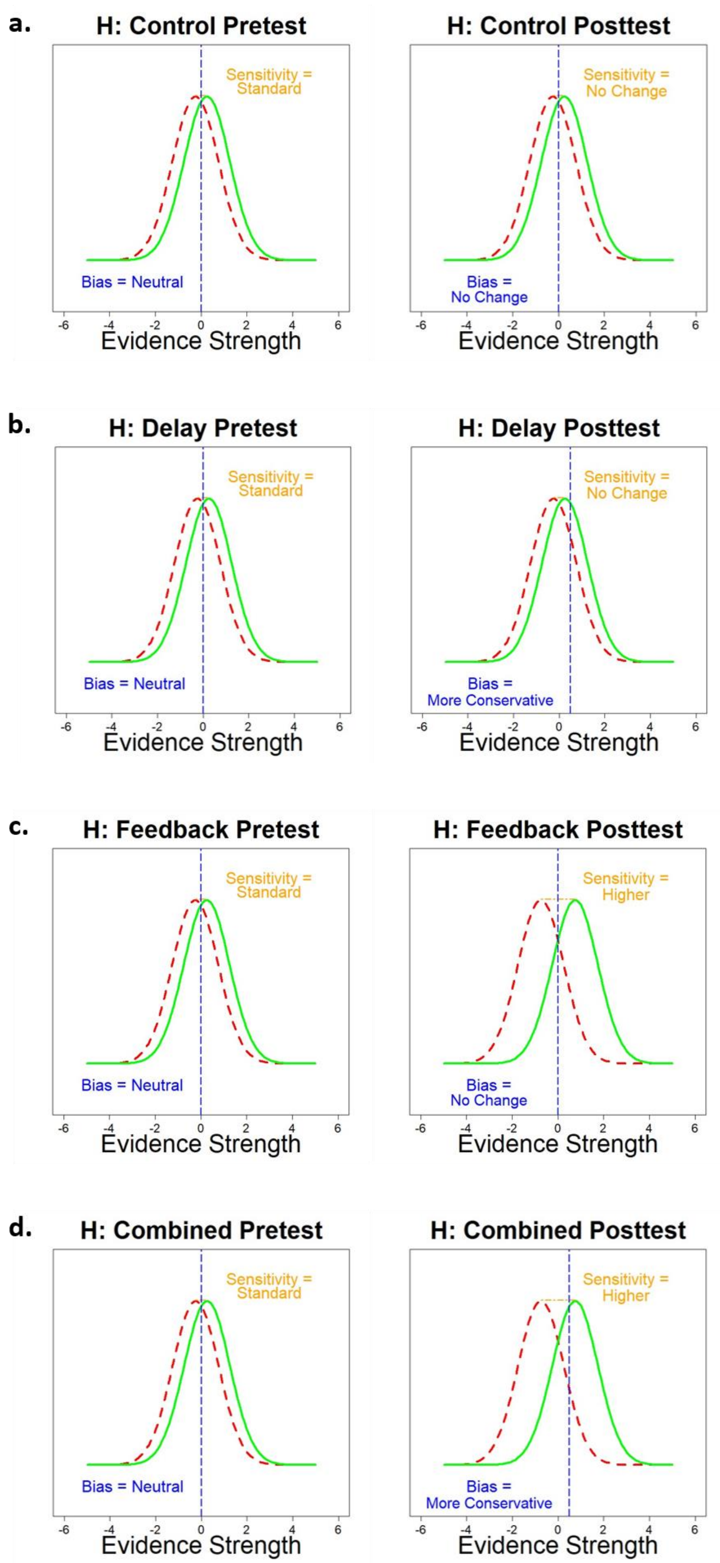

Figure 24. Hypothesized Study 4 bias (c) and sensitivity (d') for each intervention condition and time of measurement.

Results

The SDT analysis showed that overall, participants had no bias when responding to the videos (*c* = -0.02, *SE* = 0.12, *p* = .894) and participants were not significantly sensitive to the female conversation partner's sexual interest (*d'* = 0.23, *SE* = 0.21, *p* < .275). There was no main effect of time of measurement (X^2 (1, *N* = 118) = 0.79, *p* = .374) or condition (X^2 (3, *N* = 118) = 4.86, *p* = .183) on bias, suggesting that there was not a response bias difference overall between the pre- and posttests or between the intervention conditions. Similarly, there was no main effect of time of measurement (X^2 (1, *N* = 118) = 0.60, *p* = .439) or condition (X^2 (3, *N* = 118) = 0.21, *p* = .976) on sensitivity either.

The interaction between time of measurement and condition did not significantly affect bias (X^2 (3, *N* = 119) = 2.37, *p* = .500) or sensitivity (X^2 (2, *N* = 119) = 2.72, *p* = .437), contrary to hypotheses. Since this was a hypothesized interaction, biases and sensitivities were examined for each sex in each of the sex ratio conditions (see Table 9).

Table 9. Sensitivities and biases for each pre- and posttest based on the intervention condition they were assigned. Standard error for each estimate in parentheses. Negative biases indicate liberal "yes"-biases; positive biases indicate conservative "no"-biases.

Condition	Pretest	Posttest
Control		
Bias	0.01 (0.19)	0.23 (0.19)
Sensitivity	-0.01 (0.32)	0.42 (0.32)
Delay		

Bias	-0.03 (0.20)	0.22 (0.20)
Sensitivity	0.19 (0.32)	0.28 (0.32)
Feedback		
Bias	-0.18 (0.19)	-0.10 (0.19)
Sensitivity	0.07 (0.32)	0.43 (0.32)
Combined		
Bias	-0.25 (0.19)	-0.04 (0.19)
Sensitivity	0.02 (0.32)	0.46 (0.32)

While the time of measurement × condition interaction did not significantly affect bias or sensitivity, comparing the pre- and post-test scores for each condition reveals weak behavioral trends in the directions hypothesized (Figure 25). The Delay condition was expected to result in little change to sensitivity and a more conservative bias. Participants in this condition became slightly more sensitive and slightly more conservative (Figure 25b). The Feedback condition was expected to result in higher sensitivity and little change to bias. Participants in this condition became slightly more sensitive and had minimal change to bias (Figure 25c). The Combined condition was expected to result in higher sensitivity and more conservative biases. Participants in this condition became slightly more sensitive and slightly more conservative (Figure 25d). However, these were all hypothesized to be more than that seen in the control condition, which showed a slight increase in sensitivity and a slightly more conservative bias (Figure 25a). In fact, the change in sensitivity between the pre- and posttests was nearly the same for the Control, Feedback, and Combined conditions. Additionally, the change in bias was nearly the same for the Control, Delay, and Combined conditions.

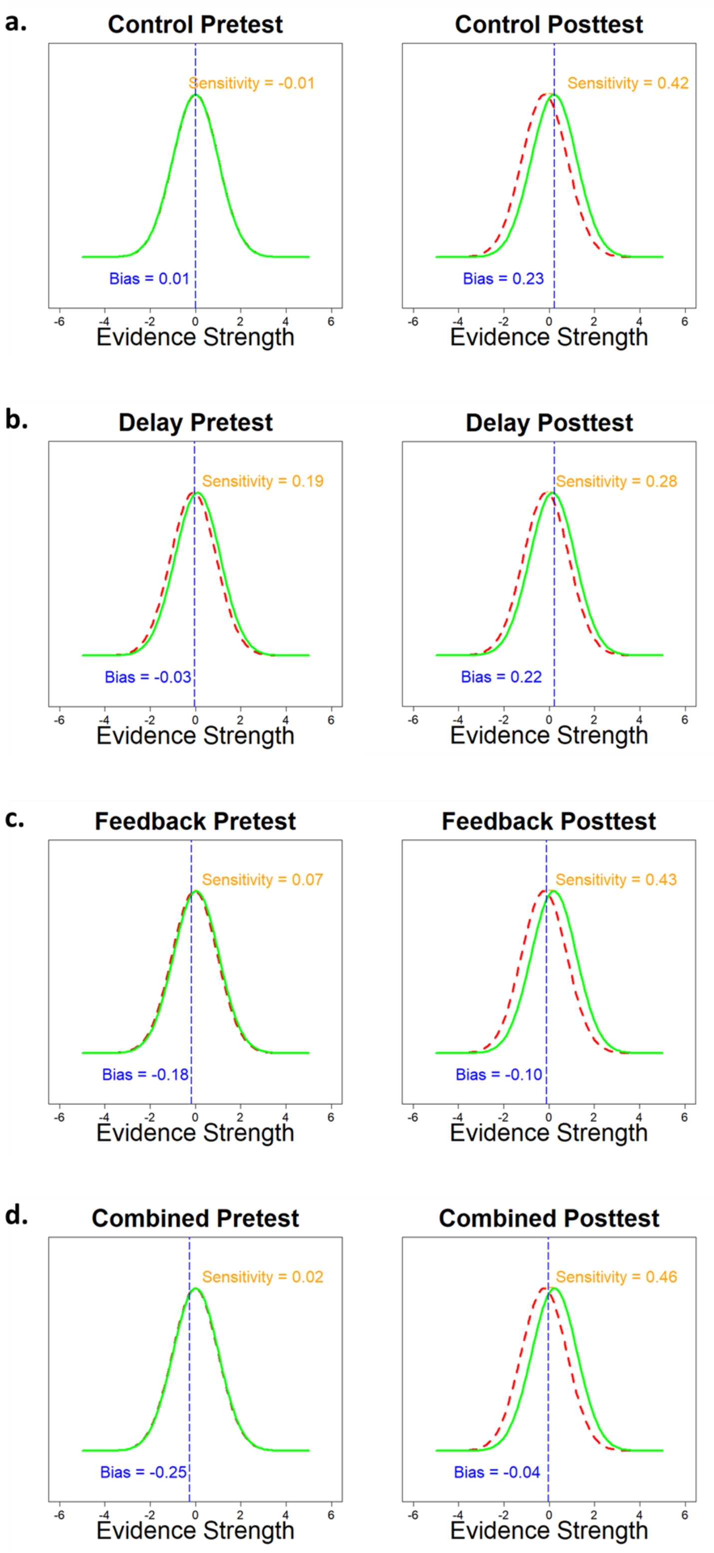

Figure 25. Study 4 bias (*c*) and sensitivity (*d′*) for each intervention condition and time of measurement.

Discussion

Like in Study 1, these results indicate that people may not be specifically relying on bias or sensitivity. As in the previous studies, there was no evidence that men were overperceiving interest compared to actual interest communicated. There was no effect of time of measurement or condition on bias or sensitivity, suggesting that pre- and post-tests were not different just due to time of measurement and that conditions were not different. Contrary to hypotheses, there was no significant interaction between pre-/posttest and conditions. However, there are weak trends in bias/sensitivity as hypothesized. Those in the Delay condition were expected to have a more conservative bias and there was a slight conservative shift. Those in the Feedback condition were expected to have a higher sensitivity and there was a slight increase in sensitivity. Those in the Combined condition were expected to become more conservative and more sensitive, and there were slight shifts in those predicted directions. However, the Control condition was expected to have no change, and instead, there was a more conservative bias and a higher sensitivity.

Interestingly, the Delay condition, instead of altering bias to be more conservative, seemed to dampen the increase in sensitivity shown in the Control condition. Similarly, the Feedback condition seemed to dampen the conservative change in bias shown in the Control condition. This indicates that these targeted changes may in fact be focusing effects where they were hypothesized to be focused (i.e., altering decision outcomes focuses change on bias and altering feedback focuses change on sensitivity), but that the manipulation may not have been strong enough to build on changes caused simply by the presence of any intervention.

Chapter 7 - General Discussion

Videos displaying an opposite sex dyad talking were used as stimuli to examine the male sexual overperception effect using Signal Detection Theory. Study 1 attempted to replicate the results of Brandner et al. (2021) using more ecologically realistic video stimuli which included more ambiguous signals, but failed to replicate sensitivity effects, suggesting that participants were not particularly sensitive or biased in their responses, regardless of sex. Study 2 directly altered signal/noise ratio, testing the flexibility of the cognitive mechanism by adjusting proximate influences on bias. Participants who saw more disinterested opposite-sex individuals did have a slightly conservative “no”-bias. However, participants who saw more interested opposite-sex individuals did not have a more liberal bias than in Study 1. Study 3 tested competing hypotheses about whether sex ratio manipulations alter bias via signal-to-noise ratio or decision outcomes. Results showed mild support for manipulated sex ratios altering decision outcomes, but only for male participants, whereas sex ratios did not appear to alter bias for female participants. Finally, Study 4 tested four interventions that aimed to manipulate bias and/or sensitivity. The pre-/posttest biases and sensitivities were not significantly different depending on the manipulation condition; however results did trend in the hypothesized directions. Manipulations seemed to focus changes on sensitivity and bias accordingly; however the interventions did not amplify effects, and instead dampened other effects compared to the control intervention. Across the studies, mating-relevant traits such as Mate Value, Short-Term Mating Orientation, Long-Term Mating Orientation, Life History Strategy, and Sexual Aggression showed minimal effects on sensitivity or bias. Additionally, across the studies, the traditional male sexual overperception bias was not found, suggesting that the male sexual overperception effect could be mitigated by recent cultural shifts or previous analytical methods could be flawed.

Implications

This research enhances theories and methodological approaches in Error Management Theory (EMT) research, Signal Detection Theory (SDT) research, and sexual overperception research by combining the strengths of all three to advance knowledge and understanding in the fields of Cognitive, Social, and Evolutionary Psychology. These studies build upon EMT using SDT analyses and hypothesis generation, SDT research is improved by adding ultimate causes of behavior to the already well-developed proximate causes of behaviors, and the strengths of each are combined to better understand sexual overperception, or the lack thereof.

Perhaps the most important implication of this research is the expansion of EMT using SDT. The benefits of SDT over EMT are numerous (Brandner et al., 2021). The video methodology used here expands on this synthesis by reducing the largest flaw in previous syntheses of EMT and SDT – a lack of a “true” answer to compare with. While the previous research estimated truth using consensus, the video methodology allows for a self-reported “truth” captured at the time of video creation, as close to the real truth of sexual interest communicated as possible (assuming truthful self-reporting of sexual interest, a caveat that is present in all research on sexual interest). The synthesis of EMT and SDT helps establish a superior way of evaluating sexual overperception that avoids the pitfalls of difference scores, and tests novel hypotheses that could not be generated by EMT alone. The precision and standardized metrics from SDT help compare studies across time, allowing for an accurate comparison between studies and topic areas. Additionally, this methodology can be used for research on other biases explained through EMT, such as commitment skepticism (Haselton &

Buss, 2000).

Additionally, this research increases knowledge about the abilities and biases different people have about sexual communication, allowing for more transparent dialogues about sexual interest and empowering individuals to make informed, healthy decisions about their sexual behavior. Identification of individuals and situations where sexual interest and intents are often misinterpreted can aid in locating populations at-risk of sexual harassment or assault and improve sexual assault prevention policies.

Limitations

Task Difficulty and Sample

Like all studies, the studies presented here have limitations. One of the largest limitations is regarding the video stimuli. While video stimuli are certainly more realistic than vignettes, which are commonly used in this research (e.g., Edmondson & Conger, 1995; Kowalski, 1993; Haselton & Buss, 2000; DeSouza et al., 1992; Abbey & Harnish, 1995; Fisher & Walters, 2003), it is unclear whether the videos communicated sexual interest/disinterest in a way that was perceptible by an observer, or if instead participants were inattentive. While previous literature on thin-slicing has shown that 30s is sufficient to judge expressive behaviors (Ambady & Rosenthal, 1992), it is unclear whether mating-relevant traits can be consciously thin-sliced (unlike major personality traits which can be determined from thin slices; e.g., Carney et al., 2007). These studies operated under the assumption that thin slices of attraction could still evoke different behaviors from an observer, as thinly sliced interactions have outcomes on attraction (e.g., Tidwell et al., 2012). However, the low sensitivities found in the studies suggest that participants were often guessing when responding. This could be due to a variety of potential reasons.

The first potential cause could be that this task is simply too difficult. Previous research shows that simplified tasks which eliminate some cues (i.e., photos or vignettes; Edmondson & Conger, 1995; Tomich & Schuster, 1996) result in higher rates of sexual overperception. Perhaps it is easier to judge fewer cues than more cues. This was somewhat mitigated by the muting of the video clips, which reduces the number of potential cues. However, it is also possible that the lack of audio could eliminate a number of non-verbal cues in tone, inflection, and speech patterns which could be signaling sexual interest or disinterest. In fact, several participants noted in the open-ended comments at the end of the survey that the task was very difficult and that they wished they could have heard audio to help them decide, for example, one participant stated, *"It was difficult to determine whether or not an individual was flirting based on the positioning and lack of audio. In a normal scenario, such as at a bar or store, it would be far easier to observe and judge whether the interaction was flirting or not."* Another participant commented, *"If there was sound to the many videos, the attraction (or not) between the young men and women would have been more obvious."* Future studies may need to incorporate longer clips and potentially reintroduce audio recordings to allow for a more comprehensive evaluation of sexual interest. Alternatively, future research could include videos recorded as if the target was communicating with the observer (camera focused on the target's face rather than wide angle shots capturing both conversation partners) to attempt to clarify the cues.

Another possibility is that people are simply not good at perceiving interest as stimuli become more realistic. While perceptions of interest carry great importance for reproductive success and thus genetic fitness, it is possible that sexual communication itself could have evolved to be ambiguous and difficult to detect. This is particularly true for female sexual communication, who may have benefitted from the concealment of sexual interest as they evaluate potential mates (e.g., Trivers, 1972). This intrasexual difference in reproductive goals could have resulted in an ill-tuned cognitive mechanism, like that of (somewhat) concealed ovulation in women (e.g., Burley, 1979; Strassman, 1981; c.f. Haselton & Gildersleeve, 2016; Krems et al., 2021). As before, some participants commented on the difficulty of the study. One participant in Study 4 (with interventions) stated, *"What are the rules! Just when I thought I had figured out what the signals were to show sexual interest...you proved me wrong. Again and again. I don't think I did very well."* Other participants commented that they had expected more overt cues, writing, *"I would expect more dramatization and posturing when pursuing a romantic partner. Fluttering of the eyelashes, flip of the hair, puckering of the lips."* Unfortunately, if the task is truly difficult due to evolutionary pressures, it may not be possible to change the methodology to make it less demanding, and instead future research could focus on improving participant performance through interventions, like those in Study 4, but perhaps stronger with greater consequences or feedback.

Of course, another possible reason for poor performance is that the studies were conducted using online samples during the COVID-19 pandemic. While mTurk samples have been previously shown to have more attentive participants than undergraduate subject pool participants (Hauser & Schwarz, 2016), they also tend to be WEIRD samples (Henrich et al., 2010a, b) which reduce generalizability. Additionally, non-WEIRD samples may have not been as affected by recent cultural shifts in WEIRD cultures, such as the #MeToo movement. Recent research regarding mTurk and COVID-19 found that current mTurkers are less attentive than pre-pandemic samples, likely explained by new mTurkers joining due to job market issues related to COVID-19 (Arechar & Rand, 2021). Additionally, researchers have found evidence of a "quality crisis" with recent mTurk research (Kennedy et al., 2020). It is important to consider the conflicting goals between researchers and mTurkers; while researchers want high quality data, mTurkers are looking to make money. The more jobs they take, the more money they make, and therefore, mTurkers are unintentionally incentivized to spend as little attention and time on each job as possible.

This was demonstrated numerous times in the open-ended comments where several mTurkers described the survey as being too long. This might result in mTurkers "tabbing out" during videos to do other tasks while the timer runs, reducing attention. This effect could be driving the extremely low sensitivity. Future research will need to include additional data collection, ideally in in-person lab settings to limit distractions and reduce incentivization present on mTurk. Additionally, replication in cross-cultural studies will be necessary to determine if the findings from these studies go beyond WEIRD samples to describe human behavior more broadly.

Similarly, the temporal period in which the research was conducted could affect the task difficulty. This data is collected post-#MeToo movement, a cultural event that has focused national attention on sexual assault. This could influence participants to underestimate sexual interest, especially on behalf of women. For example, one participant wrote, *"Hard to tell between simple kindness and flirting. Especially today where it is all too easy for men to be looked at as sexual harrasers[sic]."* If this is the case, the proximate negative consequences of an overperception may be weighted more heavily than the ultimate evolutionary fitness consequences.

However, other participants noted that they were using other heuristics when judging interest, and specifically ones that would result in overperception of interest, such as one participant who stated, *"I have observed a lot in my life and I can honestly say from what I have* *seen in these 66 years on earth is that a man is always interested in sex. They talk sex amongst each other and they are experts on sexual innuendo. Just my two cents."* Other participants stated that the age range of the targets was similarly influential on their answers, for example, *"most ppl [sic] in 20's want to have sex"*. The quantity of comments indicating a heuristic of overestimating interest was higher than those who indicated a heuristic of underestimating interest, suggesting that they knew they were overperceiving interest in these cases.

Other Causes of Sexual Overperception

Additionally, these studies do not address other theories of what causes sexual overperception. Since these studies do not find any evidence of sexual overperception, they cannot evaluate other theories of why the effect exists. These theories include the general oversexualization hypothesis (Abbey, 1982; 1991) which states that men are more sexual and therefore overperceive sex in all domains, the media hypothesis (Abbey, 1991) which states that media creates sexual scripts of women resisting advances while the man pursues, resulting in men perceiving disinterest as interest, and the default-model hypotheses (Shotland & Craig, 1998), which states that men feel more desire than women and project that desire onto women they are interested in. If anything, the results found in these studies provide evidence against these theories (and EMT) due to the lack of evidence for sexual overperception as a whole.

Moreover, within EMT, this study cannot address whether sensitivity and bias are driven by behaviors or cognitions. Discussion in sexual overperception research has previously centered on whether overperception is caused by an actual belief that others are interested in them, despite reality, or if people simply behave in this way strategically and consciously ignore reality (e.g., McKay & Efferson, 2010; Perilloux & Kurzban, 2015; Murray et al., 2017; Perilloux &

Kurzban, 2017; Engeler & Raghubir, 2018). These studies are not able to address whether bias and sensitivity are affected by true beliefs or strategic choices instead. Future research may be able to help address this however, using these stimuli; for example, priming participants with intrasexual competition motivations may increase strategic decision-making which will help determine if individuals can strategically adopt different biases and sensitivities based on context.

Future Directions

As previously discussed, the methodology used here is extremely beneficial to the creation of future studies. Most impactful will be its use on other EMT-studied topics. EMT has been used to study a variety of social biases. The video stimuli developed here can be used on areas of communication biases to ensure that SDT analyses can be based on real "truth" of communication. For example, future research on commitment skepticism (Haselton & Buss, 2000) could use similarly generated videos, except using couples/non-couples rather than people who are or are not sexually interested in each other. Additional variations could be used, for example including camera angles where the target individuals are truly communicating with someone they are attracted to, but made to look like they are communicating with the participants (i.e., facing the camera instead of a wide-angle shot).

Another benefit of the video stimuli is the additional individual differences data collected. Many studies in sexual overperception have focused on target characteristics, for example, examining how target attractiveness might affect overperception (Perilloux, et al., 2012; Levesque et al., 2006). Other individual differences might also affect overperception, such as extraversion, sexual narcissism, or other traits. For this reason, a variety of personality and individual differences measures were included in the creation of these videos (see Video Creation for more information about which individual difference scales were included). At the time of these studies, there were not enough videos to allow for the analysis of these individual differences (as collection was stopped due to the COVID-19 pandemic and the need to social distance/wear masks), but future video collection will ensure a wide range of individual differences which can be used as predictors to see if target characteristics influence sensitivity or bias. Identifying which individuals are more or less likely to be understood correctly will assist in developing more specific interventions to help address sexual assault.

Finally, future research should include individuals of all genders and sexual orientations. Due to coding restrictions, LGBT+ participants were excluded from data analysis. Much research on evolutionary psychology topics is based in heteronormative processes of attraction, mate selection, retention, and relationships. The exclusion of LGBT+ participants limits the conclusions that can be made about human nature – if a population is purposefully excluded, it is not being accurately described. Future research should aim to include LGBT+ targets in the video stimuli as well as LGBT+ participants. Sexual orientation may have theoretical reasons to alter sensitivity and bias to cues, for example, a male-heavy sex ratio both increases the pool of potential mates and the pool of potential competitors if the participant is a gay man. Sexual orientation may similarly interact with other manipulations; for example, if individuals are first judging a potential partner to determine their sexual orientation (sometimes called "gaydar"; e.g., Rieger et al., 2010), then judging the potential partner's attractiveness, sexual over- or under-perception is dependent on the expression of sexual orientation for LGBT+ populations. These facets should be explored in future research, especially as it relates to sexual assault, as the percentage of gender minorities who are sexually assaulted is similar to that of women (23% of transgender, genderqueer, or nonbinary students; Cantor et al., 2019).

Conclusions

This set of studies uses strong methods and analyses, but find no evidence of the male sexual overperception effect. Moreover, mating-relevant individual differences do not appear to affect bias or sensitivity. There was weak evidence that adjusting base rate of signal-to-noise and sex ratio primes may affect bias for some populations. Finally, interventions developed using Signal Detection Theory did not significantly change bias or sensitivity, but did trend in hypothesized directions, suggesting that stronger manipulations may affect bias and sensitivity. These projects may imply that the male sexual overperception effect is not a stable effect and proximate causes of behavior such as cultural norms may be more influential than ultimate causes of behavior such as evolved biases. Alternatively, previous methods and analyses could be flawed, generating false positives. However, these conclusions are tempered by the limitations presented here, which necessitate replication, perhaps using in-person laboratory conditions instead of online environments.

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Appendix A - Model Comparisons

Study 1

Random effects structures were determined partially by empirical means and partially by theoretical means. Specifically, it was expected that there would be a random effect of sensitivity and bias for each participant and a random effect of bias for each video. However, alterations to the predicted random effects structures were tested empirically in case a pared down model was necessary to fit the data.

Table 10. AIC values for different random effects structures tested in Study 1. The random effects structure with the lowest AIC value was chosen for the analysis model and is bolded below.

Random Effects Structure	AIC
1. Random effect of bias for each participant	6399.61
2. Random effect of sensitivity for each participant	Singular Fit
3. Random effect of bias and sensitivity for each participant	Singular Fit
4. Random effect of bias for each participant and random effect of bias for each video	**5222.79**
5. Random effect of sensitivity for each participant and random effect of bias for each video	Singular Fit
6. Random effect of bias and sensitivity for each participant and random effect of bias for each video	Singular Fit

Study 2

Random effects structures were determined partially by empirical means and partially by theoretical means. Specifically, it was expected that there would be a random effect of sensitivity and bias for each participant and a random effect of bias for each video. However, alterations to the predicted random effects structures were tested empirically in case a pared down model was necessary to fit the data.

Table 11. AIC values for different random effects structures tested in Study 2. The random effects structure with the lowest AIC value was chosen for the analysis model and is bolded below.

Random Effects Structure	AIC
1. Random effect of bias for each participant	6433.29
2. Random effect of sensitivity for each participant	6847.63
3. Random effect of bias and sensitivity for each participant	6434.54
4. Random effect of bias for each participant and random effect of bias for each video	**5539.18**
5. Random effect of sensitivity for each participant and random effect of bias for each video	6117.97
6. Random effect of bias and sensitivity for each participant and random effect of bias for each video	Singular Fit

Study 3

Random effects structures were determined partially by empirical means and partially by theoretical means. Specifically, it was expected that there would be a random effect of sensitivity and bias for each participant and a random effect of bias for each video. However, alterations to the predicted random effects structures were tested empirically in case a pared down model was necessary to fit the data.

Table 12. AIC values for different random effects structures tested in Study 3. The random effects structure with the lowest AIC value was chosen for the analysis model and is bolded below.

Random Effects Structure	AIC
1. Random effect of bias for each participant	6283.34
2. Random effect of sensitivity for each participant	6556.28
3. Random effect of bias and sensitivity for each participant	6251.73
4. Random effect of bias for each participant and random effect of bias for each video	**5381.73**
5. Random effect of sensitivity for each participant and random effect of bias for each video	5805.84
6. Random effect of bias and sensitivity for each participant and random effect of bias for each video	5384.48

Study 4

Random effects structures were determined partially by empirical means and partially by theoretical means. Specifically, it was expected that there would be a random effect of sensitivity and bias for each participant and a random effect of bias for each video. However, alterations to the predicted random effects structures were tested empirically in case a pared down model was necessary to fit the data.

Table 13. AIC values for different random effects structures tested in Study 4. The random effects structure with the lowest AIC value was chosen for the analysis model and is bolded below.

Random Effects Structure	AIC
1. Random effect of bias for each participant	6218.70
2. Random effect of sensitivity for each participant	Singular Fit
3. Random effect of bias and sensitivity for each participant	Singular Fit
4. Random effect of bias for each participant and random effect of bias for each video	**5326.23**
5. Random effect of sensitivity for each participant and random effect of bias for each video	Singular Fit
6. Random effect of bias and sensitivity for each participant and random effect of bias for each video	Singular Fit

Appendix B - R-Code

```
library(readxl)
library(lme4)
library(ggplot2)
library(ggpubr)
library(lsr)
library(nlme)
library(psych)
library(emmeans)
library(car)
library(gridExtra)
library(multcomp)
library(lmerTest)
library(effects)
library(tidyr)
library(dplyr)



# STUDY 1 *********************************************************

dat1 <- read_excel("Study 1 SDT Data for R.xlsx")
View(dat1)
summary(dat1)
describe(dat1)

dat1$Truth<- dat1$`TrueFInterest (-.5=N)`
dat1$Answer<- dat1$Answer
dat1$Sex<-as.factor(dat1$Sex)
dat1$Sex<- C(dat1$Sex, sum) #sets to effect coding rather than dummy coding
print(attributes(dat1$Sex))
dat1$Video <- dat1$Video
dat1$Participant <- dat1$`P#`
dat1$c.MV<-scale(dat1$MV, scale=FALSE)
dat1$c.STMO<-scale(dat1$STMO, scale=FALSE)
dat1$c.LTMO<-scale(dat1$LTMO, scale=FALSE)
dat1$c.K<-scale(dat1$K, scale=FALSE)
dat1$c.SexAgg<-scale(dat1$SexAggro, scale=FALSE)

summary(dat1)
```

```
mod1.1<-glmer(Answer~  +(1|`Participant`), data= dat1, family=binomial(link="probit"),control
= glmerControl(optimizer = "bobyqa"))

mod1.2<-glmer(Answer~  +(Truth-1|`Participant`), data= dat1,
family=binomial(link="probit"),control = glmerControl(optimizer = "bobyqa")) #Singular Fit

mod1.3<-glmer(Answer~  +(Truth|`Participant`), data= dat1,
family=binomial(link="probit"),control = glmerControl(optimizer = "bobyqa")) #Singular Fit

mod1.4<-glmer(Answer~  +(1|`Participant`)+(1|Video), data= dat1,
family=binomial(link="probit"),control = glmerControl(optimizer = "bobyqa"))

mod1.5<-glmer(Answer~  +(Truth-1|`Participant`)+(1|Video), data= dat1,
family=binomial(link="probit"),control = glmerControl(optimizer = "bobyqa")) #Singular Fit

mod1.6<-glmer(Answer~  +(Truth|`Participant`)+(1|Video), data= dat1,
family=binomial(link="probit"),control = glmerControl(optimizer = "bobyqa")) #Singular Fit


AIC(mod1.1, mod1.4)
#1.4 without sensitivities is the best random effects structure


SDT1<-glmer(Answer~Truth*Sex +Truth*c.STMO +Truth*c.LTMO +Truth*c.MV +Truth*c.K
+Truth*c.SexAgg +(1|`Participant`)+(1|Video), data= dat1,
family=binomial(link="probit"),control = glmerControl(optimizer = "bobyqa", optCtrl =
list(maxfun=2e5)))
summary(SDT1)
emmeans(SDT1, ~Sex, at=list(Truth=0)) #this gives us -c
emtrends(SDT1, ~Sex, var="Truth")  #this gives us d'

vif(SDT1)
hist(resid(SDT1),main=" ")


emt1 <- read_excel("study 1 EMT Data for R.xlsx")
View(emt1)
summary(emt1)
describe(emt1)

emt1$Sex<-as.factor(emt1$Sex)
emt1$Sex<- C(emt1$Sex, sum) #sets to effect coding rather than dummy coding
print(attributes(emt1$Sex))
emt1$c.MV<-scale(emt1$MV, scale=FALSE)
emt1$c.STMO<-scale(emt1$STMO, scale=FALSE)
emt1$c.LTMO<-scale(emt1$LTMO, scale=FALSE)
```

```
emt1$c.K<-scale(emt1$K, scale=FALSE)
emt1$c.SexAgg<-scale(emt1$SexAggro, scale=FALSE)
summary(emt1)


EMTs1<-lm(AveMisper~Sex +c.MV +c.STMO +c.LTMO +c.K +c.SexAgg, data=emt1)
summary(EMTs1)
hist(resid(EMTs1))
vif(EMTs1)

emmeans(EMTs1, ~Sex) #gives model estimated misperceptions by sex

sextest1<-t.test(emt1$AveMisper ~ emt1$Sex, alternative="two.sided")
sextest1


Scales1 <- read_excel("Study 1 Scales.xlsx")

MV1 <- select(Scales1, 2:5)
STMO1 <- select(Scales1, 6:15)
LTMO1 <- select(Scales1, 16:22)
Self1 <- select(Scales1, 23:28)
GenAlt1 <- select(Scales1, 29:34)
Religion1 <- select(Scales1, 35:40)
Partner1 <- select(Scales1, 41:46)
Parents1 <- select(Scales1, 47:52)
Family1 <- select(Scales1, 53:58)
Friends1 <- select(Scales1, 59:64)
SA1 <- select(Scales1, 65:66)


View(MV1)
View(STMO1)
View(LTMO1)
View(Self1)
View(GenAlt1)
View(Religion1)
View(Partner1)
View(Parents1)
View(Family1)
View(Friends1)
View(SA1)

alpha(STMO1)
alpha(LTMO1)
alpha(MV1)
```

```
alpha(Self1)
alpha(GenAlt1)
alpha(Religion1)
alpha(Partner1)
alpha(Parents1)
alpha(Family1)
alpha(Friends1)
alpha(SA1)


# STUDY 2 Skewed Signal to Noise Ratios
********************************************************

dat2 <- read_excel("Study 2 SDT for R.xlsx")
View(dat2)
summary(dat2)
describe(dat2)

dat2$Truth<- dat2$`TrueInterest (-.5=N)`
dat2$Answer<- dat2$Answer
dat2$ORDER<- log(dat2$ORDER)
dat2$Sex<-as.factor(dat2$Sex)
dat2$Sex<- C(dat2$Sex, sum) #sets to effect coding rather than dummy coding
print(attributes(dat2$Sex))
dat2$Condition<-as.factor(dat2$Condition)
dat2$Condition<- C(dat2$Condition, sum) #sets to effect coding rather than dummy coding
print(attributes(dat2$Condition))
dat2$Video <- dat2$Videocode
dat2$Participant <- dat2$`P#`
dat2$c.MV<-scale(dat2$MV, scale=FALSE)
dat2$c.STMO<-scale(dat2$STMO, scale=FALSE)
dat2$c.LTMO<-scale(dat2$LTMO, scale=FALSE)
dat2$c.K<-scale(dat2$K, scale=FALSE)
dat2$c.SexAgg<-scale(dat2$SA, scale=FALSE)

summary(dat2)

mod2.1<-glmer(Answer~  +(1|`Participant`), data= dat2, family=binomial(link="probit"),control
= glmerControl(optimizer = "bobyqa"))

mod2.2<-glmer(Answer~  +(Truth-1|`Participant`), data= dat2,
family=binomial(link="probit"),control = glmerControl(optimizer = "bobyqa"))

mod2.3<-glmer(Answer~  +(Truth|`Participant`), data= dat2,
family=binomial(link="probit"),control = glmerControl(optimizer = "bobyqa"))
```

```
mod2.4<-glmer(Answer~  +(1|`Participant`)+(1|Video), data= dat2,
family=binomial(link="probit"),control = glmerControl(optimizer = "bobyqa"))

mod2.5<-glmer(Answer~  +(Truth-1|`Participant`)+(1|Video), data= dat2,
family=binomial(link="probit"),control = glmerControl(optimizer = "bobyqa"))

mod2.6<-glmer(Answer~  +(Truth|`Participant`)+(1|Video), data= dat2,
family=binomial(link="probit"),control = glmerControl(optimizer = "bobyqa")) #singular


AIC(mod2.1, mod2.2, mod2.3, mod2.4, mod2.5)
#2.4 without sensitivities is the best random effects structure


SDT2<-glmer(Answer~Truth*Sex +Truth*c.STMO +Truth*c.LTMO +Truth*c.MV +Truth*c.K
+Truth*c.SexAgg +Truth*Condition +Truth*ORDER +Truth*Condition*ORDER
+(1|`Participant`)+(1|Video), data= dat2, family=binomial(link="probit"),control =
glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun=2e5)))
summary(SDT2)
Anova(SDT2, type=3) #correct one

marg2<-emmeans(SDT2, list(pairwise ~ Condition), adjust = "none",pbkrtest.limit = 4000,
lmerTest.limit=4000) # none = Fisher's LSD
marg2

emmeans(SDT2, ~Sex, at=list(Truth=0)) #this gives us -c for sex
emtrends(SDT2, ~Sex, var="Truth")  #this gives us d' for sex
emmeans(SDT2, ~Condition, at=list(Truth=0)) #this gives us -c for condition
emtrends(SDT2, ~Condition, var="Truth")  #this gives us d' for condition

emtrends(SDT2, ~Condition, var="ORDER") #-c for order changes per condition

# sensitivity order condition
emtrends(SDT2, ~Condition|ORDER, var="Truth", at=list(ORDER=c(10,20,30,40)))


vif(SDT2)
#hist(resid(SDT2),main=" ")


Scales2 <- read_excel("Study 2 Scales.xlsx")

MV2 <- select(Scales2, 2:5)
STMO2 <- select(Scales2, 6:15)
LTMO2 <- select(Scales2, 16:22)
Self2 <- select(Scales2, 23:28)
```

```
GenAlt2 <- select(Scales2, 29:34)
Religion2 <- select(Scales2, 35:40)
Partner2 <- select(Scales2, 41:46)
Parents2 <- select(Scales2, 47:52)
Family2 <- select(Scales2, 53:58)
Friends2 <- select(Scales2, 59:64)
SA2 <- select(Scales2, 65:66)


View(MV2)
View(STMO2)
View(LTMO2)
View(Self2)
View(GenAlt2)
View(Religion2)
View(Partner2)
View(Parents2)
View(Family2)
View(Friends2)
View(SA2)


alpha(STMO2)
alpha(LTMO2)
alpha(MV2)
alpha(Self2)
alpha(GenAlt2)
alpha(Religion2)
alpha(Partner2)
alpha(Parents2)
alpha(Family2)
alpha(Friends2)
alpha(SA2)



# STUDY 3 Skewed Sex Ratios
*********************************************************

dat3 <- read_excel("Study 3 SDT for R.xlsx")
View(dat3)
summary(dat3)
describe(dat3)


dat3$Truth<- dat3$`TrueInterest (-.5=N)`
```

```
dat3$Answer<- dat3$Answer
dat3$ORDER<- log(dat3$ORDER)
dat3$Sex<-as.factor(dat3$Sex)
dat3$Sex<- C(dat3$Sex, sum) #sets to effect coding rather than dummy coding
print(attributes(dat3$Sex))
dat3$Condition<-as.factor(dat3$Condition)
dat3$Condition<- C(dat3$Condition, sum) #sets to effect coding rather than dummy coding
print(attributes(dat3$Condition))
dat3$Video <- dat3$Video
dat3$Participant <- dat3$`P#`
dat3$c.MV<-scale(dat3$MV, scale=FALSE)
dat3$c.STMO<-scale(dat3$STMO, scale=FALSE)
dat3$c.LTMO<-scale(dat3$LTMO, scale=FALSE)
dat3$c.K<-scale(dat3$K, scale=FALSE)
dat3$c.SexAgg<-scale(dat3$SA, scale=FALSE)

summary(dat3)

mod3.1<-glmer(Answer~  +(1|`Participant`), data= dat3, family=binomial(link="probit"),control
= glmerControl(optimizer = "bobyqa"))

mod3.2<-glmer(Answer~  +(Truth-1|`Participant`), data= dat3,
family=binomial(link="probit"),control = glmerControl(optimizer = "bobyqa"))

mod3.3<-glmer(Answer~  +(Truth|`Participant`), data= dat3,
family=binomial(link="probit"),control = glmerControl(optimizer = "bobyqa"))

mod3.4<-glmer(Answer~  +(1|`Participant`)+(1|Video), data= dat3,
family=binomial(link="probit"),control = glmerControl(optimizer = "bobyqa"))

mod3.5<-glmer(Answer~  +(Truth-1|`Participant`)+(1|Video), data= dat3,
family=binomial(link="probit"),control = glmerControl(optimizer = "bobyqa"))

mod3.6<-glmer(Answer~  +(Truth|`Participant`)+(1|Video), data= dat3,
family=binomial(link="probit"),control = glmerControl(optimizer = "bobyqa"))


AIC(mod3.1, mod3.2, mod3.3, mod3.4, mod3.5, mod3.6)
#3.4 without sensitivities is the best random effects structure


SDT3<-glmer(Answer~Truth*Condition*Sex +Truth*c.STMO +Truth*c.LTMO +Truth*c.MV
+Truth*c.K +Truth*c.SexAgg  +(1|`Participant`)+(1|Video), data= dat3,
family=binomial(link="probit"),control = glmerControl(optimizer = "bobyqa", optCtrl =
list(maxfun=2e5)))
summary(SDT3)
```

```
Anova(SDT3, type=3)


emmeans(SDT3, ~Sex, at=list(Truth=0)) #this gives us -c
emtrends(SDT3, ~Sex, var="Truth")  #this gives us d'
emmeans(SDT3, ~Condition, at=list(Truth=0)) #this gives us -c
emtrends(SDT3, ~Condition, var="Truth")  #this gives us d'

emmeans(SDT3, ~Sex|Condition, at=list(Truth=0))
emtrends(SDT3, ~Sex|Condition, var="Truth")


vif(SDT3)
hist(resid(SDT3),main=" ")


Scales3 <- read_excel("Study 3 Scales.xlsx")

MV3 <- select(Scales3, 2:5)
STMO3 <- select(Scales3, 6:15)
LTMO3 <- select(Scales3, 16:22)
Self3 <- select(Scales3, 23:28)
GenAlt3 <- select(Scales3, 29:34)
Religion3 <- select(Scales3, 35:40)
Partner3 <- select(Scales3, 41:46)
Parents3 <- select(Scales3, 47:52)
Family3 <- select(Scales3, 53:58)
Friends3 <- select(Scales3, 59:64)
SA3 <- select(Scales3, 65:66)

View(MV3)
View(STMO3)
View(LTMO3)
View(Self3)
View(GenAlt3)
View(Religion3)
View(Partner3)
View(Parents3)
View(Family3)
View(Friends3)
View(SA3)

alpha(STMO3)
alpha(LTMO3)
alpha(MV3)
alpha(Self3)
```

```
alpha(GenAlt3)
alpha(Religion3)
alpha(Partner3)
alpha(Parents3)
alpha(Family3)
alpha(Friends3)
alpha(SA3)


# STUDY 4 Intervention
***********************************************************

dat4 <- read_excel("Study 4 SDT for R.xlsx")
View(dat4)
summary(dat4)
describe(dat4)


dat4$Truth<- dat4$`TrueInterest (-.5=N)`
dat4$Answer<- dat4$Answer
dat4$Condition<-as.factor(dat4$`Training Condition`)
dat4$Condition<- C(dat4$Condition, sum) #sets to effect coding rather than dummy coding
dat4$PreOrPost<-as.factor(dat4$PrePost)
dat4$PreOrPost<- C(dat4$PreOrPost, sum) #sets to effect coding rather than dummy coding
print(attributes(dat4$PreOrPost))
dat4$Video <- dat4$Video
dat4$Participant <- dat4$`P#`

summary(dat4)

mod4.1<-glmer(Answer~  +(1|`Participant`), data= dat4, family=binomial(link="probit"),control
= glmerControl(optimizer = "bobyqa"))

mod4.2<-glmer(Answer~  +(Truth-1|`Participant`), data= dat4,
family=binomial(link="probit"),control = glmerControl(optimizer = "bobyqa")) #Singular Fit

mod4.3<-glmer(Answer~  +(Truth|`Participant`), data= dat4,
family=binomial(link="probit"),control = glmerControl(optimizer = "bobyqa")) #Singular Fit

mod4.4<-glmer(Answer~  +(1|`Participant`)+(1|Video), data= dat4,
family=binomial(link="probit"),control = glmerControl(optimizer = "bobyqa"))

mod4.5<-glmer(Answer~  +(Truth-1|`Participant`)+(1|Video), data= dat4,
family=binomial(link="probit"),control = glmerControl(optimizer = "bobyqa")) #Singular Fit
```

```
mod4.6<-glmer(Answer~  +(Truth|`Participant`)+(1|Video), data= dat4,
family=binomial(link="probit"),control = glmerControl(optimizer = "bobyqa")) #Singular Fit


AIC(mod4.1, mod4.4)
#4.4 without sensitivities is the best random effects structure


SDT4<-glmer(Answer~ Truth*PreOrPost*Condition  +(1|`Participant`)+(1|Video), data= dat4,
family=binomial(link="probit"),control = glmerControl(optimizer = "bobyqa", optCtrl =
list(maxfun=2e5)))
summary(SDT4)
Anova(SDT4, type=3)

emmeans(SDT4, ~PreOrPost, at=list(Truth=0)) #this gives us -c
emtrends(SDT4, ~PreOrPost, var="Truth")  #this gives us d'
emmeans(SDT4, ~Condition, at=list(Truth=0)) #this gives us -c
emtrends(SDT4, ~Condition, var="Truth")  #this gives us d'
emmeans(SDT4, ~PreOrPost|Condition, at=list(Truth=0))
#pre and post per condition)

emtrends(SDT4, ~PreOrPost|Condition , var="Truth")
hist(resid(SDT4),main=" ")



########## HYPOTHESIS FIGURES####################################


#######Study1 Hypothesized individual diffs##########

hypSTMOc <-
  ggplot() + lims(x = c(-5,5), y = c(-5,5))+
  annotate("segment",x = -5, y = 0,xend = 5,yend = 0,color="violetred1",lwd=2) +
  annotate("segment",x = -5, y = 0,xend = 5,yend = 0,color="violetred1",lwd=15, alpha=.3) +
  ggtitle("Hypothesized: STMO & c")+
  labs(y = "Bias (c)", x = "Deviations from Average STMO")
hypSTMOc

hypSTMOd <-
  ggplot() + lims(x = c(-5,5), y = c(-5,5))+
  annotate("segment",x = -5, y = 0,xend = 5,yend = 0,color="violetred1",lwd=2) +
  annotate("segment",x = -5, y = 0,xend = 5,yend = 0,color="violetred1",lwd=15, alpha=.3) +
  ggtitle("Hypothesized: STMO & d'")+
  labs(y = "Sensitivity (d')", x = "Deviations from Average STMO")
hypSTMOd
```

```
hypLTMOc <-
  ggplot() + lims(x = c(-5,5), y = c(-5,5))+
  annotate("segment",x = -5, y = 0,xend = 5,yend = 0,color="lightsalmon",lwd=2) +
  annotate("segment",x = -5, y = 0,xend = 5,yend = 0,color="lightsalmon",lwd=15, alpha=.3) +
  ggtitle("Hypothesized: LTMO & c")+
  labs(y = "Bias (c)", x = "Deviations from Average LTMO")
hypLTMOc

hypLTMOd <-
  ggplot() + lims(x = c(-5,5), y = c(-5,5))+
  annotate("segment",x = -5, y = 0,xend = 5,yend = 0,color="lightsalmon",lwd=2) +
  annotate("segment",x = -5, y = 0,xend = 5,yend = 0,color="lightsalmon",lwd=15, alpha=.3) +
  ggtitle("Hypothesized: LTMO & d'")+
  labs(y = "Sensitivity (d')", x = "Deviations from Average LTMO")
hypLTMOd


hypMVc <-
  ggplot() + lims(x = c(-5,5), y = c(-5,5))+
  annotate("segment",x = -5, y = 0,xend = 5,yend = 0,color="seagreen2",lwd=2) +
  annotate("segment",x = -5, y = 0,xend = 5,yend = 0,color="seagreen2",lwd=15, alpha=.3) +
  ggtitle("Hypothesized: Mate Value & c")+
  labs(y = "Bias (c)", x = "Deviations from Average Mate Value")
hypMVc

hypMVd <-
  ggplot() + lims(x = c(-5,5), y = c(-5,5))+
  annotate("segment",x = -5, y = 0,xend = 5,yend = 0,color="seagreen2",lwd=2) +
  annotate("segment",x = -5, y = 0,xend = 5,yend = 0,color="seagreen2",lwd=15, alpha=.3) +
  ggtitle("Hypothesized: Mate Value & d'")+
  labs(y = "Sensitivity (d')", x = "Deviations from Average Mate Value")
hypMVd


hypKc <-
  ggplot() + lims(x = c(-5,5), y = c(-5,5))+
  annotate("segment",x = -5, y = 0,xend = 5,yend = 0,color="steelblue1",lwd=2) +
  annotate("segment",x = -5, y = 0,xend = 5,yend = 0,color="steelblue1",lwd=15, alpha=.3) +
  ggtitle("Hypothesized: Life History & c")+
  labs(y = "Bias (c)", x = "Deviations from Average Life History")
hypKc

hypKd <-
  ggplot() + lims(x = c(-5,5), y = c(-5,5))+
```

```
  annotate("segment",x = -5, y = 0,xend = 5,yend = 0,color="steelblue1",lwd=2) +
  annotate("segment",x = -5, y = 0,xend = 5,yend = 0,color="steelblue1",lwd=15, alpha=.3) +
  ggtitle("Hypothesized: Life History & d'")+
  labs(y = "Sensitivity (d')", x = "Deviations from Average Life History")
hypKd


hypSAc <-
  ggplot() + lims(x = c(-5,5), y = c(-5,5))+
  annotate("segment",x = -5, y = -2.5,xend = 5,yend = 2.5,color="mediumorchid1",lwd=2) +
  annotate("segment",x = -5, y = -2.5,xend = 5,yend = 2.5,color="mediumorchid1",lwd=15,
alpha=.3) +
  ggtitle("Hypothesized: Sexual Aggression & c")+
  labs(y = "Bias (c)", x = "Deviations from Average Sexual Aggression")
hypSAc

hypSAd <-
  ggplot() + lims(x = c(-5,5), y = c(-5,5))+
  annotate("segment",x = -5, y = 0,xend = 5,yend = 0,color="mediumorchid1",lwd=2) +
  annotate("segment",x = -5, y = 0,xend = 5,yend = 0,color="mediumorchid1",lwd=15, alpha=.3)
+
  ggtitle("Hypothesized: Sexual Aggression & d'")+
  labs(y = "Sensitivity (d')", x = "Deviations from Average Sexual Aggression")
hypSAd

#######Study1 Hypothesized sex diffs##########
#STUDY 1 Men
sensiMx<-c(-1, 1)
sensiMy<-c(0.4,0.4)
dprimeM = 2
cM = 0.25
plot(function(x) dnorm(x, mean=-dprimeM/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="Hypothesized for Men", xlim=c(-6,6),
ylim=c(-.1, 0.5), cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprimeM/2), -5,5, add=T, col="green", lwd=4)
lines(sensiMx, sensiMy, col="orange", lwd=2, lty="twodash")
abline(v=cM, col="blue", lwd=2, lty="longdash")
text(-2.8,-0.05,"Bias = More Liberal", col="blue",cex=1.9)
text(-2.8,-0.09,"than W", col="blue",cex=1.9)
text(3.1,0.425,"Sensitivity = High", col="orange",cex=1.9)


#STUDY 1 women
sensiMx<-c(-1, 1)
sensiMy<-c(0.4,0.4)
dprimeM = 2
```

```
cM = 0.5
plot(function(x) dnorm(x, mean=-dprimeM/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="Hypothesized for Women", xlim=c(-6,6),
ylim=c(-.1, 0.5), cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprimeM/2), -5,5, add=T, col="green", lwd=4)
lines(sensiMx, sensiMy, col="orange", lwd=2, lty="twodash")
abline(v=cM, col="blue", lwd=2, lty="longdash")
text(-2.8,-0.05,"Bias = More", col="blue",cex=1.9)
text(-2.8,-0.09,"Conservative than M", col="blue",cex=1.9)
text(3.2,0.425,"Sensitivity = High", col="orange",cex=1.9)

#######Study 2 Hypothesized condition diffs##########
#STUDY 2 interested
sensiMx<-c(-0.5, 0.5)
sensiMy<-c(0.4,0.4)
dprimeM = 1
cM = -0.25
plot(function(x) dnorm(x, mean=-dprimeM/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="H for 75% Interest", xlim=c(-6,6), ylim=c(-
.1, 0.5), cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprimeM/2), -5,5, add=T, col="green", lwd=4)
lines(sensiMx, sensiMy, col="orange", lwd=2, lty="twodash")
abline(v=cM, col="blue", lwd=2, lty="longdash")
text(-3.5,-0.05,"Bias = More", col="blue",cex=1.9)
text(-3.5,-0.09,"Liberal", col="blue",cex=1.9)


#STUDY 2 Neutral
sensiMx<-c(-0.5, 0.5)
sensiMy<-c(0.4,0.4)
dprimeM = 1
cM = 0
plot(function(x) dnorm(x, mean=-dprimeM/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="H for 50% Interest", xlim=c(-6,6), ylim=c(-
.1, 0.5), cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprimeM/2), -5,5, add=T, col="green", lwd=4)
lines(sensiMx, sensiMy, col="orange", lwd=2, lty="twodash")
abline(v=cM, col="blue", lwd=2, lty="longdash")
text(-3.5,-0.05,"Bias = Neutral", col="blue",cex=1.9)

#STUDY 2 Disinterested
sensiMx<-c(-0.5, 0.5)
sensiMy<-c(0.4,0.4)
dprimeM = 1
cM = 0.25
```

```
plot(function(x) dnorm(x, mean=-dprimeM/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="H for 25% Interest", xlim=c(-6,6), ylim=c(-
.1, 0.5), cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprimeM/2), -5,5, add=T, col="green", lwd=4)
lines(sensiMx, sensiMy, col="orange", lwd=2, lty="twodash")
abline(v=cM, col="blue", lwd=2, lty="longdash")
text(-3.5,-0.05,"Bias = More", col="blue",cex=1.9)
text(-3.5,-0.09,"Conservative", col="blue",cex=1.9)

#######Study 2 Hypothesized ordercondition diffs##########
hypCondOr <-
  ggplot() + lims(x = c(0,40), y = c(-5,5))+
  annotate("segment",x = 0, y = 0,xend = 40,yend = 2.5,color="coral2",lwd=2) +
  annotate("segment",x = 0, y = 0,xend = 40,yend = 2.5,color="coral2",lwd=15, alpha=.3) +
  annotate("segment",x = 0, y = 0,xend = 40,yend = 0,color="springgreen3",lwd=2) +
  annotate("segment",x = 0, y = 0,xend = 40,yend = 0,color="springgreen3",lwd=15, alpha=.3) +
  annotate("segment",x = 0, y = 0,xend = 40,yend = -2.5,color="steelblue2",lwd=2) +
  annotate("segment",x = 0, y = 0,xend = 40,yend = -2.5,color="steelblue2",lwd=15, alpha=.3) +

  ggtitle("Hypothesized: Condition:Order Interaction")+
  labs(y = "Bias (c)", x = "Trial Order")

hypCondOr

#######Study 3 Hypothesized skewed per sex##########

#STUDY 3 H Disadvantaged
sensi25Fx<-c(-0.5, 0.5)
sensi25Fy<-c(0.4,0.4)
dprime25FM = 1
cStN = 0.25
cDO = -0.25
plot(function(x) dnorm(x, mean=-dprime25FM/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="H: Disadvantaged", xlim=c(-6,6), ylim=c(-
.1, 0.5), cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprime25FM/2), -5,5, add=T, col="green", lwd=4)
abline(v=cDO, col="mediumorchid2", lwd=2, lty="longdash")
text(-3.5,-0.05,"DO Bias = More", col="mediumorchid2",cex=1.9)
text(-3.5,-0.09,"Liberal", col="mediumorchid2",cex=1.9)
abline(v=cStN, col="violetred1", lwd=2, lty="longdash")
text(3.5,-0.05,"StN Bias = More", col="violetred1",cex=1.9)
text(3.5,-0.09,"Conservative", col="violetred1",cex=1.9)

#STUDY 3 H advantaged
sensi25Fx<-c(-0.5, 0.5)
sensi25Fy<-c(0.4,0.4)
```

```
dprime25FM = 1
cStN = -0.25
cDO = 0.25
plot(function(x) dnorm(x, mean=-dprime25FM/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="H: Advantaged", xlim=c(-6,6), ylim=c(-.1,
0.5), cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprime25FM/2), -5,5, add=T, col="green", lwd=4)
abline(v=cDO, col="mediumorchid2", lwd=2, lty="longdash")
text(3.5,-0.05,"DO Bias = More", col="mediumorchid2",cex=1.9)
text(3.5,-0.09,"Liberal", col="mediumorchid2",cex=1.9)
abline(v=cStN, col="violetred1", lwd=2, lty="longdash")
text(-3.5,-0.05,"StN Bias = More", col="violetred1",cex=1.9)
text(-3.5,-0.09,"Conservative", col="violetred1",cex=1.9)

#STUDY 3 H neutral
sensi25Fx<-c(-0.5, 0.5)
sensi25Fy<-c(0.4,0.4)
dprime25FM = 1
cB = 0
plot(function(x) dnorm(x, mean=-dprime25FM/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="H: Neutral", xlim=c(-6,6), ylim=c(-.1, 0.5),
cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprime25FM/2), -5,5, add=T, col="green", lwd=4)
abline(v=cB, col="slategray", lwd=2, lty="longdash")
text(-3.25,-0.05,"Both Biases = Neutral", col="slategray",cex=1.8)

#######Study 4 Hypothesized interventions##########

#STUDY 4 ALL PRETEST
sensix<-c(-0.25, 0.25)
sensiy<-c(0.4,0.4)
dprime = 0.5
c = 0
#plot(function(x) dnorm(x, mean=-dprime/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="H: Control Pretest", xlim=c(-6,6), ylim=c(-
.1, 0.5), cex.main=3, cex.lab=3, cex.axis=1.5)
#plot(function(x) dnorm(x, mean=-dprime/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="H: Delay Pretest", xlim=c(-6,6), ylim=c(-
.1, 0.5), cex.main=3, cex.lab=3, cex.axis=1.5)
#plot(function(x) dnorm(x, mean=-dprime/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="H: Feedback Pretest", xlim=c(-6,6),
ylim=c(-.1, 0.5), cex.main=3, cex.lab=3, cex.axis=1.5)
#plot(function(x) dnorm(x, mean=-dprime/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="H: Combined Pretest", xlim=c(-6,6),
ylim=c(-.1, 0.5), cex.main=3, cex.lab=3, cex.axis=1.5)
```

```
plot(function(x) dnorm(x, mean=dprime/2), -5,5, add=T, col="green", lwd=4)
lines(sensix, sensiy, col="orange", lwd=2, lty="twodash")
abline(v=c, col="blue", lwd=2, lty="longdash")
text(-3,-0.05,"Bias = Neutral", col="blue",cex=2)
text(3,0.45,"Sensitivity =", col="orange",cex=2)
text(3,0.42,"Standard", col="orange",cex=2)

#STUDY 4 Control Posttest
sensix<-c(-0.25, 0.25)
sensiy<-c(0.4,0.4)
dprime = 0.5
c = 0
plot(function(x) dnorm(x, mean=-dprime/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="H: Control Posttest", xlim=c(-6,6),
ylim=c(-.1, 0.5), cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprime/2), -5,5, add=T, col="green", lwd=4)
lines(sensix, sensiy, col="orange", lwd=2, lty="twodash")
abline(v=c, col="blue", lwd=2, lty="longdash")
text(-3,-0.05,"Bias =", col="blue",cex=2)
text(-3,-0.09,"No Change", col="blue",cex=1.9)
text(3,0.45,"Sensitivity =", col="orange",cex=2)
text(3,0.41,"No Change", col="orange",cex=2)


#STUDY 4 Delay Posttest
sensix<-c(-0.25, 0.25)
sensiy<-c(0.4,0.4)
dprime = 0.5
c = 0.5
plot(function(x) dnorm(x, mean=-dprime/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="H: Delay Posttest", xlim=c(-6,6), ylim=c(-
.1, 0.5), cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprime/2), -5,5, add=T, col="green", lwd=4)
lines(sensix, sensiy, col="orange", lwd=2, lty="twodash")
abline(v=c, col="blue", lwd=2, lty="longdash")
text(-3,-0.05,"Bias =", col="blue",cex=2)
text(-3,-0.09,"More Conservative", col="blue",cex=1.9)
text(3,0.45,"Sensitivity =", col="orange",cex=2)
text(3,0.41,"No Change", col="orange",cex=2)


#STUDY 4 Feedback Posttest
sensix<-c(-0.75, 0.75)
sensiy<-c(0.4,0.4)
dprime = 1.5
c = 0
```

```
plot(function(x) dnorm(x, mean=-dprime/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="H: Feedback Posttest", xlim=c(-6,6),
ylim=c(-.1, 0.5), cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprime/2), -5,5, add=T, col="green", lwd=4)
lines(sensix, sensiy, col="orange", lwd=2, lty="twodash")
abline(v=c, col="blue", lwd=2, lty="longdash")
text(-3,-0.05,"Bias =", col="blue",cex=2)
text(-3,-0.09,"No Change", col="blue",cex=1.9)
text(3,0.45,"Sensitivity =", col="orange",cex=2)
text(3,0.41,"Higher", col="orange",cex=2)


#STUDY 4 Combined Posttest
sensix<-c(-0.75, 0.75)
sensiy<-c(0.4,0.4)
dprime = 1.5
c = 0.5
plot(function(x) dnorm(x, mean=-dprime/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="H: Combined Posttest", xlim=c(-6,6),
ylim=c(-.1, 0.5), cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprime/2), -5,5, add=T, col="green", lwd=4)
lines(sensix, sensiy, col="orange", lwd=2, lty="twodash")
abline(v=c, col="blue", lwd=2, lty="longdash")
text(-3,-0.05,"Bias =", col="blue",cex=2)
text(-3,-0.09,"More Conservative", col="blue",cex=1.9)
text(3,0.45,"Sensitivity =", col="orange",cex=2)
text(3,0.41,"Higher", col="orange",cex=2)





### RESULTS FIGURES###

###################STUDY 1##############################################
#STUDY 1 Men
sensiMx<-c(-0.16, 0.16)
sensiMy<-c(0.4,0.4)
dprimeM = 0.32
cM = 0.06
plot(function(x) dnorm(x, mean=-dprimeM/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="Men", xlim=c(-6,6), ylim=c(-.1, 0.5),
cex.main=3, cex.lab=3, cex.axis=1.5)
```

```
plot(function(x) dnorm(x, mean=dprimeM/2), -5,5, add=T, col="green", lwd=4)
lines(sensiMx, sensiMy, col="orange", lwd=2, lty="twodash")
abline(v=cM, col="blue", lwd=2, lty="longdash")
text(-2,-0.05,"Bias = 0.06", col="blue",cex=2)
text(2.9,0.425,"Sensitivity = 0.32", col="orange",cex=2)


#STUDY 1 women
sensiWx<-c(-0.095, 0.095)
sensiWy<-c(0.4,0.4)
dprimeW = 0.19
cW = 0.05
plot(function(x) dnorm(x, mean=-dprimeW/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="Women", xlim=c(-6,6), ylim=c(-.1, 0.5),
cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprimeW/2), -5,5, add=T, col="green", lwd=4)
lines(sensiWx, sensiWy, col="orange", lwd=2, lty="twodash")
abline(v=cW, col="blue", lwd=2, lty="longdash")
text(-2,-0.05,"Bias = 0.05", col="blue",cex=2)
text(2.9,0.425,"Sensitivity = 0.19", col="orange",cex=2)

# PLOT Changes in bias (c)  over c.STMO
STMOc1 = as.data.frame(emmeans(SDT1, ~c.STMO, at=list(c.STMO=seq(-4,4))))
STMOc1$emmean = -STMOc1$emmean # Turn -c into c
ggplot(STMOc1, aes(y=emmean, x=c.STMO)) + geom_line(color="violetred1",size=1) +
   theme(legend.position = "none")+
   geom_ribbon(aes(ymin=emmean-SE, ymax=emmean+SE), alpha=.3, col=NA,
fill="violetred1") +
   ylab("Bias (c)") +
   xlab("Deviations from Average STMO")+
   scale_x_continuous(limits = c(-5, 5)) +
   scale_y_continuous(limits = c(-5,5))

#  PLOT Changes in sensitivity (d') over c.STMO
STMOd1 = as.data.frame(emtrends(SDT1, ~c.STMO, var="Truth", at=list(c.STMO=seq(-4,4))))
ggplot(STMOd1, aes(y=Truth.trend, x=c.STMO)) + geom_line(color="violetred1",size=1) +
  theme(legend.position = "none")+
  geom_ribbon(aes(ymin=Truth.trend-SE, ymax=Truth.trend+SE), alpha=.3, col=NA,
fill="violetred1") +
  ylab("Sensitivy (d')") +
  xlab("Deviations from Average STMO")+
  scale_x_continuous(limits = c(-5, 5)) +
  scale_y_continuous(limits = c(-5,5))


# PLOT Changes in bias (c)  over c.LTMO
```

```
LTMOc1 = as.data.frame(emmeans(SDT1, ~c.LTMO, at=list(c.LTMO=seq(-4,4))))
LTMOc1$emmean = -LTMOc1$emmean # Turn -c into c
ggplot(LTMOc1, aes(y=emmean, x=c.LTMO)) + geom_line(color="lightsalmon",size=1) +
  theme(legend.position = "none")+
  geom_ribbon(aes(ymin=emmean-SE, ymax=emmean+SE), alpha=.3, col=NA,
fill="lightsalmon") +
  ylab("Bias (c)") +
  xlab("Deviations from Average LTMO")+
  scale_x_continuous(limits = c(-5, 5)) +
  scale_y_continuous(limits = c(-5,5))

#  PLOT Changes in sensitivity (d') over c.LTMO
LTMOd1 = as.data.frame(emtrends(SDT1, ~c.LTMO, var="Truth", at=list(c.LTMO=seq(-4,4))))
ggplot(LTMOd1, aes(y=Truth.trend, x=c.LTMO)) + geom_line(color="lightsalmon",size=1) +
  theme(legend.position = "none")+
  geom_ribbon(aes(ymin=Truth.trend-SE, ymax=Truth.trend+SE), alpha=.3, col=NA,
fill="lightsalmon") +
  ylab("Sensitivy (d')") +
  xlab("Deviations from Average LTMO")+
  scale_x_continuous(limits = c(-5, 5)) +
  scale_y_continuous(limits = c(-5,5))


# PLOT Changes in bias (c)  over c.MV
MVc1 = as.data.frame(emmeans(SDT1, ~c.MV, at=list(c.MV=seq(-4,4))))
MVc1$emmean = -MVc1$emmean # Turn -c into c
ggplot(MVc1, aes(y=emmean, x=c.MV)) + geom_line(color="seagreen2",size=1) +
  theme(legend.position = "none")+
  geom_ribbon(aes(ymin=emmean-SE, ymax=emmean+SE), alpha=.3, col=NA,
fill="seagreen2") +
  ylab("Bias (c)") +
  xlab("Deviations from Average Mate Value")+
  scale_x_continuous(limits = c(-5, 5)) +
  scale_y_continuous(limits = c(-5,5))

#  PLOT Changes in sensitivity (d') over c.MV
MVd1 = as.data.frame(emtrends(SDT1, ~c.MV, var="Truth", at=list(c.MV=seq(-4,4))))
ggplot(MVd1, aes(y=Truth.trend, x=c.MV)) + geom_line(color="seagreen2",size=1) +
  theme(legend.position = "none")+
  geom_ribbon(aes(ymin=Truth.trend-SE, ymax=Truth.trend+SE), alpha=.3, col=NA,
fill="seagreen2") +
  ylab("Sensitivy (d')") +
  xlab("Deviations from Average Mate Value")+
  scale_x_continuous(limits = c(-5, 5)) +
  scale_y_continuous(limits = c(-5,5))
```

```
# PLOT Changes in bias (c)  over c.K
LHc1 = as.data.frame(emmeans(SDT1, ~c.K, at=list(c.K=seq(-4,4))))
LHc1$emmean = -LHc1$emmean # Turn -c into c
ggplot(LHc1, aes(y=emmean, x=c.K)) + geom_line(color="steelblue1",size=1) +
  theme(legend.position = "none")+
  geom_ribbon(aes(ymin=emmean-SE, ymax=emmean+SE), alpha=.3, col=NA,
fill="steelblue1") +
  ylab("Bias (c)") +
  xlab("Deviations from Average Life History")+
  scale_x_continuous(limits = c(-5, 5)) +
  scale_y_continuous(limits = c(-5,5))

#  PLOT Changes in sensitivity (d') over c.K
LHd1 = as.data.frame(emtrends(SDT1, ~c.K, var="Truth", at=list(c.K=seq(-4,4))))
ggplot(LHd1, aes(y=Truth.trend, x=c.K)) + geom_line(color="steelblue1",size=1) +
  theme(legend.position = "none")+
  geom_ribbon(aes(ymin=Truth.trend-SE, ymax=Truth.trend+SE), alpha=.3, col=NA,
fill="steelblue1") +
  ylab("Sensitivy (d')") +
  xlab("Deviations from Average Life History")+
  scale_x_continuous(limits = c(-5, 5)) +
  scale_y_continuous(limits = c(-5,5))


# PLOT Changes in bias (c)  over c.SexAgg
SAc1 = as.data.frame(emmeans(SDT1, ~c.SexAgg, at=list(c.SexAgg=seq(-4,4))))
SAc1$emmean = -SAc1$emmean # Turn -c into c
ggplot(SAc1, aes(y=emmean, x=c.SexAgg)) + geom_line(color="mediumorchid1",size=1) +
  theme(legend.position = "none")+
  geom_ribbon(aes(ymin=emmean-SE, ymax=emmean+SE), alpha=.3, col=NA,
fill="mediumorchid1") +
  ylab("Bias (c)") +
  xlab("Deviations from Average Sexual Aggression")+
  scale_x_continuous(limits = c(-5, 5)) +
  scale_y_continuous(limits = c(-5,5))

#  PLOT Changes in sensitivity (d') over c.SexAgg
SAd1 = as.data.frame(emtrends(SDT1, ~c.SexAgg, var="Truth", at=list(c.SexAgg=seq(-4,4))))
ggplot(SAd1, aes(y=Truth.trend, x=c.SexAgg)) + geom_line(color="mediumorchid1",size=1) +
  theme(legend.position = "none")+
  geom_ribbon(aes(ymin=Truth.trend-SE, ymax=Truth.trend+SE), alpha=.3, col=NA,
fill="mediumorchid1") +
  ylab("Sensitivy (d')") +
  xlab("Deviations from Average Sexual Aggression")+
  scale_x_continuous(limits = c(-5, 5)) +
```

```
  scale_y_continuous(limits = c(-5,5))



#################STUDY 2############################################
#STUDY 2 Men
sensiM2x<-c(-0.045, 0.045)
sensiM2y<-c(0.4,0.4)
dprimeM2 = 0.09
cM2 = 0.21
plot(function(x) dnorm(x, mean=-dprimeM2/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="Men", xlim=c(-6,6), ylim=c(-.1, 0.5),
cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprimeM2/2), -5,5, add=T, col="green", lwd=4)
lines(sensiM2x, sensiM2y, col="orange", lwd=2, lty="twodash")
abline(v=cM2, col="blue", lwd=2, lty="longdash")
text(-2,-0.05,"Bias = 0.21", col="blue",cex=2)
text(3,0.425,"Sensitivity = 0.09", col="orange",cex=2)


#STUDY 2 women
sensiW2x<-c(-0.055, 0.055)
sensiW2y<-c(0.4,0.4)
dprimeW2 = 0.11
cW2 = -0.05
plot(function(x) dnorm(x, mean=-dprimeW2/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="Women", xlim=c(-6,6), ylim=c(-.1, 0.5),
cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprimeW2/2), -5,5, add=T, col="green", lwd=4)
lines(sensiW2x, sensiW2y, col="orange", lwd=2, lty="twodash")
abline(v=cW2, col="blue", lwd=2, lty="longdash")
text(-2.5,-0.05,"Bias = -0.05", col="blue",cex=2)
text(2.9,0.425,"Sensitivity = 0.11", col="orange",cex=2)


# PLOT Changes in bias (c) for each condition over order
toplot = as.data.frame(emmeans(SDT2, ~Condition|ORDER, at=list(ORDER=seq(1,40))))
toplot$emmean = -toplot$emmean # Turn -c into c
ggplot(toplot, aes(y=emmean, x=ORDER, col=Condition)) + geom_line() +
  geom_ribbon(aes(ymin=emmean-SE, ymax=emmean+SE, fill=Condition), alpha=.3, col=NA)
+
  ylab("Bias (c)")  +
  scale_y_continuous(limits = c(-7,5))

#  PLOT Changes in sensitivity (d')
```

```
toplot = as.data.frame(emtrends(SDT2, ~Condition|ORDER, var="Truth",
at=list(ORDER=seq(1,40))))
ggplot(toplot, aes(y=Truth.trend, x=ORDER, col=Condition)) + geom_line() +
  geom_ribbon(aes(ymin=Truth.trend-SE, ymax=Truth.trend+SE, fill=Condition), alpha=.3,
col=NA) +
  ylab("Sensitivy (d')")  +
  scale_y_continuous(limits = c(-8,5))



# PLOT Changes in bias (c)  over c.STMO
STMOc2 = as.data.frame(emmeans(SDT2, ~c.STMO, at=list(c.STMO=seq(-4,4))))
STMOc2$emmean = -STMOc2$emmean # Turn -c into c
ggplot(STMOc2, aes(y=emmean, x=c.STMO)) + geom_line(color="violetred1",size=1) +
  theme(legend.position = "none")+
  geom_ribbon(aes(ymin=emmean-SE, ymax=emmean+SE), alpha=.3, col=NA,
fill="violetred1") +
  ylab("Bias (c)") +
  xlab("Deviations from Average STMO")+
  scale_x_continuous(limits = c(-5, 5)) +
  scale_y_continuous(limits = c(-5,5))

#  PLOT Changes in sensitivity (d') over c.STMO
STMOd2 = as.data.frame(emtrends(SDT2, ~c.STMO, var="Truth", at=list(c.STMO=seq(-4,4))))
ggplot(STMOd2, aes(y=Truth.trend, x=c.STMO)) + geom_line(color="violetred1",size=1) +
  theme(legend.position = "none")+
  geom_ribbon(aes(ymin=Truth.trend-SE, ymax=Truth.trend+SE), alpha=.3, col=NA,
fill="violetred1") +
  ylab("Sensitivy (d')") +
  xlab("Deviations from Average STMO")+
  scale_x_continuous(limits = c(-5, 5)) +
  scale_y_continuous(limits = c(-5,5))


# PLOT Changes in bias (c)  over c.LTMO
LTMOc2 = as.data.frame(emmeans(SDT2, ~c.LTMO, at=list(c.LTMO=seq(-4,4))))
LTMOc2$emmean = -LTMOc2$emmean # Turn -c into c
ggplot(LTMOc2, aes(y=emmean, x=c.LTMO)) + geom_line(color="lightsalmon",size=1) +
  theme(legend.position = "none")+
  geom_ribbon(aes(ymin=emmean-SE, ymax=emmean+SE), alpha=.3, col=NA,
fill="lightsalmon") +
  ylab("Bias (c)") +
  xlab("Deviations from Average LTMO")+
  scale_x_continuous(limits = c(-5, 5)) +
  scale_y_continuous(limits = c(-5,5))
```

```
#  PLOT Changes in sensitivity (d') over c.LTMO
LTMOd2 = as.data.frame(emtrends(SDT2, ~c.LTMO, var="Truth", at=list(c.LTMO=seq(-4,4))))
ggplot(LTMOd2, aes(y=Truth.trend, x=c.LTMO)) + geom_line(color="lightsalmon",size=1) +
  theme(legend.position = "none")+
  geom_ribbon(aes(ymin=Truth.trend-SE, ymax=Truth.trend+SE), alpha=.3, col=NA,
fill="lightsalmon") +
  ylab("Sensitivy (d')") +
  xlab("Deviations from Average LTMO")+
  scale_x_continuous(limits = c(-5, 5)) +
  scale_y_continuous(limits = c(-5,5))


# PLOT Changes in bias (c)  over c.MV
MVc2 = as.data.frame(emmeans(SDT2, ~c.MV, at=list(c.MV=seq(-4,4))))
MVc2$emmean = -MVc2$emmean # Turn -c into c
ggplot(MVc2, aes(y=emmean, x=c.MV)) + geom_line(color="seagreen2",size=1) +
  theme(legend.position = "none")+
  geom_ribbon(aes(ymin=emmean-SE, ymax=emmean+SE), alpha=.3, col=NA,
fill="seagreen2") +
  ylab("Bias (c)") +
  xlab("Deviations from Average Mate Value")+
  scale_x_continuous(limits = c(-5, 5)) +
  scale_y_continuous(limits = c(-5,5))

#  PLOT Changes in sensitivity (d') over c.MV
MVd2 = as.data.frame(emtrends(SDT2, ~c.MV, var="Truth", at=list(c.MV=seq(-4,4))))
ggplot(MVd2, aes(y=Truth.trend, x=c.MV)) + geom_line(color="seagreen2",size=1) +
  theme(legend.position = "none")+
  geom_ribbon(aes(ymin=Truth.trend-SE, ymax=Truth.trend+SE), alpha=.3, col=NA,
fill="seagreen2") +
  ylab("Sensitivy (d')") +
  xlab("Deviations from Average Mate Value")+
  scale_x_continuous(limits = c(-5, 5)) +
  scale_y_continuous(limits = c(-5,5))


# PLOT Changes in bias (c)  over c.K
LHc2 = as.data.frame(emmeans(SDT2, ~c.K, at=list(c.K=seq(-4,4))))
LHc2$emmean = -LHc2$emmean # Turn -c into c
ggplot(LHc2, aes(y=emmean, x=c.K)) + geom_line(color="steelblue1",size=1) +
  theme(legend.position = "none")+
  geom_ribbon(aes(ymin=emmean-SE, ymax=emmean+SE), alpha=.3, col=NA,
fill="steelblue1") +
  ylab("Bias (c)") +
  xlab("Deviations from Average Life History")+
  scale_x_continuous(limits = c(-5, 5)) +
```

```
  scale_y_continuous(limits = c(-5,5))

#  PLOT Changes in sensitivity (d') over c.K
LHd2 = as.data.frame(emtrends(SDT2, ~c.K, var="Truth", at=list(c.K=seq(-4,4))))
ggplot(LHd2, aes(y=Truth.trend, x=c.K)) + geom_line(color="steelblue1",size=1) +
  theme(legend.position = "none")+
  geom_ribbon(aes(ymin=Truth.trend-SE, ymax=Truth.trend+SE), alpha=.3, col=NA,
fill="steelblue1") +
  ylab("Sensitivy (d')") +
  xlab("Deviations from Average Life History")+
  scale_x_continuous(limits = c(-5, 5)) +
  scale_y_continuous(limits = c(-5,5))


# PLOT Changes in bias (c)  over c.SexAgg
SAc2 = as.data.frame(emmeans(SDT2, ~c.SexAgg, at=list(c.SexAgg=seq(-4,4))))
SAc2$emmean = -SAc2$emmean # Turn -c into c
ggplot(SAc2, aes(y=emmean, x=c.SexAgg)) + geom_line(color="mediumorchid1",size=1) +
  theme(legend.position = "none")+
  geom_ribbon(aes(ymin=emmean-SE, ymax=emmean+SE), alpha=.3, col=NA,
fill="mediumorchid1") +
  ylab("Bias (c)") +
  xlab("Deviations from Average Sexual Aggression")+
  scale_x_continuous(limits = c(-5, 5)) +
  scale_y_continuous(limits = c(-5,5))

#  PLOT Changes in sensitivity (d') over c.SexAgg
SAd2 = as.data.frame(emtrends(SDT2, ~c.SexAgg, var="Truth", at=list(c.SexAgg=seq(-4,4))))
ggplot(SAd2, aes(y=Truth.trend, x=c.SexAgg)) + geom_line(color="mediumorchid1",size=1) +
  theme(legend.position = "none")+
  geom_ribbon(aes(ymin=Truth.trend-SE, ymax=Truth.trend+SE), alpha=.3, col=NA,
fill="mediumorchid1") +
  ylab("Sensitivy (d')") +
  xlab("Deviations from Average Sexual Aggression")+
  scale_x_continuous(limits = c(-5, 5)) +
  scale_y_continuous(limits = c(-5,5))




###################STUDY 3##############################################
#STUDY3 Men
sensiM3x<-c(-0.175, 0.175)
sensiM3y<-c(0.4,0.4)
```

```
dprimeM3 = 0.35
cM3 = -0.06
plot(function(x) dnorm(x, mean=-dprimeM3/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="Men", xlim=c(-6,6), ylim=c(-.1, 0.5),
cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprimeM3/2), -5,5, add=T, col="green", lwd=4)
lines(sensiM3x, sensiM3y, col="orange", lwd=2, lty="twodash")
abline(v=cM3, col="blue", lwd=2, lty="longdash")
text(-2.2,-0.05,"Bias = -0.06", col="blue",cex=2)
text(3,0.425,"Sensitivity = 0.35", col="orange",cex=2)


#STUDY 3 women
sensiW3x<-c(-0.045, 0.045)
sensiW3y<-c(0.4,0.4)
dprimeW3 = 0.09
cW3 = -0.09
plot(function(x) dnorm(x, mean=-dprimeW3/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="Women", xlim=c(-6,6), ylim=c(-.1, 0.5),
cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprimeW3/2), -5,5, add=T, col="green", lwd=4)
lines(sensiW3x, sensiW3y, col="orange", lwd=2, lty="twodash")
abline(v=cW3, col="blue", lwd=2, lty="longdash")
text(-2.5,-0.05,"Bias = -0.09", col="blue",cex=2)
text(2.9,0.425,"Sensitivity = 0.09", col="orange",cex=2)



#STUDY 3 Skewed M
sensi25Fx<-c(-0.075, 0.075)
sensi25Fy<-c(0.4,0.4)
dprime25F = 0.16
c25F = -0.15
plot(function(x) dnorm(x, mean=-dprime25F/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="Skewed Male", xlim=c(-6,6), ylim=c(-.1,
0.5), cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprime25F/2), -5,5, add=T, col="green", lwd=4)
lines(sensi25Fx, sensi25Fy, col="orange", lwd=2, lty="twodash")
abline(v=c25F, col="blue", lwd=2, lty="longdash")
text(-2.5,-0.05,"Bias = -0.15", col="blue",cex=2)
text(3.2,0.425,"Sensitivity = 0.16", col="orange",cex=2)


#STUDY 3 Even
sensi50Fx<-c(-0.1, 0.1)
sensi50Fy<-c(0.4,0.4)
```

```
dprime50F = 0.20
c50F = -0.17
plot(function(x) dnorm(x, mean=-dprime50F/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="Even", xlim=c(-6,6), ylim=c(-.1, 0.5),
cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprime50F/2), -5,5, add=T, col="green", lwd=4)
lines(sensi50Fx, sensi50Fy, col="orange", lwd=2, lty="twodash")
abline(v=c50F, col="blue", lwd=2, lty="longdash")
text(-2.5,-0.05,"Bias = -0.17", col="blue",cex=2)
text(2.9,0.425,"Sensitivity = 0.20", col="orange",cex=2)


#STUDY 3 Skewed Female
sensi75Fx<-c(-0.15, 0.15)
sensi75Fy<-c(0.4,0.4)
dprime75F = 0.30
c75F = 0.09
plot(function(x) dnorm(x, mean=-dprime75F/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="Skewed Female", xlim=c(-6,6), ylim=c(-.1,
0.5), cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprime75F/2), -5,5, add=T, col="green", lwd=4)
lines(sensi75Fx, sensi75Fy, col="orange", lwd=2, lty="twodash")
abline(v=c75F, col="blue", lwd=2, lty="longdash")
text(-2.5,-0.05,"Bias = 0.09", col="blue",cex=2)
text(3,0.425,"Sensitivity = 0.30", col="orange",cex=2)




################divided by sex
#STUDY 3 Skewed M M
sensi25FMx<-c(-0.135, 0.135)
sensi25FMy<-c(0.4,0.4)
dprime25FM = 0.27
c25FM = -0.24
plot(function(x) dnorm(x, mean=-dprime25FM/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="Disadvantaged Men", xlim=c(-6,6),
ylim=c(-.1, 0.5), cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprime25FM/2), -5,5, add=T, col="green", lwd=4)
lines(sensi25FxM, sensi25FyM, col="orange", lwd=2, lty="twodash")
abline(v=c25FM, col="blue", lwd=2, lty="longdash")
text(-2.5,-0.05,"Bias = -0.24", col="blue",cex=2)
text(3.2,0.425,"Sensitivity = 0.27", col="orange",cex=2)

#STUDY 3 Skewed M F
sensi25FFx<-c(-0.025, 0.025)
```

```
sensi25FFy<-c(0.4,0.4)
dprime25FF = 0.05
c25FF = -0.07
plot(function(x) dnorm(x, mean=-dprime25FF/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="Advantaged Women", xlim=c(-6,6),
ylim=c(-.1, 0.5), cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprime25FF/2), -5,5, add=T, col="green", lwd=4)
lines(sensi25FxMF, sensi25FyF, col="orange", lwd=2, lty="twodash")
abline(v=c25FF, col="blue", lwd=2, lty="longdash")
text(-2.5,-0.05,"Bias = -0.07", col="blue",cex=2)
text(3.2,0.425,"Sensitivity = 0.05", col="orange",cex=2)



#STUDY 3 Even M
sensi50FMx<-c(-0.14, 0.14)
sensi50FMy<-c(0.4,0.4)
dprime50FM = 0.28
c50FM = -0.20
plot(function(x) dnorm(x, mean=-dprime50FM/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="Neutral Men", xlim=c(-6,6), ylim=c(-.1,
0.5), cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprime50FM/2), -5,5, add=T, col="green", lwd=4)
lines(sensi50FMx, sensi50FMy, col="orange", lwd=2, lty="twodash")
abline(v=c50FM, col="blue", lwd=2, lty="longdash")
text(-2.5,-0.05,"Bias = -0.20", col="blue",cex=2)
text(2.9,0.425,"Sensitivity = 0.28", col="orange",cex=2)

#STUDY 3 Even F
sensi50FFx<-c(-0.065, 0.065)
sensi50FFy<-c(0.4,0.4)
dprime50FF = 0.13
c50FF = -0.14
plot(function(x) dnorm(x, mean=-dprime50FF/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="Neutral Women", xlim=c(-6,6), ylim=c(-.1,
0.5), cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprime50FF/2), -5,5, add=T, col="green", lwd=4)
lines(sensi50FFx, sensi50FFy, col="orange", lwd=2, lty="twodash")
abline(v=c50FF, col="blue", lwd=2, lty="longdash")
text(-2.5,-0.05,"Bias = -0.14", col="blue",cex=2)
text(2.9,0.425,"Sensitivity = 0.13", col="orange",cex=2)



#STUDY 3 Skewed Female M
```

```
sensi75FMx<-c(-0.255, 0.255)
sensi75FMy<-c(0.4,0.4)
dprime75FM = 0.51
c75FM = 0.25
plot(function(x) dnorm(x, mean=-dprime75FM/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="Advantaged Men", xlim=c(-6,6), ylim=c(-
.1, 0.5), cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprime75FM/2), -5,5, add=T, col="green", lwd=4)
lines(sensi75FMx, sensi75FMy, col="orange", lwd=2, lty="twodash")
abline(v=c75FM, col="blue", lwd=2, lty="longdash")
text(-2.5,-0.05,"Bias = 0.25", col="blue",cex=2)
text(3,0.425,"Sensitivity = 0.51", col="orange",cex=2)

#STUDY 3 Skewed Female F
sensi75FFx<-c(-0.05, 0.05)
sensi75FFy<-c(0.4,0.4)
dprime75FF = 0.1
c75FF = -0.06
plot(function(x) dnorm(x, mean=-dprime75FF/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="Disadvantaged Women", xlim=c(-6,6),
ylim=c(-.1, 0.5), cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprime75FF/2), -5,5, add=T, col="green", lwd=4)
lines(sensi75FFx, sensi75FFy, col="orange", lwd=2, lty="twodash")
abline(v=c75FF, col="blue", lwd=2, lty="longdash")
text(-2.5,-0.05,"Bias = -0.06", col="blue",cex=2)
text(3,0.425,"Sensitivity = 0.1", col="orange",cex=2)

# PLOT Changes in bias (c)  over c.STMO
STMOc3 = as.data.frame(emmeans(SDT3, ~c.STMO, at=list(c.STMO=seq(-4,4))))
STMOc3$emmean = -STMOc3$emmean # Turn -c into c
ggplot(STMOc3, aes(y=emmean, x=c.STMO)) + geom_line(color="violetred1",size=1) +
  theme(legend.position = "none")+
  geom_ribbon(aes(ymin=emmean-SE, ymax=emmean+SE), alpha=.3, col=NA,
fill="violetred1") +
  ylab("Bias (c)") +
  xlab("Deviations from Average STMO")+
  scale_x_continuous(limits = c(-5, 5)) +
  scale_y_continuous(limits = c(-5,5))

#  PLOT Changes in sensitivity (d') over c.STMO
STMOd3 = as.data.frame(emtrends(SDT3, ~c.STMO, var="Truth", at=list(c.STMO=seq(-4,4))))
ggplot(STMOd3, aes(y=Truth.trend, x=c.STMO)) + geom_line(color="violetred1",size=1) +
  theme(legend.position = "none")+
  geom_ribbon(aes(ymin=Truth.trend-SE, ymax=Truth.trend+SE), alpha=.3, col=NA,
fill="violetred1") +
  ylab("Sensitivy (d')") +
```

```
  xlab("Deviations from Average STMO")+
  scale_x_continuous(limits = c(-5, 5)) +
  scale_y_continuous(limits = c(-5,5))


# PLOT Changes in bias (c)  over c.LTMO
LTMOc3 = as.data.frame(emmeans(SDT3, ~c.LTMO, at=list(c.LTMO=seq(-4,4))))
LTMOc3$emmean = -LTMOc3$emmean # Turn -c into c
ggplot(LTMOc3, aes(y=emmean, x=c.LTMO)) + geom_line(color="lightsalmon",size=1) +
  theme(legend.position = "none")+
  geom_ribbon(aes(ymin=emmean-SE, ymax=emmean+SE), alpha=.3, col=NA,
fill="lightsalmon") +
  ylab("Bias (c)") +
  xlab("Deviations from Average LTMO")+
  scale_x_continuous(limits = c(-5, 5)) +
  scale_y_continuous(limits = c(-5,5))

#  PLOT Changes in sensitivity (d') over c.LTMO
LTMOd3 = as.data.frame(emtrends(SDT3, ~c.LTMO, var="Truth", at=list(c.LTMO=seq(-4,4))))
ggplot(LTMOd3, aes(y=Truth.trend, x=c.LTMO)) + geom_line(color="lightsalmon",size=1) +
  theme(legend.position = "none")+
  geom_ribbon(aes(ymin=Truth.trend-SE, ymax=Truth.trend+SE), alpha=.3, col=NA,
fill="lightsalmon") +
  ylab("Sensitivy (d')") +
  xlab("Deviations from Average LTMO")+
  scale_x_continuous(limits = c(-5, 5)) +
  scale_y_continuous(limits = c(-5,5))


# PLOT Changes in bias (c)  over c.MV
MVc3 = as.data.frame(emmeans(SDT3, ~c.MV, at=list(c.MV=seq(-4,4))))
MVc3$emmean = -MVc3$emmean # Turn -c into c
ggplot(MVc3, aes(y=emmean, x=c.MV)) + geom_line(color="seagreen2",size=1) +
  theme(legend.position = "none")+
  geom_ribbon(aes(ymin=emmean-SE, ymax=emmean+SE), alpha=.3, col=NA,
fill="seagreen2") +
  ylab("Bias (c)") +
  xlab("Deviations from Average Mate Value")+
  scale_x_continuous(limits = c(-5, 5)) +
  scale_y_continuous(limits = c(-5,5))

#  PLOT Changes in sensitivity (d') over c.MV
MVd3 = as.data.frame(emtrends(SDT3, ~c.MV, var="Truth", at=list(c.MV=seq(-4,4))))
ggplot(MVd3, aes(y=Truth.trend, x=c.MV)) + geom_line(color="seagreen2",size=1) +
  theme(legend.position = "none")+
```

```
  geom_ribbon(aes(ymin=Truth.trend-SE, ymax=Truth.trend+SE), alpha=.3, col=NA,
fill="seagreen2") +
  ylab("Sensitivy (d')") +
  xlab("Deviations from Average Mate Value")+
  scale_x_continuous(limits = c(-5, 5)) +
  scale_y_continuous(limits = c(-5,5))


# PLOT Changes in bias (c)  over c.K
LHc3 = as.data.frame(emmeans(SDT3, ~c.K, at=list(c.K=seq(-4,4))))
LHc3$emmean = -LHc3$emmean # Turn -c into c
ggplot(LHc3, aes(y=emmean, x=c.K)) + geom_line(color="steelblue1",size=1) +
  theme(legend.position = "none")+
  geom_ribbon(aes(ymin=emmean-SE, ymax=emmean+SE), alpha=.3, col=NA,
fill="steelblue1") +
  ylab("Bias (c)") +
  xlab("Deviations from Average Life History")+
  scale_x_continuous(limits = c(-5, 5)) +
  scale_y_continuous(limits = c(-5,5))

#  PLOT Changes in sensitivity (d') over c.K
LHd3 = as.data.frame(emtrends(SDT3, ~c.K, var="Truth", at=list(c.K=seq(-4,4))))
ggplot(LHd3, aes(y=Truth.trend, x=c.K)) + geom_line(color="steelblue1",size=1) +
  theme(legend.position = "none")+
  geom_ribbon(aes(ymin=Truth.trend-SE, ymax=Truth.trend+SE), alpha=.3, col=NA,
fill="steelblue1") +
  ylab("Sensitivy (d')") +
  xlab("Deviations from Average Life History")+
  scale_x_continuous(limits = c(-5, 5)) +
  scale_y_continuous(limits = c(-5,5))


# PLOT Changes in bias (c)  over c.SexAgg
SAc3 = as.data.frame(emmeans(SDT3, ~c.SexAgg, at=list(c.SexAgg=seq(-4,4))))
SAc3$emmean = -SAc3$emmean # Turn -c into c
ggplot(SAc3, aes(y=emmean, x=c.SexAgg)) + geom_line(color="mediumorchid1",size=1) +
  theme(legend.position = "none")+
  geom_ribbon(aes(ymin=emmean-SE, ymax=emmean+SE), alpha=.3, col=NA,
fill="mediumorchid1") +
  ylab("Bias (c)") +
  xlab("Deviations from Average Sexual Aggression")+
  scale_x_continuous(limits = c(-5, 5)) +
  scale_y_continuous(limits = c(-5,5))

#  PLOT Changes in sensitivity (d') over c.SexAgg
SAd3 = as.data.frame(emtrends(SDT3, ~c.SexAgg, var="Truth", at=list(c.SexAgg=seq(-4,4))))
```

```
ggplot(SAd3, aes(y=Truth.trend, x=c.SexAgg)) + geom_line(color="mediumorchid1",size=1) +
  theme(legend.position = "none")+
  geom_ribbon(aes(ymin=Truth.trend-SE, ymax=Truth.trend+SE), alpha=.3, col=NA,
fill="mediumorchid1") +
  ylab("Sensitivy (d')") +
  xlab("Deviations from Average Sexual Aggression")+
  scale_x_continuous(limits = c(-5, 5)) +
  scale_y_continuous(limits = c(-5,5))


################STUDY4####################################################
#STUDY 4 CONTROL PRETEST
sensiControlx<-c(-0.005, 0.005)
sensiControly<-c(0.4,0.4)
dprimeControl = -0.01
cControl = 0.01
plot(function(x) dnorm(x, mean=-dprimeControl/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="Control Pretest", xlim=c(-6,6), ylim=c(-.1,
0.5), cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprimeControl/2), -5,5, add=T, col="green", lwd=4)
lines(sensiControlx, sensiControly, col="orange", lwd=2, lty="twodash")
abline(v=cControl, col="blue", lwd=2, lty="longdash")
text(-2,-0.05,"Bias = 0.01", col="blue",cex=2)
text(2.5,0.425,"Sensitivity = -0.01", col="orange",cex=2)


#STUDY 4 CONTROL POSTTEST
sensi2Controlx<-c(-0.21, 0.21)
sensi2Controly<-c(0.4,0.4)
dprime2Control = 0.42
c2Control = 0.23
plot(function(x) dnorm(x, mean=-dprime2Control/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="Control Posttest", xlim=c(-6,6), ylim=c(-.1,
0.5), cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprime2Control/2), -5,5, add=T, col="green", lwd=4)
lines(sensi2Controlx, sensi2Controly, col="orange", lwd=2, lty="twodash")
abline(v=c2Control, col="blue", lwd=2, lty="longdash")
text(-2,-0.05,"Bias = 0.23", col="blue",cex=2)
text(3.5,0.425,"Sensitivity = 0.42", col="orange",cex=2)




#STUDY 4 Delay PRETEST
```

```
sensiDex<-c(-0.095, 0.095)
sensiDey<-c(0.4,0.4)
dprimeDe = 0.19
cDe = -0.03
plot(function(x) dnorm(x, mean=-dprimeDe/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="Delay Pretest", xlim=c(-6,6), ylim=c(-.1,
0.5), cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprimeDe/2), -5,5, add=T, col="green", lwd=4)
lines(sensiDex, sensiDey, col="orange", lwd=2, lty="twodash")
abline(v=cDe, col="blue", lwd=2, lty="longdash")
text(-2.1,-0.05,"Bias = -0.03", col="blue",cex=2)
text(3,0.425,"Sensitivity = 0.19", col="orange",cex=2)


#STUDY 4 Delay POSTTEST
sensiDe2x<-c(-0.14, 0.14)
sensiDe2y<-c(0.4,0.4)
dprimeDe2 = 0.28
cDe2 = 0.22
plot(function(x) dnorm(x, mean=-dprimeDe2/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="Delay Posttest", xlim=c(-6,6), ylim=c(-.1,
0.5), cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprimeDe2/2), -5,5, add=T, col="green", lwd=4)
lines(sensiDe2x, sensiDe2y, col="orange", lwd=2, lty="twodash")
abline(v=cDe2, col="blue", lwd=2, lty="longdash")
text(-2.1,-0.05,"Bias = 0.22", col="blue",cex=2)
text(3,0.425,"Sensitivity = 0.28", col="orange",cex=2)


#STUDY 4 Feedback PRETEST
sensiFex<-c(-0.035, 0.035)
sensiFey<-c(0.4,0.4)
dprimeFe = 0.07
cFe = -0.18
plot(function(x) dnorm(x, mean=-dprimeFe/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="Feedback Pretest", xlim=c(-6,6), ylim=c(-
.1, 0.5), cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprimeFe/2), -5,5, add=T, col="green", lwd=4)
lines(sensiFex, sensiFey, col="orange", lwd=2, lty="twodash")
abline(v=cFe, col="blue", lwd=2, lty="longdash")
text(-2.2,-0.05,"Bias = -0.18", col="blue",cex=2)
text(3,0.425,"Sensitivity = 0.07", col="orange",cex=2)
```

```
#STUDY 4 Feedback POSTTEST
sensiFe2x<-c(-0.215, 0.215)
sensiFe2y<-c(0.4,0.4)
dprimeFe2 = 0.43
cFe2 = -0.10
plot(function(x) dnorm(x, mean=-dprimeFe2/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="Feedback Posttest", xlim=c(-6,6), ylim=c(-
.1, 0.5), cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprimeFe2/2), -5,5, add=T, col="green", lwd=4)
lines(sensiFe2x, sensiFe2y, col="orange", lwd=2, lty="twodash")
abline(v=cFe2, col="blue", lwd=2, lty="longdash")
text(-2.2,-0.05,"Bias = -0.10", col="blue",cex=2)
text(3,0.425,"Sensitivity = 0.43", col="orange",cex=2)



#STUDY 4 COMBINED PRETEST
sensiCx<-c(-0.005, 0.005)
sensiCy<-c(0.4,0.4)
dprimeC = 0.02
cC = -0.25
plot(function(x) dnorm(x, mean=-dprimeC/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="Combined Pretest", xlim=c(-6,6), ylim=c(-
.1, 0.5), cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprimeC/2), -5,5, add=T, col="green", lwd=4)
lines(sensiCx, sensiCy, col="orange", lwd=2, lty="twodash")
abline(v=cC, col="blue", lwd=2, lty="longdash")
text(-2.3,-0.05,"Bias = -0.25", col="blue",cex=2)
text(3,0.425,"Sensitivity = 0.02", col="orange",cex=2)


#STUDY 4 COMBINED POSTTEST
sensiC2x<-c(-0.23, 0.23)
sensiC2y<-c(0.4,0.4)
dprimeC2 = 0.46
cC2 = -0.04
plot(function(x) dnorm(x, mean=-dprimeC2/2), -5,5, lty="dashed", lwd=4, col="red",
xlab="Evidence Strength", ylab="",yaxt="n", main="Combined Posttest", xlim=c(-6,6), ylim=c(-
.1, 0.5), cex.main=3, cex.lab=3, cex.axis=1.5)
plot(function(x) dnorm(x, mean=dprimeC2/2), -5,5, add=T, col="green", lwd=4)
lines(sensiC2x, sensiC2y, col="orange", lwd=2, lty="twodash")
abline(v=cC2, col="blue", lwd=2, lty="longdash")
text(-2.3,-0.05,"Bias = -0.04", col="blue",cex=2)
text(3,0.425,"Sensitivity = 0.46", col="orange",cex=2)
```