

Reduced judgment updating to concurrent social feedback in abstinent individuals with methamphetamine use disorder

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Abstract

Background

Social environments shape substance use and recovery, yet how individuals with methamphetamine use disorder (MUD) revise judgments when multiple social sources provide concurrent feedback remains unclear. We examined whether abstinent individuals with MUD differed from healthy controls in their sensitivity to peer and societal feedback.

Methods

Thirty-eight abstinent individuals with MUD and 49 healthy controls completed a facial-attractiveness task involving initial ratings, computer-generated feedback labeled as peer and societal ratings, and revised ratings. A trial-level mixed-effects model estimated associations between rating change and discrepancies between each feedback source and the initial judgment. Secondary computational analyses compared source-specific weighting, equal-weight composite, and convergence-dependent formulations using Bayesian information criterion, model recovery, and leave-one-participant-out prediction.

Results

Across 13,310 valid trials, participants with MUD showed lower sensitivity to both peer feedback (control–MUD slope difference = 0.077, 95% CI [0.040, 0.114]; Holm-adjusted $p < .001$) and societal feedback (difference = 0.036, 95% CI [0.004, 0.068]; Holm-adjusted $p = .027$). The equal-weight composite model was favored by Bayesian information criterion for 31 of 49 controls and 32 of 38 participants with MUD, although asymmetric model recovery limited mechanistic interpretation. Held-out prediction reduced mean squared error relative to no update by 11.3% in controls (95% CI [6.9%, 14.6%]) and 2.7% in MUD (95% CI [–0.7%, 5.2%]).

Conclusions

Abstinent individuals with MUD showed reduced judgment updating to concurrent peer and societal feedback. These findings characterize altered feedback sensitivity in a social judgment task, while its relationship to everyday social functioning and recovery remains to be established.

Introduction

Methamphetamine use disorder (MUD) is a major public-health challenge characterized by persistent drug use despite adverse consequences [1–3]. Chronic methamphetamine exposure is associated with neurotoxic effects, psychotic symptoms, and cognitive deficits [4–6]. Social relationships provide an important context for substance use and recovery, shaping exposure to drug-related influences, access to support, and opportunities for behavioral change [7–9]. Prior work has examined social conformity and social decision-making in substance use disorders [10, 11], including recent evidence of decision-making signatures in MUD [12]. Social-value [13], social-reinforcement [14], and observational-learning [15] studies provide broader accounts of how social information can guide updating. Reviews have also considered prefrontal dysfunction in addiction [16] and neurobiological and computational accounts of social conformity [17]. However, these findings leave unresolved how individuals with MUD revise an existing judgment when multiple social sources provide feedback at the same time.

Social influence may reflect informational considerations, such as treating others' judgments as evidence, or normative considerations, such as maintaining agreement with a group [18, 19]. Social comparison [20], conformity [21], compliance [22], and social-impact accounts [23] describe related influence processes. A meta-analysis also documents variation in conformity across settings [24]. Studies of social judgment updating have related discrepancies between personal and others' evaluations to subsequent changes in ratings [10, 25, 26]. However, paradigms presenting a single consensus signal provide limited information about the relative influence of concurrent sources. Presenting peer and societal feedback together therefore allows their associations with judgment updating to be examined within the same trial [27–29].

Multisource updating can be described using several related formulations. Information-integration theory [30] and research on multiple advice inputs [29, 31, 32] motivate examining how several social inputs are combined. Consensus-formation models [33] and advice-taking research [34, 35] provide related accounts. Social influence can propagate through collective dynamics [36], and social information can improve group estimation [37]. Recent work further shows that feature-based learning can shape social-learning strategies [38]. In the present study, a source-specific model assigned separate weights to peer and societal discrepancies, an equal-weight composite model constrained the two contributions to be equal, and a convergence-amplification model allowed their combined influence to vary with directional agreement. These

formulations make distinguishable predictions only in some parameter regimes: equal source weights and zero amplification produce overlapping predictions. Their comparison can therefore assess descriptive adequacy and parsimony, but cannot by itself establish how social information is represented or the order in which it is processed [39, 40]. Broader computational-psychiatry frameworks motivate such descriptive modeling [41, 42], and general reinforcement-learning accounts provide a further formal background [43, 44].

In the present study, abstinent individuals with MUD and healthy controls completed a facial-attractiveness judgment task in which they revised initial ratings after viewing concurrent, computer-generated feedback labeled as peer and societal ratings. The primary analysis examined group differences in sensitivity to each feedback discrepancy while simultaneously accounting for the other. We also examined whether the group difference varied between sources. Secondary analyses characterized updating across feedback configurations and evaluated the descriptive and predictive value of the three computational formulations. By separating concurrent source sensitivities from overall judgment change, this study aimed to clarify how social feedback updating differs in abstinent individuals with MUD.

Methods

Participants and recruitment

A total of 45 individuals with methamphetamine use disorder (MUD) were recruited from local drug rehabilitation centers, and 51 healthy controls (HCs) were recruited from the local community. The study protocol was approved by the Research Ethics Board of Shanghai Jiao Tong University (Approval number: 20260479I). Participants with MUD were eligible if they (1) met the diagnostic criteria for MUD in the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5) [45]; (2) reported using methamphetamine, but no other illicit drugs, for at least 1 year; and (3) had used methamphetamine at least 3 times per week for at least 1 consecutive month, at a daily dose exceeding 0.1 g. General exclusion criteria included a current major medical condition or current psychiatric disorder other than MUD. Methamphetamine craving scores were assessed using the visual analog scale (VAS; 0–100, where 0 indicates the weakest craving and 100 the strongest). Of 45 participants with MUD and 51 potential controls recruited, 38 and 49, respectively, were included in the analysis after applying the education and task eligibility criteria. 4 participants with MUD were excluded before task because of inadequate education years. The remaining 3 participants with MUD and 2 healthy participants were excluded due to failure in catch trials in experiment.

HCs had no psychiatric disorder or substance use disorder. All participants were right-handed, had completed more than six years of formal education, and provided written informed consent in accordance with the Declaration of Helsinki [46]. Participants with MUD reported a mean current abstinence duration of 16.7 months (SD = 12.4). Age, education, and sex are summarized in Table 1.

Table 1
Demographic and clinical characteristics of participant

Characteristics	MUD (N = 38)	HC (N = 49)	Statistics	P values
Male(female)	16(22)	17(32)	$\chi^2 = 0.50$	p = 0.48
Age(years)	37.00(7.08)	35.91(4.97)	z=-1.10	p = 0.271
Education(years)	9.65(3.04)	10.06(2.05)	z=-1.11	p = 0.269
Total years of methamphetamine use (years)	9.52(7.60)	NA	-	-
Methamphetamine dose before abstinence (g/day)	0.41g(0.45)	NA	-	-
Duration of current abstinence (month)	16.7(12.4)	NA	-	-
Number of DSM-5 symptoms	5.18 (4.25)	NA	-	-
VAS Craving	43.7(20.54)	NA	-	-

Data are presented as mean (SD) for continuous variables and n for categorical variables. Group comparisons used a chi-square test for sex and Mann–Whitney U tests for continuous variables, with standardized z values reported. All tests were two-sided. MUD, methamphetamine use disorder; HC, healthy controls; NA, not applicable.

Multisource social information integration task

Participants completed a multisource social-information integration task based on facial-attractiveness judgments [10, 25, 47–49]. Participants attended in groups of three, each comprising a participant and two mutually familiar peers, and completed the task individually at

separate terminals without communicating. On each trial, participants rated a face on a 10-point scale, viewed two ratings labeled as peer and societal ratings, and then provided a final attractiveness rating.

Participants were told that the peer rating was rated by his familiar peers, who attend the task simultaneously, while the societal rating was made by general public sample. Both feedback values were in fact generated by the experimental program and presented with peer and societal source labels. The task therefore measured responses to labeled social feedback rather than to independently observed opinions from two groups. All participants were then fully debriefed in person by the experimenter. The debriefing explained the true purpose of the study, disclosed that the feedback participants had received was randomly generated and did not reflect their actual peer or societal rating.

The task contained 153 experimental trials per participant. The primary analysis included 13,310 valid trials: 7,497 from controls and 5,813 from participants with MUD. 1 trial was deleted due to lack of response. Details of the peer-familiarity assessment, source-label instructions, boundary-condition re-presentation, trial randomization and display-order counterbalancing, absence of a post-task manipulation check or performance-contingent incentives, and debriefing are provided in the Supplementary Methods.

Facial stimuli were drawn from the CAS-PEAL face database [50]. Candidate front-facing, neutral-expression images were screened and standardized before the experiment. An independent sample of 10 raters evaluated the attractiveness of each face using the same 10-point scale used in the experimental task. Faces with moderate mean attractiveness ratings were retained. The stimulus-selection procedure was intended to reduce, rather than eliminate, floor and ceiling responses. Each face would only appear once in the task. If participants choose extreme ratings that hit the boundary in certain conditions, additional faces and trials will be added until they undergo the condition.

The final stimulus set comprised 160 unique faces. Image-screening and standardization procedures, rater demographics, inter-rater reliability (ICCs), the numerical selection criterion, normative attractiveness statistics, and counterbalancing are reported in the Supplementary Methods.

Behavioral and Computational Analyses

Trial-Wise Computational Formulation

A valid trial was a non-catch experimental trial with recorded initial, peer, societal, and final ratings. Let s_i denote the initial self-rating, p_i the peer rating, g_i the societal rating, and s'_i the final self-rating. The observed rating update was defined as

$$\Delta R_i = s'_i - s_i$$

The peer and societal inputs were expressed as discrepancies from the initial self-rating:

$$\Delta S_{peer} = p_i - s_i$$

$$\Delta S_{societal} = g_i - s_i$$

The sign of each discrepancy indicated its direction relative to the initial judgment, and its absolute magnitude indicated the distance between the initial and social ratings. The continuous discrepancy variables formed the basis of the primary trial-wise analysis.

Configuration referred to the relation among the initial rating and the two feedback values; both sources were displayed on every trial. Source-aligned refers to the initial score identical to the source, while source-dominant refers to the main influence source in conflict conditions. For illustration, using an initial rating of ($s_i = 5$), Conditions 1–8 can be represented by (s_i, p_i, g_i) as follows: Condition 1 (5,5,5); Condition 2 (5,5,7); Condition 3 (5,7,5); Condition 4 (5,7,7); Condition 5 (5,7,9); Condition 6 (5,3,7); Condition 7 (5,2,6); and Condition 8 (5,6,2). A source matching the initial rating had a discrepancy of zero; Condition 1 was a zero-discrepancy reference condition and was not classified as updating toward or away from either source. For the secondary analyses, Conditions 4–6 were pooled as the dual-source conflict level : they represented, respectively, a common discrepant rating, three distinct ratings, and opposite equidistant ratings. Full generation rules and eight-condition sensitivity estimates are provided in Supplementary Tables 1 and 7.

Secondary source-directed behavioral indices

Secondary source-directed indices expressed rating change relative to each feedback source and were analyzed in separate linear mixed-effects models. Peer-directed updating was defined as:

$$\Delta Score_{peer} = sign_{peer} \times |\Delta R_i| / (|s_i - p_i| + \sigma_{peer})$$

For societal-directed updating, the corresponding index was defined as:

$$\Delta Score_{societal} = sign_{societal} \times |\Delta R_i| / (|s_i - g_i| + \sigma_{societal})$$

For each source k (peer or societal), let ΔR_i = final rating – initial rating and d_k = source rating $_k$ – initial rating. The direction term was coded as $sign_k = 0$ when $\Delta R_i = 0$; $sign_k = -1$ when $\Delta R_i \neq 0$ and $d_k = 0$. Updates that crossed a source rating remained coded as toward that source ($sign_k = +1$), because coding was based on the direction of change from the initial rating. The direction terms $sign_{peer}$ and $sign_{societal}$ were positive when the rating update was directed toward the corresponding social source. Negative values denote movement coded as away from the relevant source under the stated scoring rule; they do not by themselves indicate rejection of that source. The complete direction-coding rules are provided in the Supplementary Methods.

The source-directed indices used post hoc, group-specific stabilizing constants and were therefore treated as secondary. The post hoc constants were $\sigma_{peer} = 2.06$ and $\sigma_{societal} = 2.08$ for HCs, and $\sigma_{peer} = \sigma_{societal} = 2.27$ for participants with MUD. They were the empirical standard deviations of the corresponding initial source discrepancies within each diagnostic group. Their group contrasts may depend on this scaling choice and should be interpreted alongside analyses using common constants and raw rating change. As for sensitivity analyses, we repeated the analyses using pooled constants from all valid trials ($\sigma_{peer} = 2.13$; $\sigma_{societal} = 2.17$) and fixed constants of 1 and 3. Across specifications, the same four peer-directed (absolute estimates, 0.035–0.180) and three societal-directed (0.047–0.347) HC-MUD contrasts survived Holm correction; their signs were unchanged and their 95% CIs excluded zero, whereas all remaining contrast CIs spanned zero. The three-way interactions remained significant across specifications (all $p < 0.001$; Supplementary Methods).

Statistical analysis of behavioral updating

Analyses were conducted in R (version 4.5.2) [51] using lme4 (version 1.1–38) [52]. Omnibus fixed effects were evaluated using Satterthwaite-adjusted tests [53]. Configuration-specific HC-MUD contrasts from the secondary models used asymptotic z tests ($df = Inf$), because emmeans used asymptotic inference when the number of observations exceeded its lmerTest and pbkrtest limits. For each family of post hoc contrasts, we report the contrast estimate, unadjusted 95% CI, the test statistic and degrees of freedom where applicable, and the Holm-adjusted p value [54]. The primary families comprised the four source slopes and the two group-difference contrasts. For each secondary outcome and sensitivity specification, the family comprised six HC-MUD contrasts across the three social-cue configurations and two cue-congruency levels.

The primary behavioral outcome was the raw signed rating change ($\Delta R_i = s'_i - s_i$). Concurrent sensitivity to peer and societal feedback was estimated using the following simultaneous-source linear mixed-effects model:

$$\Delta R_i \sim Group \times (\Delta S_{peer, i} + \Delta S_{societal, i}) + (1 + \Delta S_{peer, i} + \Delta S_{societal, i} | participant) + (1 | face)$$

The discrepancy predictors were entered in their original rating-scale units without centering or scaling, and Group was treatment-coded with HCs as the reference level. The model used maximum likelihood, an unstructured participant-level random-effects covariance, participant-specific intercepts and slopes for both discrepancy signals, and a crossed face random intercept. Specified linear contrasts compared peer and societal slopes. Complete fixed-effect estimates and 95% confidence intervals are reported in Supplementary Table 5; variance components, random-effect correlations, and the singular-fit assessment are reported in Supplementary Table 6.

Source-directed behavioral indices were analyzed as secondary outcomes. Separate models were fitted for peer- and societal-directed updating, with $\Delta Score_{peer}$ and $\Delta Score_{societal}$ entered as dependent variables, respectively. The two models were specified as:

$$\Delta Score_{peer} \sim Group \times social - cue configuration \times cue congruency + (1 + social - cue configuration | participant)$$

$$\Delta Score_{societal} \sim Group \times social - cue configuration \times cue congruency + (1 + social - cue configuration | participant)$$

Models were fitted using maximum likelihood with the bobyqa optimizer. Alternative random-effects specifications and their convergence diagnostics are reported in the Supplementary Methods to show how the final estimable models were obtained. Model simplification was based on singularity and estimability, not on the statistical significance of the behavioral contrasts.

Significant omnibus effects were decomposed using estimated marginal means with Holm-adjusted post hoc tests [54]. Exploratory craving- and sex-related analyses are reported in Supplementary Tables 2 and 3. Complete condition-specific estimates are reported in Supplementary Table 4, and the eight original conditions are shown separately in Supplementary Table 7.

Candidate computational models

We formalized three candidate formulations of multisource social integration: source-specific independent integration, an equal-weight composite, and convergence-dependent amplification [18, 19, 28–31, 33]. These formulations were implemented as the independent-source model, the equal-weight composite model, and the convergence-amplification model, respectively. They were not treated as mutually exclusive mechanisms. Under the parameterization described below, the independent-source model provided the encompassing source-specific formulation:

$$\Delta R_i = b_0 + \omega_p \Delta \text{Score}_{\text{peer},i} + \omega_g \Delta \text{Score}_{\text{societal},i} + \epsilon_i.$$

The equal-weight composite model constrained the independent-source model by setting $\omega_p = \omega_g = \omega_s / 2$. The convergence-amplification model reduced to the independent-source model when $\gamma = 0$. Thus, model selection assessed relative adequacy within a set of overlapping formulations, not mutually exclusive psychological mechanisms.

$$\Delta R_i \sim \mathcal{N}(\mu_i, \sigma^2)$$

Independent-Source model

The independent-source model estimated separate peer and societal discrepancy weights:

$$\Delta R = b_0 + \omega_p \Delta S_p + \omega_g \Delta S_g + \epsilon$$

The intercept b_0 represented predicted rating change when both feedback discrepancies were zero. ω_p and ω_g quantify sensitivity to peer and societal discrepancies, respectively.

The equal-weight composite model represented the two discrepancies using their arithmetic mean:

$$\Delta R = b_0 + \omega_s \left(\frac{p + g}{2} - s \right) + \epsilon$$

Here, $M_i = (p_i + g_i) / 2 - s_i$ and ω_s indexes sensitivity to this equal-weight composite discrepancy. This formulation tests a parsimonious equal-weight prediction but does not establish that the two sources were psychologically pooled.

Convergence-Amplification model

The convergence-amplification model retained separate source discrepancies and allowed their combined influence to vary with directional agreement:

$$\Delta R = b_0 + (\omega_p \Delta S_p + \omega_g \Delta S_g) (1 + \gamma C) + \epsilon$$

C_i coded the specified relation between the two feedback discrepancies; γ , the convergence-related modulation parameter, quantified the change in their combined influence when $C_i = 1$. Specifically, $C_i = 1$ when $\Delta S_{\text{peer},i} \Delta S_{\text{societal},i} > 0$, and $C_i = 0$ when their product was ≤ 0 , including trials in which either discrepancy was zero. $\gamma = 0$ yielded the independent-source formulation without an additional convergence effect. In the implemented optimization, ω_p , ω_g , γ , b_0 and $\log \sigma$ were unconstrained real-valued parameters, allowing negative source weights and convergence-related amplification or attenuation. The derived residual standard deviation was $\sigma = \exp[\log \sigma] > 0$. The model therefore had five free parameters for BIC ($\omega_p, \omega_g, \gamma, b_0, \log \sigma$); the independent-source and equal-weight composite models had four and three, respectively. All models assumed Gaussian residual variation.

Model estimation and comparison

Each candidate model was fitted separately to each participant's trial-wise data by maximum likelihood. Optimizer and multistart settings, parameter constraints, residual-variance estimation, failed-fit handling, and checks for local optima are reported in the Supplementary Methods.

Individual-level models were compared using the Bayesian information criterion (BIC) [55]. The transformation from BIC to descriptive model responsibilities, group-level Dirichlet summaries, software settings, and interpretive limitations are detailed in the Supplementary Methods. These summaries were not treated as evidence for a uniquely identified mechanism [56, 57].

Model validation

Validation comprised held-out ΔR prediction, empirical model and parameter recovery, and parameter-space identifiability analyses [39, 40]. Full procedures and simulation settings are provided in the Supplementary Methods.

The primary predictive check used leave-one-participant-out cross-validation of ΔR . Predicted final-rating correlations were not treated as independent validation because observed and predicted final ratings both contain the initial rating.

Leave-one-participant-out validation assessed prediction for an unseen participant within the same diagnostic group and task. It did not test generalization to a new task, stimulus set, or clinical outcome. For each fold, all valid trials from one participant were held out, and the equal-weight composite model was fitted to all valid trials from the remaining participants in that group. Fold-specific estimates of b_0 and ω_s were applied to the held-out participant's composite discrepancy, $M_i = (p_i + g_i) / 2 - s_i$, to predict ΔR_i . The no-update baseline predicted $\Delta R_i = 0$, the intercept-only baseline used the training-fold mean ΔR , and the source-specific baseline was fitted within each training fold. Relative held-out MSE reduction was defined as $100 \times [1 - MSE_{model} / MSE_{no - update}]$, with MSE aggregated across all held-out trials within each diagnostic group; this measure is distinct from the conventional centered-outcome R^2 . No data-derived preprocessing parameters were estimated or shared across folds. Pearson's r , RMSE, MAE, and comparisons with the alternative baselines are reported in Supplementary Table 9.

Results

Behavioral results

Lower sensitivity to both feedback sources in participants with MUD

To determine how peer and societal information jointly shaped judgment updating on each trial, we first fitted the simultaneous-source model. The model included 13,310 valid trials from 87 participants and 153 faces and showed no singular fit. Sensitivity to both peer and societal discrepancies was lower in participants with MUD than in controls (HC–MUD slope difference: peer = 0.077, 95% CI [0.040, 0.114], Holm-adjusted ($p < 0.001$); societal = 0.036, 95% CI [0.004, 0.068], Holm-adjusted ($p = 0.027$)). Peer slopes were 0.117 in controls (95% CI [0.093, 0.142]) and 0.041 in MUD (95% CI [0.013, 0.069]); societal slopes were 0.071 (95% CI [0.050, 0.092]) and 0.035 (95% CI [0.011, 0.059]), respectively. The HC–MUD difference in peer slopes exceeded the corresponding difference in societal slopes by 0.041 (95% CI [0.005, 0.076], $t(87.37) = 2.29$, Holm-adjusted $p = 0.049$), indicating a larger group difference for peer discrepancy. The peer–societal slope contrast was significant in controls (difference = 0.046, Holm-adjusted ($p < 0.001$)) but was not detected in MUD (difference = 0.005, Holm-adjusted ($p = 0.684$)). Thus, participants with MUD showed reduced sensitivity to both social sources when the discrepancies were modeled concurrently, with a larger direct group difference for peer discrepancy. Complete fixed-effect estimates and 95% CIs are provided in Supplementary Table 5; random-effects estimates and the diagnostic summary are provided in Supplementary Table 6.

Secondary analyses described how source-directed indices varied across feedback configurations (Supplementary Table 4). Because the dual-source conflict category combined three structurally distinct conditions, Conditions 4–6 were examined separately (Supplementary Table 7). Because these indices were transformations of the same rating changes, they were interpreted as complementary descriptions rather than independent replications.

Societal-directed updating varied across feedback configurations

As a complementary configuration-specific analysis, we examined whether the concurrent source sensitivities were expressed differently in societal-directed updating across social-cue configurations. For $\Delta \text{Score}_{\text{societal}}$, we found a significant Group $\times$ social-cue configuration $\times$ cue congruency interaction in a linear mixed-effects model ($F(2, 13191.60) = 55.01$, $p < 0.001$; Fig. 2c).

In the peer-aligned configuration, the societal-directed index was numerically higher in controls than in participants with MUD, but the contrast did not survive Holm correction (estimated difference = 0.022, SE = 0.0108, adjusted $p = .094$). In the societal-aligned configuration, controls

showed a more negative societal-directed index (estimated difference = - 0.152, SE = 0.0114, adjusted $p < .001$), consistent with greater movement away from the initial, societal-aligned rating toward the discrepant peer rating.

In peer-dominant conflict, controls showed a more negative societal-directed index than participants with MUD (difference = - 0.055, Holm-adjusted $p < .001$). The corresponding group contrast was not significant in societal-dominant conflict (difference = 0.013, $p = .237$).

Individuals with MUD showed reduced peer-directed updating under competing social information

We next examined whether the group difference also extended to peer-directed updating under competing social information in $\Delta Score_{peer}$ model. The three-way interaction was again significant ($F(2, 13186.21) = 40.91$, $p < 0.001$; Fig. 2d). The peer-directed index showed a configuration-dependent group effect. In the peer-aligned configuration, controls had a more negative peer-directed index than participants with MUD; this describes the same rating changes from a different source-relative scale (HC: EMM = - 0.196, SE = 0.0118; MUD: EMM = - 0.108, SE = 0.0125; difference = - 0.088, SE = 0.0110, $z = - 8.05$, Holm-adjusted $p < 0.001$). The corresponding societal-directed contrast did not survive Holm correction (difference = 0.022, Holm-adjusted $p = 0.094$), indicating that inference from the two source-relative indices was not fully consistent in this configuration. Interpretation therefore prioritized the primary raw- ΔR analysis and sensitivity analyses using common stabilizing constants. In the societal-aligned configuration, controls showed stronger peer-directed updating (HC: EMM = 0.064; MUD: EMM = 0.023; difference = 0.041, SE = 0.0111, $z = 3.73$, Holm-adjusted $p < 0.001$).

In conflict configurations, controls showed greater peer-directed updating in peer-dominant conflict (difference = 0.037, SE = 0.0132, $z = 2.83$, Holm-adjusted $p = .009$), whereas the societal-dominant contrast was not significant (difference = - 0.012, SE = 0.0110, $z = - 1.07$, Holm-adjusted $p = .285$).

The primary analysis indicated lower sensitivity to both feedback sources in MUD, while secondary analyses described variation in group contrasts across specific configurations.

Computational model results

The equal-weight composite model had the lowest BIC but was not uniquely identifiable

Having identified configuration-dependent behavioral signatures, we next conducted a secondary, descriptive comparison within the specified candidate set. All models predicted ΔR from peer and societal discrepancies (Fig. 3a,b). The independent-source model retained separate weights, the equal-weight composite model combined the discrepancies with equal weight, and the convergence-amplification model scaled source-specific effects by directional agreement. Because the latter formulations are nested or partially overlapping, the comparison indicates relative descriptive adequacy.

The equal-weight composite model had the lowest BIC for 31 of 49 controls and 32 of 38 participants with MUD. This preference supported a relatively parsimonious description within the tested set, but did not identify a unique psychological representation.

Prediction targeted rating change rather than final ratings. Relative to no update, the equal-weight composite model reduced held-out MSE by 11.3% in controls (95% CI [6.9%, 14.6%]; Fig. 3d) and 2.7% in MUD (95% CI [- 0.7%, 5.2%]; Fig. 3c). The MUD interval included no improvement over this baseline.

Model recovery was asymmetric [39, 40]. Across 20 simulations per participant and generating model, the equal-weight composite model was recovered in 96.3% of datasets, whereas data generated by the independent-source and convergence-amplification models were assigned to the equal-weight composite model in 70.0% and 63.4% of cases, respectively (Fig. 3f; Supplementary Figure S1A; Supplementary Methods). Recovery of the generating model was 37.3%, 96.3%, and 20.2% in HCs and 17.8%, 96.2%, and 14.2% in participants with MUD, respectively. This asymmetry indicates overlapping predictions under the present task structure and limits mechanistic interpretation of BIC preferences. Parameter-recovery results are reported in Supplementary Table 8.

Parameter-space simulations showed that exact parameter overlap made some formulations observationally equivalent, whereas near-overlap reduced their discriminability under the present sample size, task structure, and noise levels (Supplementary Figure S1B-F). Thus, BIC preferences within the candidate set could not identify a unique psychological representation.

Individuals with MUD showed reduced equal-weight composite weighting

Across all participants, the equal-weight composite feedback-sensitivity parameter was lower in MUD than in controls (means: 0.073 and 0.183; controls-minus-MUD difference = 0.111, 95% bootstrap CI [0.055, 0.165]; Hedges' $g = 0.79$).

Discussion

Abstinent individuals with MUD showed weaker updating of attractiveness judgments in response to both peer and societal feedback than healthy controls. In the primary analysis, lower sensitivity to each source was evident when both discrepancies were modeled simultaneously. Secondary analyses described variation in group differences across feedback configurations. The equal-weight composite model provided a parsimonious description within the candidate set, and its feedback-sensitivity parameter was lower in MUD. These findings characterize social feedback use in a controlled task; they do not establish a unique integration mechanism.

The behavioral findings extend work on social cognition and decision-making in stimulant use disorders by examining two simultaneously presented sources [58, 59]. The primary analysis supported lower sensitivity to both sources in MUD, while secondary contrasts varied by configuration. In particular, the societal-directed contrast in the peer-aligned condition did not survive Holm correction and should not be treated as an established group difference. Greater rating change in controls also cannot be assumed to represent better adaptation, because attractiveness judgments have no objectively correct target. Lower updating may reflect differences in feedback credibility, confidence in initial judgments, task engagement, or the use of social information; the present task did not separate these possibilities.

The computational comparison should be interpreted as a comparison of related statistical descriptions. The equal-weight composite formulation is a constrained source-specific model, and the convergence-amplification formulation includes the source-specific model when γ is zero. Preference for the simpler formulation therefore does not demonstrate that participants first formed a shared social reference or used the same latent architecture across groups. It is also compatible with unequal source slopes in the group-level behavioral analysis: participant-level BIC comparisons penalize additional parameters, whereas the mixed-effects analysis estimates source differences across participants. Recovery asymmetry and the small held-out gain from separate source weights further limit claims about a distinct pooling mechanism.

The composite-feedback parameter is best treated as a task-derived summary whose individual-level reliability and clinical relevance remain unestablished. Its held-out prediction improved on no update more clearly in controls than in MUD, and the MUD interval included no improvement. Before considering clinical applications, future studies should assess test–retest reliability, replicate the group difference, and examine associations with independently measured social functioning [60, 61]. Should those prerequisites be met, intervention studies could evaluate whether task-derived measures change alongside established behavioral treatments for drug use [62] and methamphetamine dependence [63, 64]. Such work should relate change to independently measured outcomes and evaluate proposed mediating processes [65]. The present data do not establish it as a biomarker or treatment target.

Several limitations qualify these findings. The group comparison was observational, so differences cannot be attributed specifically to methamphetamine exposure or abstinence. Recruitment from rehabilitation centers and the community may have introduced differences in treatment context and social experience. The subjective rating task did not assess social functioning or clinical outcomes. Confidence in initial judgments and engagement with the task also remain alternative explanations.

Several limitations should be considered. First, the observational comparison cannot determine whether the group differences preceded methamphetamine use, followed exposure, or reflected treatment and abstinence-related experiences. Recruitment from rehabilitation centers and the community also limits separation of diagnostic status from social context. Second, the computer-generated feedback tested responses to source labels, and no post-task manipulation check established whether the groups believed or trusted those labels to a similar extent. Initial confidence and task engagement were not directly assessed, leaving these as alternative explanations. Third, the sample comprised 87 participants, despite the large number of repeated trials; the study was not preregistered and had no a priori sample-size calculation. The precision and reproducibility of higher-order and configuration-specific effects therefore require further evaluation. Finally, group-specific scaling of the secondary indices, unequal condition frequencies, bounded responses, and potential dependence within shared sessions constrain interpretation. These considerations support prioritizing the raw-rating analysis and interpreting secondary results according to the assumptions of each measure.

In conclusion, abstinent individuals with MUD showed lower sensitivity to concurrent peer and societal feedback during judgment updating. A simple composite-feedback formulation summarized this pattern, while model overlap and limited predictive gains in MUD constrained mechanistic and individual-level interpretation. The findings provide a basis for investigating when reduced social feedback updating is expressed and whether it has consequences for everyday social functioning and recovery.

Declarations

Competing interests

The authors report no conflicts of interest.

Statement

The study was not a clinical trial and did not have a clinical trial number. Clinical trial number: not applicable.

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Author Contribution

Yutong Li wrote the main manuscript text. Quanhao Yu provided suggestions on Figure 1-3. Qianli Zou offered resource in drug rehabilitation center. Bo yang, Zhang hao and Yutong wan supervised the manuscript. Di Zhao conceptualized and revised the manuscript. All authors reviewed the manuscript.

Data Availability

Data and code availability All data supporting the findings of this study are available within the paper and its Supplementary Information. De-identified trial-level behavioral data and analysis-ready files supporting the findings of this study will be deposited in the same public repository upon publication. Custom code used for data preprocessing, statistical analyses, computational-model fitting, simulation-based model-recovery analyses, and figure generation will be made publicly available upon publication in a public GitHub repository and archived on Zenodo to obtain a versioned DOI.

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Figures

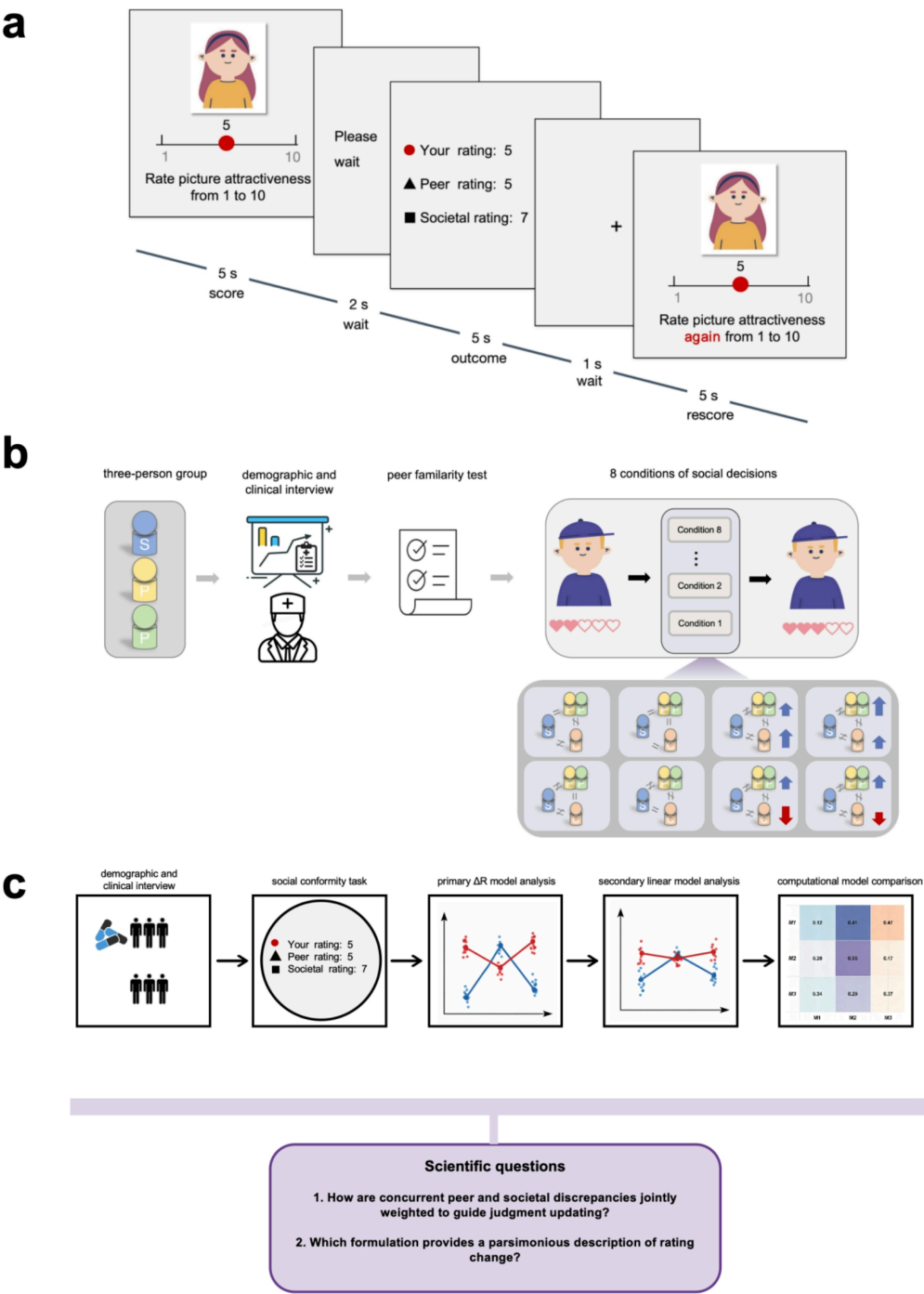


Figure 1

Task and analysis workflow. Participants revised attractiveness ratings after viewing computer-generated feedback labeled as peer and societal ratings. Primary analyses modeled raw rating change; secondary analyses examined configuration-specific indices and compared overlapping computational formulations.

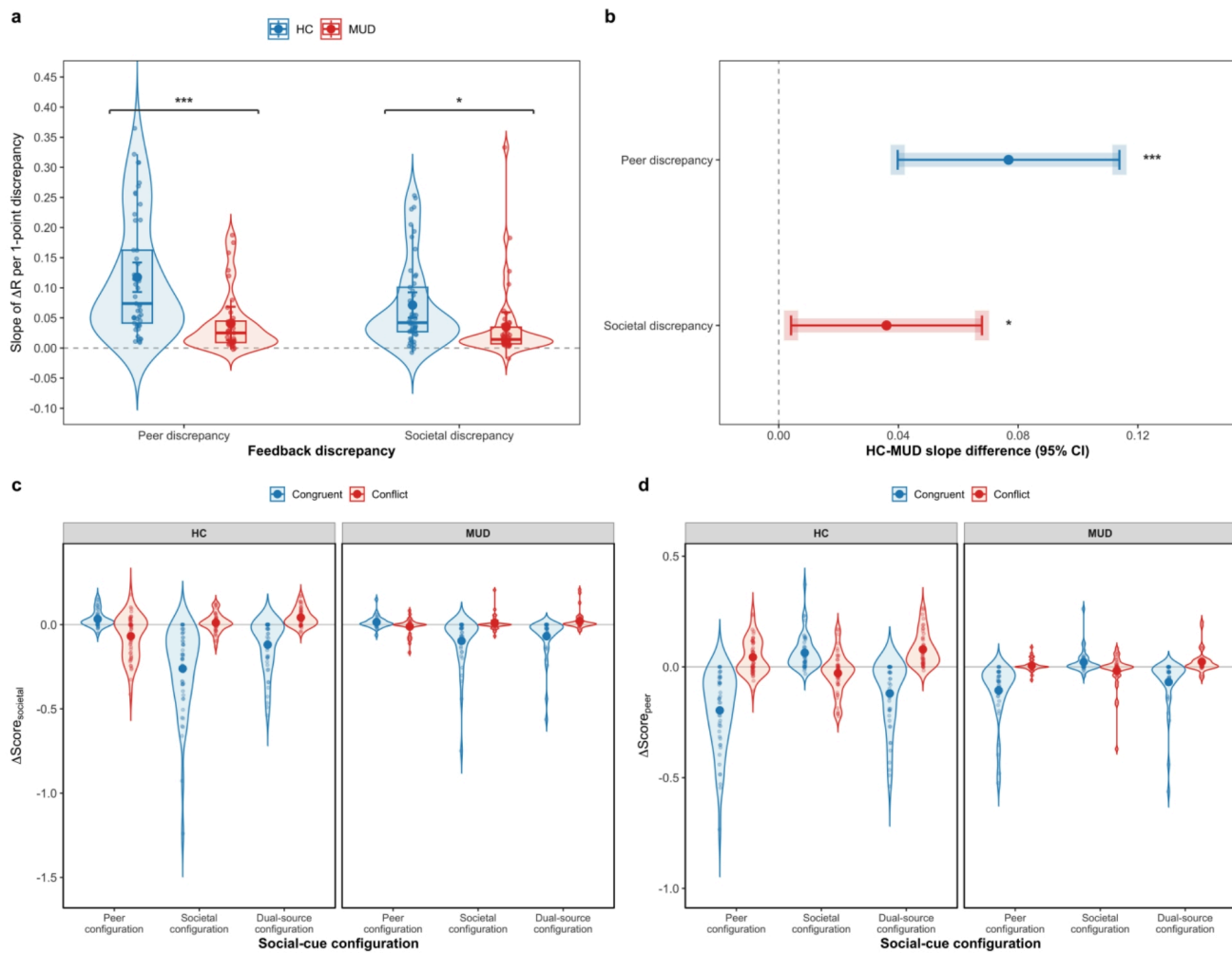


Figure 2

Primary simultaneous-source and secondary source-directed mixed-effects analyses. (a), Group-specific slopes relating trial-wise rating change (ΔR) to peer and societal discrepancies in the simultaneous-source model. Large points and error bars show fixed-effect slope estimates and 95% CIs. Brackets and stars indicate the prespecified HC-MUD slope contrasts (* Holm-adjusted $p < 0.05$; *** Holm-adjusted $p < 0.001$). (b), Direct HC-MUD differences in peer and societal discrepancy slopes. Points and horizontal intervals show contrast estimates and unadjusted 95% CIs; stars denote the same Holm-adjusted contrasts as in a. (c,d), Secondary source-directed indices, $\Delta \text{Score}_{\text{societal}}$ (c) and $\Delta \text{Score}_{\text{peer}}$ (d), stratified by social-cue configuration, cue congruency, and group. Large points and error bars show estimated marginal means $\pm$ SE. Peer and societal configurations include the peer- and societal-aligned congruent conditions (Conditions 2 and 3) and the corresponding peer- and societal-dominant conflict conditions (Conditions 7 and 8).

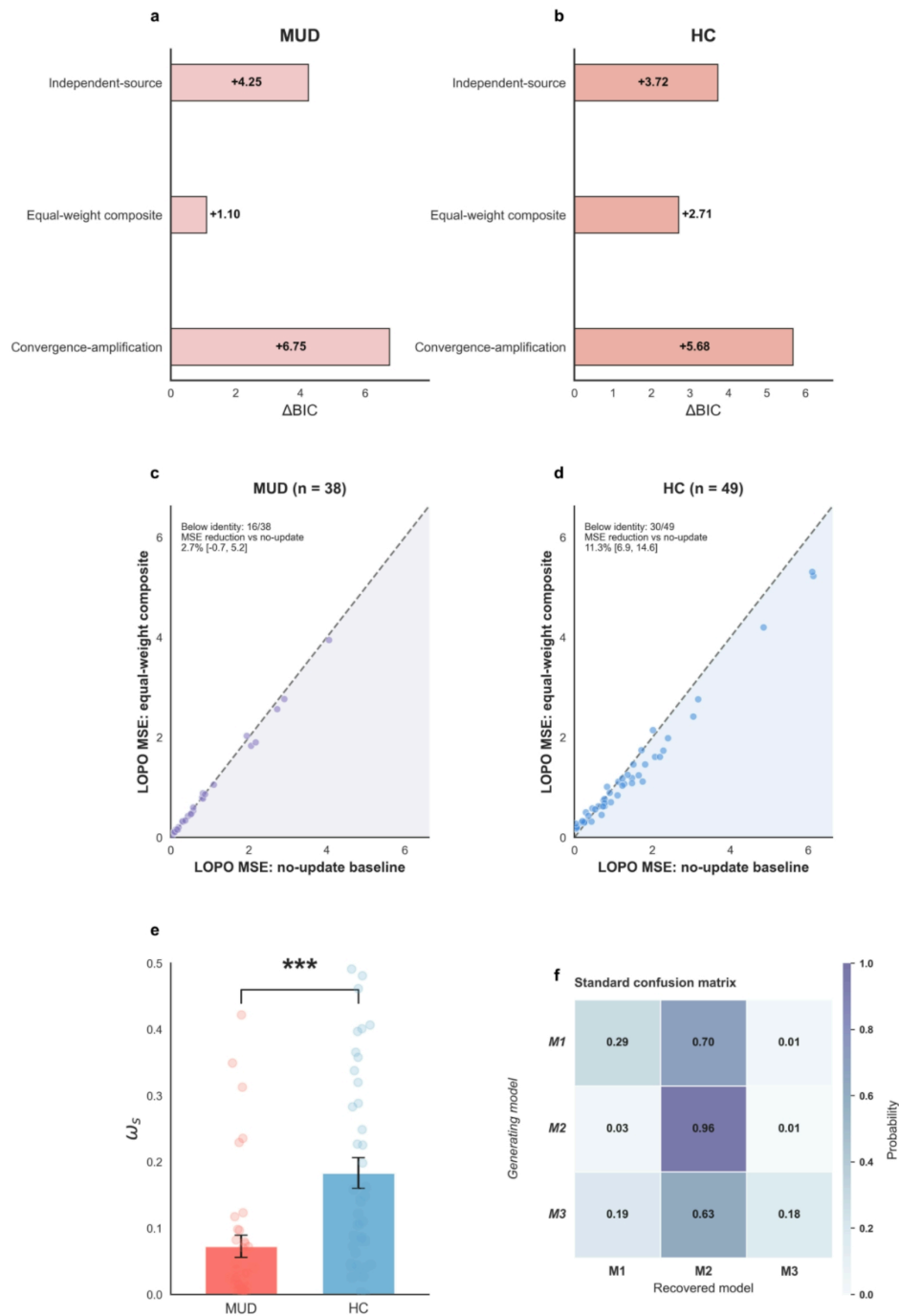


Figure 3

Model comparison, predictive check, parameter differences and model recoverability.

Group-level model comparison based on ΔBIC for the MUD group (a) and healthy-control (HC) group (b). For each participant, ΔBIC was calculated as the BIC of each candidate model minus that participant's lowest BIC across the three candidate models. Bars show the group mean of these participant-level ΔBIC values. Lower ΔBIC values indicate stronger relative model evidence. Within the specified candidate set, the equal-weight composite model showed the best relative fit across both groups. Panels c and d show participant-level held-out MSE in MUD and controls, respectively. Points below the identity line indicate lower error for the equal-weight composite model than for no update. Each point represents one participant. The dashed diagonal is the identity line ($y = x$), indicating equal held-out error for the two models;

points below the line indicate lower error for the equal-weight composite model. Percentages report the group-level relative reduction in aggregate held-out MSE, calculated as $100 \times [1 - \text{MSE}_{\text{equal-weight composite}} / \text{MSE}_{\text{no-update}}]$; they are not participant-level or clinical prediction-accuracy measures. e. Group comparison of the ω_s parameter from the equal-weight composite model. The y-axis denotes ω_s , the feedback-sensitivity coefficient in the equal-weight composite model. Points represent participants; bars show means and error bars show SEM. f. Standard model-recovery confusion matrix. Rows indicate generating models and columns indicate selected models: M1, independent-source; M2, equal-weight composite; M3, convergence-amplification. Values are row-normalized selection proportions.

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