Cognitive Strategies for Peer Judgments

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Abstract

How do people make judgments about characteristics of their immediate their peers? We investigate what cognitive strategies underlie peer judgments, what group-level patterns of judgments these strategies produce, and whether they generate accurate judgments. We develop a general model that allows for comparison of different cognitive strategies including ego projection, probability matching, and three memory-based strategies. We examine it using a unique data set including self-reports and estimates of peer substance use among homeless youth (N=239). We find evidence for the adaptive use of strategies that are most appropriate given the information available from one's personal experience and social environment. On the group level, the pattern of judgments sometimes resembles false consensus and sometimes false uniqueness, but overall shows a high level of accuracy.

Keywords: Social judgment, substance use, false consensus, ego projection, memory, inference

Cognitive Strategies for Peer Judgments

Many public policy initiatives rely on social comparison processes to influence behaviors ranging from reducing alcohol and tobacco consumption to saving energy and voting (Allcott, 2011; Berkowitz, 2005). Despite the large literature investigating accuracy of people's judgments of individuals (Bernard et al., 1984; Freeman et al., 1987; Funder, 1995) and groups (Krueger, 1998, 2000, 2007; Krueger & Clement, 1994, 1997; Robbins & Krueger, 2005) there are surprisingly few studies that develop and test computational models of the cognitive strategies people use to make such judgments (Galesic et al., 2018; Pachur et al., 2013; Schulze et al., 2021).

In this paper we present a general model of how people make judgments about their peers and use it to compare different cognitive strategies underlying these judgments. Specifically, we study social judgments where the judgments and the accuracy of judgments of peer behaviors are of great importance: perception of peers' substance use. These perceptions affect individual substance use, especially among youth (D'Amico & McCarthy, 2006). In particular, homeless youth report remarkably elevated rates of substance use (Thompson et al., 2003) and peer influence is a significant factor in the emergence of their substance use (Barman-Adhikari et al., 2015; Tyler, 2008; Wenzel et al., 2010). We use sociometric data about two populations of homeless youth, including self-reports of own substance use and judgments of peers' use (Barman-Adhikari et al., 2020). As we describe next, we investigate three research questions: 1) What cognitive strategies do these people rely on to produce judgments of peers' substance use?, 2) What group-level patterns of judgments do these strategies produce?, 3) Do strategies that people use to make peer judgments produce accurate answers?

Strategies used to derive peer judgments

Our first research question is what specific strategies people rely on when estimating peers' substance use. Although several quantitative models exist that are specifically aimed at explaining social judgments and impression formation, ranging from exemplar-based theories (Smith & Zárate, 1992) to connectionist models (Kunda & Thagard, 1996; Van Overwalle & Labiouse, 2004), there are no quantitative comparisons of how well models of different cognitive strategies predict how people make peer judgments.

We develop a general model of peer judgments that assumes *three sources of information* that people can rely on to make estimates of the frequency of different behaviors among their peers: their own behavior, information they have about the overall population, and direct experience with their peers. If people have little direct experience with the behavior of their peers (for example, if their peers use substances only in private) they might assume that their peers are like them, that their peers are different from them, or that their peers are as likely to be substance users as is an average person in the overall population of interest. If people have directly observed the behavior of their peers or can observe cues about their peer's substance use, they can use that source of information in addition to or instead of information about themselves and the overall population.

Within the general model, we specify and compare *five plausible cognitive strategies* that use different sources of information. The first strategy is pure *ego projection*, which assumes that one's peers are mostly like oneself (Epley et al., 2004; Kruger, 1999). For example, an individual who does not use a particular substance might estimate that most or all of their peers are also nonusers. The second strategy is *probability matching* (Gaissmaier & Schooler, 2008; Vulkan, 2000), which relies solely on generalized knowledge about the frequency of substance use among one's peers. It uses this knowledge to make judgments about individual peers. For example, if one knows that half of one's peers are likely to be users, but is not sure which ones, one might randomly assign an individual peer to either a user or a nonuser category. The next three strategies we investigate rely not only on one but on two different sources of knowledge. These *memory-based strategies* assume an imperfect recall of peers' specific behaviors or behavioral cues, and combine it with knowledge about oneself (ego-informed memory strategies) or about the overall population (population-informed memory strategies). Ego-informed memory strategies can have two flavors, assuming that own behavior is either common or rare. For example, an individual might assume that the substance they use is so appealing that it must also be used by others; or conversely, that their substance is so unpleasant or hard to get that they are the only ones using it. Accordingly, the *ego-common memory* strategy relies on the assumption that one's peers are mostly like oneself, while the *ego-rare memory* strategy assumes that one's peers are unlike oneself. Population-informed memory strategy uses knowledge about the population to derive judgments. This *population-memory* strategy combines general knowledge about the overall population with peer knowledge. Next, we formalize the general model and each of the strategies.

A general model for peer judgment strategies

The paradigmatic model for human decisions and judgments is the additive linear framework (Hammond, 1955; Hogarth & Karelaia, 2007; Juslin et al., 2003; Meehl, 1953; Payne et al., 1993). It takes pieces of information, or cue values, as input, weighs them, and adds them together to form a prediction. It includes several classes of models, ranging from multiple linear regression to constrained linear strategies (e.g., fixed equal weight strategies). Here we use a variant of the additive linear framework as a general model that contains different cognitive strategies that might underly peer judgments as nested models. This allows us to examine if the general model's flexibility is needed to explain the patterns of peer judgments across nonusers and users of different substances, or whether one or more nested strategies are sufficient.

In the general model, the prediction of an individual *i*'s estimate whether a peer is like oneself, $\hat{p}_{i,est\_oneself}$, is the function of two free parameters and the measured true proportion of individuals like oneself among one's peers:

$$\hat{p}_{i,est\_oneself} = r \times (1 - w) + w \times p_{i,true\_oneself}, \quad (1)$$

where $r \in [0\ 1]$ and $w \in [0\ 1]$.

The parameter *r* reflects an individual's initial hypothesis of the probability that a peer is like oneself, based on what one knows about own behavior or about the overall population. This parameter acts mostly as an intercept, although it interacts with the other parameter *w* to produce predictions. The parameter *w* reflects how well one relies on one's memory of relevant peers' behaviors or cues of those behaviors. Some of the sub models described later will constrain the parameters *r* and *w* to certain values. The term $p_{i,true\_oneself}$ is the true proportion of individuals like oneself among one's peers [1]

From this general formulation we can derive our five strategies that have different constraints on *r* and *w*. These two parameters act together to put different weights on knowledge about oneself, the broader population, and one's peers. The constraints for the different strategies are summarized in Table 1 and described next.

Ego projection strategy. This strategy assumes that when judging others one relies on one's own characteristics (Epley et al., 2004; Kruger, 1999). This strategy can capitalize on a particular structure of social environments, homophily, the tendency to be surrounded by similar

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[1] Eq. 1 can be written in several different ways. For example, it can be written as: $\hat{p}_{i,est\_oneself} = r - w \times (r - p_{i,true\_oneself})$. We choose to keep the formulation in Eq. 1, as it makes the tradeoff between the actual knowledge about one's peers ($p_{i,true\_oneself}$) and other sources of information (*r*) more clear.

others (Dawes, 1989; Dawes & Mulford, 1996; McPherson et al., 2001). A pure *ego projection strategy* assumes that substance users estimate that their peers are substance users, while nonusers will answer that their peers are nonusers. We implement a probabilistic version of this strategy that assumes that $w = 0$ and $r \in [.5\ 1]$. Thus, the model prediction of an individual's estimate of whether a peer is like oneself is:

$$\hat{p}_{i,est\_oneself} = r. \quad (2)$$

Probability matching strategy. This strategy has been investigated in other contexts (Gaissmaier & Schooler, 2008; Vulkan, 2000), but not for peer judgments. It assumes that an individual knows at least approximately the true proportion of peers like oneself, $p_{i,true\_oneself}$, in their social environment, but not necessarily which peers those are. In terms of our general model, it means that $w = 1$. Therefore, an individual's estimate of whether a peer is like oneself reflects the true proportion of such peers, $p_{i,true\_oneself}$, and the prediction from the model assuming probability matching is:

$$\hat{p}_{i,est\_oneself} = p_{i,true\_oneself}. \quad (3)$$

Ego-common memory strategy. This strategy builds on the ego projection strategy and assumes that people start from their own characteristics but then adjust their judgments based on retrieval of substance use or nonuse behaviors among peers or cues that point to substance use or nonuse. Here, $r = 1$ and $w \in [0\ 1]$, and the model prediction of an individual's estimate of whether a peer is like oneself is:

$$\hat{p}_{i,est\_oneself} = 1 \times (1 - w) + w \times p_{i,true\_oneself} \quad (4)$$

Ego-rare memory strategy. This strategy is another variant of ego projection strategy, this time starting from the assumption that nobody else shares one's own behavior, and then making adjustments based on memory of peers' behaviors or behavioral cues. In terms of our general model, it means that $r = 0$ and $w \in [0\ 1]$. Here, parameter w can be interpreted as the probability of recall of peers' behaviors or behavioral cues. The predicted estimate of whether a peer is like oneself will therefore almost always be an underestimation of the true proportion of peers like oneself:

$$\hat{p}_{i,est\_oneself} = 0 \times (1 - w) + w \times p_{i,true\_oneself}. \quad (5)$$

Population memory strategy. This strategy combines knowledge about the overall population with recall of peers' behaviors or cues about their behaviors. In the formal implementation of this strategy, r is equal to the mean of the true proportion of peers like oneself across all individuals in the population under consideration, that is $r = \bar{p}_{true\_oneself}$, making this strategy similar to the regression model by Fiedler et al. (2009). The model-predicted estimate of whether a peer is like oneself is:

$$\hat{p}_{i,est\_oneself} = \bar{p}_{true\_oneself} \times (1 - w) + w \times p_{i,true\_oneself}. \quad (6)$$

In the context of substance use, we can hypothesize different values of parameters r and w for users and nonusers, and explore these hypotheses by fitting the general model to the data. Users are likely to have more knowledge about behavioral cues of substance use and about other substance users. This might lead them to rely on their recall of peers' behaviors and behavioral cues more often than nonusers, which should show in larger values of w for users than for nonusers. Users are also likely to have a better grasp of the use of their substance in the overall population, which could be reflected in values of r closer to true proportion of users in the overall population. Conversely, nonusers could in absence of other knowledge rely more on what they know about themselves, reflected in values of r close to 1 and in smaller values of w.

Group-level patterns of peer judgments

Our second research question asks what are the group-level patterns of judgments that the strategies produce. Can our strategies produce predictions that are in line with group-level patterns commonly observed in research in social cognition and substance use? In particular, we are interested in whether the strategies can produce three well-researched patterns: false consensus (Ross et al., 1977), pluralistic ignorance (Prentice & Miller, 1993), and false uniqueness (Frable, 1993; Mullen et al., 1992). Illustrative examples of these empirical patterns as they apply to our study are shown in Figure 1.

The false consensus effect, or more generally social projection (Krueger, 1998, 2000, 2007; Krueger & Clement, 1994, 1997; Robbins & Krueger, 2005), is a phenomenon where people with a certain characteristic (e.g., behavior or opinion) believe that this characteristic is more common than do people without it. False consensus is often measured as the difference in estimated frequency of a characteristic by people who have it and people who do not (Mullen et al., 1985). This measure is suitable for investigating false consensus in judgments of broader population (e.g., general population), but it is not applicable when it comes to false consensus in judgments of one's own peers. Here, different participants will answer questions for different groups – each for their own peers. Therefore, we define false consensus as the pattern where average estimates that a peer is like oneself (average $p_{i,est\_oneself}$) is higher than the true proportion of such people among one's peers ($p_{i,true\_oneself}$). False consensus for peers' substance use is present if substance users overestimate substance use among their peers and nonusers underestimate the use, or equivalently, both nonusers and users overestimate the probability that their peers are like themselves (Figure 1A). For example, Henry et al. (2011) showed that adolescents' reports of their friends' substance use (tobacco, alcohol, and marijuana) were biased in the direction of their own use.

Pluralistic ignorance is a phenomenon where individuals privately reject a norm, but assume that a majority of others accept it, and therefore adhere to the norm. In substance use research, pluralistic ignorance is usually interpreted as a tendency for nonusers and users alike to overestimate substance use among their peers (Bourgeois & Bowen, 2001; Mäkelä, 1997; Prentice & Miller, 1993), leading to users' overestimating and nonusers' underestimating the probability that their peers are like themselves (Figure 1B). Alternatively, and closer to the traditional pluralistic ignorance interpretation but not much discussed in the substance use literature, the norm in a particular population might be that people should not use a particular substance, and that would lead to the prediction that both nonusers and users would underestimate the substance use among their peers, leading to users' underestimating and nonusers' overestimating the probability that their peers are like themselves.

In addition to false consensus and pluralistic ignorance, the social judgment literature has identified a phenomenon called false uniqueness (Frable, 1993; Mullen et al., 1992). Applied to substance use, this pattern would occur when a person who does not use a substance overestimates the probability that a peer is using, while a person who uses a substance overestimates the probability that a peer is not using, leading to the overall underestimation of the probability that a peer is like oneself (Figure 1C).

Figure 2 shows illustrative examples of how the different strategies can account for these group-level patterns, given specific pre-set values of the parameters r and w. Both the ego projection strategy and the ego-common memory strategy can produce different levels of false consensus. Pure probability matching can never produce patterns of false consensus, false uniqueness, or pluralistic ignorance. The ego-rare memory strategy can produce false uniqueness. The population memory strategy produces predictions that can be in line with both false consensus and false uniqueness patterns. Only the general model can produce all three patterns: false consensus, false uniqueness, and pluralistic ignorance, as shown in the example in Figure 2.

To explore the full space of predictions of each strategy, Figure S1 in the Supplemental Materials shows group-level patterns produced by different strategies across all possible values of the r and w parameters, for five different levels of true proportion of peers like oneself. This figure shows that the general model is the only one that can produce pluralistic ignorance across all levels of true proportion of peers like oneself, given the appropriate levels of r for the groups of users and nonusers. For instance, compare red and blue areas in the second and fourth panel on the first row. If we assume 25% of users in a population, then users would belong to the second panel (true proportion of peers like oneself = .25) and nonusers to the fourth panel (.75). The general model predicts pluralistic ignorance if the value for r is low for users (the blue area in the second panel of the first row, indicating that these individuals are predicted to underestimate the probability that a peer is like oneself) and high for nonusers (the red area in the fourth panel, these individuals are predicted to overestimate the probability that a peer is like oneself).

Explorations of the model space shown in Figure S1 also raise questions about the flexibility of the different models and how this can be accounted for in model comparisons. We address this issue in model selection by using Variational Bayesian Monte Carlo (VBMC) (Acerbi, 2018) estimates of the posterior evidence for each of the models and by comparing these results with model selection methods that only take into account the number of parameters, such as the Bayesian Information Criterion, BIC (Schwarz, 1978) and the Akaike information criterion, AIC (Akaike, 1974; Burnham & Anderson, 2002).

Accuracy of peer judgments

Our third research question asks whether strategies that people use to make judgments about their peers can produce accurate answers. There is a large literature on the accuracy of people's judgments of individuals (Bernard et al., 1984; Freeman et al., 1987; Funder, 1995). Studies include a variety of relationships from zero acquaintance (Zebrowitz & Collins, 1997) to friends, coworkers, and family (Malloy et al., 1997), and romantic partners (Gagné & Lydon, 2004); and a variety of target variables such as deception (Anderson et al., 2002), consumer preferences (Gershoff & Johar, 2006), emotional facial signals (Ansfield et al., 1995), personality (Funder & Colvin, 1988), political attitude agreement (Goel et al., 2010), sexual interest (Perilloux et al., 2012), and socio-economic and demographic information (Laumann, 1969).

The results from this line of research show that friends are fairly accurate in judging one another's characteristics, although there is also evidence suggesting a general positivity bias and ego projection in close relationships (Gagné & Lydon, 2004). Barman-Adhikari et al. (2020) find that perceptions of peer substance use among youth experiencing homelessness are relatively accurate (average proportion correct over all youth's peers' proportion correct ranged from .61 to .77, depending on the substance). This result does not necessarily rule out the possibility of ego projection. Barman-Adhikari et al. showed that the youth's social networks are characterized by a high degree of homophily by substance use (with between 63% and 75% match between peers depending on the substance). Furthermore, they show that the substance use homophily was the strongest predictor of accuracy of peer judgments, suggesting that the reasonably high level of accuracy might have been the result of ego projection. However, Barman-Adhikari et al. (2020)

focused on accuracy and network properties and did not investigate or compare how different strategies could produce the patterns of accuracy they observed.

Different cognitive strategies are expected to produce different levels of accuracy. Ego projection is typically assumed to lead to biased judgments, but there are also arguments that it can be a normatively appropriate strategy in some situations. When one belongs to the majority, which is often the case in social environments characterized by high homophily, it can be shown that it is Bayesian rational to rely on one's own characteristics when no other information is available (Dawes, 1989; Dawes & Mulford, 1996). In our study, we expect that ego projection will reach a high level of accuracy when homophily is high, but when homophily is low it will lead to incorrect judgments. Probability matching will produce well-calibrated judgments, that is the predictions will reflect the true proportions of peers like oneself. Memory-based strategies will produce more or less accurate judgments depending on the accuracy of memory for peers' behaviors and behavioral cues.

Method

We use the same data set described in Barman-Adhikari et al. (2020), but ask novel research questions about what cognitive strategies participants are using to derive peer judgments. We also expand the data set to include self-reports and judgments of peers' use for heroin and cocaine. For details, see Barman-Adhikari et al. (2020). Self-reports of substance use have methodological challenges and typically underestimate youth's substance use (Harrison, 1997). We address this problem in our study by using questions about substance use from the CDC's Youth Risk Behavior Surveillance System and specifically the Youth Risk Behavior Survey. This national survey has been conducted biannually since 1991 to assess youth risk behaviors. By using these survey questions, we also ensure that our results can be compared to other studies that have used these questions. These questions have undergone extensive reliability testing over the years, showing satisfactory results (kappa = 61%–100%, Brener et al., 2013). The validity of self-reports of substance use is ultimately difficult to assess, but many studies have tried (see e.g., Brener et al., 2003). Estimates of underreporting of youth's substance use range from close to zero (or even overreporting) to 30% depending on the substance, the criterion used (biological marker, deep interviews etc.), the specific target population, the specifics of the questions used to assess substance use, and other factors (e.g., Buchan et al., 2002). In an effort to counter some of the validity threats, we perform two sets of additional analyses to try to mitigate effects of underreporting of substance use. In the first analysis, based on the empirical ranges of underreporting, we flip different percentages of nonusers to users to assess if our model-based conclusions still hold. In the second, we analyze separately participants who reported they were nonusers of each heavy substance and who at the same time stated i) that they did not use any other heavy substance or ii) that they used some other heavy substance. The latter group is more likely to be truthful than the former, as they admit using at least one other heavy substance. If the pattern of results of these two groups are similar, this suggests that underreporting is less likely to be an issue in our data.

Participants

We used an event-based approach (Freeman & Webster, 1994) to sample participants from two drop-in centers for homeless youth in California, one in Hollywood and the other in Santa Monica. All youth accessing the drop-in centers were eligible and invited to participate. A total of N=241 participants, aged 13–25 years (see Table 2 for more details), were recruited between October 2011 and February 2012. In this article, we use data from 239 participants due to coding errors for two participants. Before conducting interviews, research staff members obtained signed voluntary informed consent from each youth 18 years of age or older and informed assent from youth between 13 and 17 years of age. All participants received $20 in the form of cash or a gift card for their participation. Institutional Review Board approval was obtained for all survey items and procedures.

Network data. Participants were asked to name their peers, that is every person they interacted with either face-to-face, on the phone, or in written forms of communication including text messages, emails, or through a social networking site. After youth finished nominating peers, the interviewer went through a series of questions regarding the different attributes of each peer. Interviewers asked for each peers' first and last name, nickname or street name, visible tattoos, age, race, gender, length known etc. A sociomatrix was created linking participants in the sample. Matches were based on: first name, last name, alias, race/ethnicity, gender, approximate age, tattoos, and agency attendance. Two independent reviewers made match decisions for all relationships.

Measures

The questionnaire included a large number of variables collected for the purpose of several concurrent studies. In this study we focus only on substance use. For analyses of the impact of network characteristics on the accuracy of peer judgments, see Barman-Adhikari et al. (2020).

Substance use. Participants reported whether they have used different substances in the previous 30 days, including alcohol (heavy drinking, i.e., drinking to the point of drunkenness), marijuana, methamphetamine, prescription drugs, heroin, and cocaine.

Peers' substance use. Participants reported for each of their peers whether they thought the peer has used different substances. For each substance and each unique dyad (i.e., participant and peer), we derived a dichotomous variable representing a match between participant's own behavior and participant's estimate of peer's behaviors ($p_{i,est\_oneself}$, where 1 represented an estimated match between oneself and the peer, and 0 represented a mismatch).

Accuracy measures. To investigate the accuracy of individual peer judgments we used the concordance between judgments (i.e., estimates of a peer being like oneself or not, $p_{i,est\_oneself}$) and actual characteristics of each peer (i.e., if the peer is like oneself). To investigate patterns of judgments of peers' substance use (e.g., false consensus), for each participant we calculated the average of participants' estimates of whether a peer is like oneself (average $p_{i,est\_oneself}$ across peers) and compared it with true proportion of peers like oneself ($p_{i,true\_oneself}$).

Fitting procedure

To investigate how different strategies accounted for judgments of peers' substance use, we compared participants' estimates of use for each individual peer with probabilistic predictions from the models of the cognitive strategies described before and in Table 1. Probability matching (Equation 3) had no free parameters, while the other strategies had one free parameter each: ego projection had a free parameter r (Equation 2), while memory-based strategies (Equations 4-6) had a free parameter w (see Table 1). In addition, the constraints on the parameters can give rise to complexity differences between the strategies over and above the number of parameters. We therefore fitted the models of the strategies with a Variational Bayesian Monte Carlo (VBMC) (Acerbi, 2018) method. VBMC is an efficient method that uses a Gaussian process as a statistical surrogate model for the posterior distribution. We also compared these fits with the Bayesian Information Criterion, BIC (Schwarz, 1978) and the Akaike information criterion AIC (Akaike, 1974; Burnham & Anderson, 2002). In order to assess the absolute level of fit for the strategies we also reported the mean squared error of the predictions (MSE).

All models were fitted to nonusers and users separately using a weighted binomial likelihood function. This was done in order to give participants with different number of peers equal weight in the fitting procedure. For VBMC, we assumed a uniform prior of the parameters.

Our main criteria for model selection are the model weights derived from the evidence lower bound (ELBO, i.e., a lower bound on the log-likelihood of observed data) for VBMC, and model weights derived from BIC and AIC. The model weights derived from BIC and AIC can be taken as estimates of the probabilities of each model's being the best model (Burnham & Anderson, 2002; Wagenmakers & Farrell, 2004).

Predictions of group level patterns

To assess the group-level patterns, we compared the mean model predicted estimates of whether a peer is like oneself (i.e., $\frac{1}{n}\sum_{i=1}^{n}\hat{p}_{i,est\_oneself}$) with the average of each participant's actual estimates of whether their peers are like oneself (i.e., $\frac{1}{n}\sum_{i=1}^{n}p_{i,est\_oneself}$) and investigated how these relate to the mean true proportion of peers like oneself ($\frac{1}{n}\sum_{i=1}^{n}p_{i,true\_oneself}$).

Results

Table 2 shows demographic characteristics of the participants. In what follows we provide results relevant for our three research questions. Table 3 shows the model weights derived from VBMC (i.e., the ELBO values), BIC, and AIC.

What cognitive strategies do people rely on to produce judgments of peers' substance use?

For nonusers, the model weights for VBMC in Table 3 show that their judgments of peers' substance use for methamphetamine, prescription drugs, and cocaine are best described by the ego projection strategy. Peer judgments of use of alcohol and marijuana are best described by the general model, while peer judgments of heroin are best described by the ego-common memory strategy. When the general model is the best, the pattern of its parameter values is most consistent with ego projection (Table 4): the r values are close to one and the w values are small. When the other strategies are the best, the general model is always the second best. There is also consistency across the model weights from the three methods, with only one instance where AIC chooses the more flexible general model over the ego-common memory strategy. Taken together, these results indicate that nonusers mainly rely on knowledge about themselves when making judgments about their peers' substance use.

For users, the model weights for VBMC in Table 3 show that judgments of peers' substance use methamphetamine, prescription drugs, and cocaine are best explained by the population memory strategy. Peer judgments of use of alcohol and marijuana are best explained by the general model, while peer judgments of heroin are best explained by the ego-rare memory strategy. When the general model is the best, ego projection or the population memory strategies are the second best, and when the population memory strategy is the best, the general model is the second best. Finally, when the ego-rare memory strategy is the best, the general model is the second best. The parameter estimates for r in the general model suggests some reliance on ego-projection, at least for alcohol (r=0.48) and marijuana (r=0.74), while the parameter estimates for w are similar to the parameter estimates of the population memory strategy. Taken together, these results indicate that users mainly use a population memory strategy, but that there is some evidence for ego-rare memory use and ego-projection.

A challenge of accounting for peer judgments is that a sizeable number of participants only have one peer (106 out of 239).[2] Therefore, we investigated if the interpretation for all

[2] Note that this is not so unusual for this data set, as the only peers that 'counted' are those that have also participated in this study. Each participant likely has other peers that were not included in the study.

participants also holds for participants that have only one peer and those who have more than one peer. The results of fitting the general model and the other strategies are shown in Tables S2 to S7 in the Supplemental Online Materials. The general conclusion still holds: there is substantial evidence for ego projection for nonusers and the population memory strategy for users. Specifically, for nonusers, the model weights in Table S2 (one peer) and Table S3 (more than one peer) show that ego projection, the ego-common memory strategy, and the general model with parameters that indicate a preponderance of ego projection (Table S4 and S6), best account for the majority of the substances across both groups of participants (11 out of 12). For users, the model weights in Table S2 (one peer) and Table S3 (more than one peer) show that we again find evidence for population memory, and some evidence for ego-rare memory and ego projection strategies among users; with the exact strategy used depending on the substance (due to the low number of participants for heroin and cocaine, the results for these substances should be interpreted with caution).

Another challenge of accounting for peer judgments based on self-reports is that participants might be reluctant to report their substance use. Although an analysis we present in the next section suggests that the pattern of results we obtained in this study is not a result of misreporting substance use, there is still a possibility that a certain percent of our participants underreported their substance use. In order to investigate the effects of underreporting, we conducted a series of sensitivity analyses where we flipped nonusers to users and fitted the models to these data. Based on the estimates of the prevalence of underreporting discussed earlier in the Methods section, we randomly flipped different percentages nonusers to users (5%, 10%, 15%, and 20%; we also investigated higher percentages up to 40% and they show the same patterns as the ones for 20%) and fitted the models with the maximum likelihood procedure described in the Methods section. We repeated this procedure 200 times for each of the percentages and calculated the average of the parameter estimates and the BIC weights for each of the models.

The results of these sensitivity analyses for nonusers and users are shown in the Supplementary Figures S2 to S7. For nonusers, the BIC weights in Figure S2 again show a predominance of ego projection. This dominance increases with the percentage of flipped nonusers for alcohol and marijuana. The parameter values of the general model also confirm this with *r* values close to one and small *w* values (Figures S4 and S5). For users, the BIC weights shown in Figure S3 indicate that the general model is the best fitting model, with BIC weights increasing with the percentage of flipped nonusers. The one exception is heroin, where the ego-rare strategy is the best fitting model, the same result as the one obtained on the original data. The dominance of the general model, which can mimic mixtures of strategies, suggests that our conclusion that users use a mix of strategies holds under a range of underreporting of substance use.

In summary, this analysis shows that nonusers predominately use ego projection, while users use a mix of strategies that uses both knowledge about the overall population, knowledge about peers, and to some extent ego-projection to derive their peer judgments. However, these model comparisons do not give direct insights into how the different strategies can account for group level patterns commonly observed in research in social cognition and substance use across different base rates of peers like themselves, something that we turn to in the next section."

What group-level patterns of judgments do these strategies produce?

Figure 3 shows the average of participants' estimates of whether their peers are like themselves, $p_{i,est\_oneself}$ (i.e., the proportion of estimates that individual peers are like themselves; *y*-axes), relative to the true proportion of such peers, $p_{i,true\_oneself}$ (*x*-axes). Participants' judgments are averaged across equal-sized bins of true proportions of peers like themselves, in order to avoid unstable estimates due to small sample sizes for some of the true proportions.

It is clear from Figure 3 that users and nonusers exhibit different patterns of their judgments of peers' substance use. The pattern for nonusers is consistent with false consensus: They overestimate the prevalence of nonusers among their peers across all substances. The pattern for users varies across substances, but overall their judgments are closer to the true proportion of peers like themselves. Their judgments of peers' use of methamphetamine and heroin are closer to the true proportions than their judgments for prescription drugs and cocaine. For marijuana, both users and nonusers have similar patterns. For prescription drugs and cocaine there is evidence for false uniqueness (compare with Figure 2).

Given the different group-level patterns of judgments produced by users and nonusers, the challenge is to find a parsimonious set of cognitive strategies that can explain judgments of both of these groups of participants. Predictions from the general model, ego projection, and probability matching, are shown in Figure S8. Predictions from the general model, the ego-common memory strategy, the ego-rare memory strategy, and the population memory strategy are shown in Figure S9.

A comparison of Figure 3 and Figure S8 shows that ego projection alone cannot explain group-level patterns of judgments for both users and nonusers. While it fits the data for nonusers quite well, for users it predicts different patterns of responses for most substances than those that are actually observed. Probability matching also do not seem to be a good candidate, as its predictions deviate from the pattern of judgments given by nonusers. A comparison of Figure 3 and Figure S9 shows that the ego-common memory strategy can account for the apparent pattern consistent with false consensus for nonusers and that the population memory strategy can account for most of the different patterns observed for users. The ego-rare memory strategy can also account for some of the patterns, especially when the true proportions are close to the identity line or underestimated, as this strategy can only make predictions between zero and the true proportions of peers like oneself (e.g., for users of prescription drugs). The general model incorporates all other strategies as special cases and is as such able to account for the patterns for both nonusers and users.

An alternative hypothesis that can explain the pattern of false consensus in Figure 3 is that users underreport their substance use, especially for the heavy substances (Harrison, 1997). In order to analyze the potential impact of underreported substance use, we analyzed the data separately for two groups of stated nonusers of each heavy substance (meth, prescription drugs, heroin, and cocaine). First, we identified those stated nonusers of each heavy substance that reported the use of another heavy substance. These participants are likely to have truthfully reported the nonuse of the particular heavy substance. Second, we identified participants who reported that they did not use any heavy substance at all. Among those participants, there might be some who did not want to reveal their substance use. We then compared the average estimates of whether a peer is like oneself for users and these two groups of nonusers. The results show (Figure S10 in the Supplemental Material) that the pattern for nonusers that reported that they used other heavy substances is very similar to the pattern for nonusers that reported that they did not use any heavy substance. In addition, there is a clear difference between these two non-user groups and the users. Taken together, this analysis suggests that the pattern of results we obtained is not a result of misreporting substance use.

Do strategies that people use to make peer judgments produce accurate answers?

Participants' estimates of their peers' use of different substances were relatively accurate (see also Barman-Adhikari et al., 2020). Nonusers were more accurate than users for four of six substances (Table 6). The overall proportions correct, however, do not give enough information about the relation between strategy use and accuracy. We therefore investigated the accuracy in the same way as we did for the estimates of the proportion of peers like oneself (Figure 3), by plotting the true proportion of peers like oneself against mean proportion correct.

Figure 4 shows accuracy of estimates produced by nonusers and users with different levels of true proportions of peers like themselves. The results suggest that a response pattern consistent with apparent false consensus is quite adaptive for nonusers when $p_{i,true\_oneself}$>.5 (i.e., homophily is high), although it leads to strong overestimation of the proportion of nonusers when $p_{i,true\_oneself}$<.5 (i.e., homophily is low). For most nonusers, this pattern of estimates produces a high level of accuracy because most of nonusers' peers are also nonusers. Specifically, participants who did not use alcohol (heavily), marijuana, methamphetamine, prescription drugs, heroin, or cocaine, had on average 61%, 39%, 76%, 76%, 91%, and 86% of peers who were also not using these substances, respectively (see Table 7). In addition, the parameter estimates for the general model (Table 4) for nonusers show that reliance on information about oneself is lower for alcohol and marijuana than for the other substances (lower values of parameter *r* and higher values of parameter *w*), which are also the two substances with the lowest proportion of peers like oneself. These results suggest that relying on oneself is often an adaptive strategy for nonusers who experience high levels of homophily, in line with Dawes (1989) argument that apparent ego projection can be rational when social environments have high homophily.

Users overall produce judgments that are closer to the proportion of people like oneself. They would not have profited from relying too much on information about themselves, as many users had low homophily of peers regarding their substance. Specifically, users of methamphetamine, prescription drugs, heroin, and cocaine, had on average 44%, 40%, 35%, and 30% of users in their peer circles (see Table 7). Only for alcohol and marijuana users had a higher percentage of peers who were also users (63% and 84%, respectively). These are also the substances for which users' judgments in Figure 3 to some extent resemble false consensus patterns and the ones where the parameter estimates (higher values of parameter *r* and lower values of parameter *w*) in the general model (Table 5) indicate more reliance on the information about oneself than for the other substances.

Taken together, the results suggest that the strategies participants use lead to quite accurate judgments even though the resulting patterns sometimes resemble false consensus effects. In addition, the results also suggest that the type of strategy that participants are using is related to the level of homophily in their networks.

Discussion

Using sociometric data, we investigate strategies underlying peer judgments of substance use. To answer our first question about what strategies people are using when estimating peers' substance use, we implement and compare five different strategies that make different assumptions about the kind of knowledge the estimates are based on, as well as a general model that gives estimates of parameters related to the five models. The results show that substance users and nonusers relied on different cognitive strategies to make judgments about substance use of their peers. Nonusers relied more on knowledge about themselves, while users relied on a combination of knowledge about the overall population, knowledge about their peers, and to some extent knowledge about themselves to derive their peer judgments.

The results for our second research question about the group level patterns across different levels of peers like themselves show that users and nonusers exhibit different patterns of peer judgments. We show that the observed patterns can be explained by assuming that judgments are based on a combination of ego projection and memory-based strategies. The final choice of strategy can be seen as an adaptive response to the cues in perceived social environments and own experience of nonusers and users. Nonusers are likely to not be present when any of their peers is using, which makes reliance on a memory-based strategy difficult. Likewise, due to their inexperience with using, they can rely on fewer valid cues to infer use. This means that assuming that others are like them can be the most appropriate strategy for nonusers as long as they have many nonusers in their network. On the other hand, users are more likely to be present when their peers are using, and are therefore more likely to encode and recall peers who are substance users. Also, because they have more experience with the substance and its users, they can likely recall more of the valid behavioral cues about their peers. For users, a similar line of reasoning could explain the difference in their pattens of judgments for methamphetamine and heroin, on the one hand, and prescription drugs on the other hand (see Figure 3). Judgments of peers' use of methamphetamine and heroin show good agreement with the actual proportion of users of those substances, while for prescription drugs and cocaine participants showed underestimation. Both methamphetamine and heroin use have profound effects on the behavior, appearance and health of users, which might further bolster the efficacy of memory-based strategies. Prescription drugs and cocaine, on the other hand, are not typically associated with such drastic changes in appearance and might lead to reliance on other sources of knowledge.

For our third research question we investigated the accuracy of peer judgments. Nonusers have a high proportion of nonusers in their network and by assuming that others are like them, they can achieve a high level of accuracy. Users, who tend to have a low proportion of users in their network, tend to employ memory-based strategies and also reach a high level of accuracy. Not only can we see adaptive behavior by comparing nonusers and users, but we can also observe the influence of people like oneself within each group. For nonusers, the level of reliance on oneself as estimated by our general model is lower for alcohol and marijuana than for the other substances. These are also the two substances with the lowest proportion of peers like oneself. For users, however, alcohol and marijuana show the highest levels of peers like oneself and the estimate of reliance on oneself in our general model is indeed higher than for the other substances. This is also the substance for which the users have the largest accuracy advantage over nonusers (.78 vs .65 proportion correct).

There are three main limitations of our study. First, it relies on self-reports of the number of peers and own substance use. Both types of questions might be subject to misreporting by participants. In order to tackle some of these challenges we used standard survey questions and additional analyses and simulations that suggest that our main conclusions about the strategies participants used to make judgments about their peers still hold. Note, however, that the additional analyses and simulations cannot completely rule out effects of misreporting by the participants, as they rely on assumptions that we were unable to verify with the data we have. For example, in our analysis of participants who reported they were nonusers of each heavy substance and those who at the same time stated that they did not use any other heavy substance or that they used some other heavy substance, we assumed that the latter group is more likely to be truthful than the former. The reasoning behind this assumption is that they admit to using at least one other heavy substance. If the pattern of results of these two groups are similar, this suggests that underreporting of substance use is less likely to be an issue in our data. However, one could also argue that these participants do not want to seem like a lost cause, so they report only one of the heavy substances. Only future studies that also include other more objective measures of substance use can give more definite answers to the possible effects of misreporting. Second, the sample of participants is restricted in that it only includes homeless youth from two drop-in centers. At present, we cannot assess the generality of our findings to a larger population of homeless youth. However, this is a problem of much of psychological research that relies on restricted populations such as university students. Testing the models of peer judgments proposed in this paper on other populations can help alleviate this problem. Third, we do not have information about the specific cues that people can use as input to different strategies or to select between strategies. Future studies could investigate cues relevant to the judgments. For example, participants could be asked about external individual cues to substance use (appearance, behavior, health issues etc.), and these could be used as inputs to different inference strategies.

To conclude, our results suggest that people use a range of strategies when making judgments about their individual peers. They can achieve a reasonable level of accuracy, flexibly adopting strategies depending on their personal experience and properties of their social networks. We hope that our paper will stimulate further investigations of cognitive strategies that people use to make judgments about their peers. This is particularly important in the current context of rapidly changing social environments, where strategies that were once useful to make accurate judgments about others' beliefs and behaviors might lose their effectiveness or backfire. Our general model for peer judgment strategies opens doors to investigating a number of possible strategies on the individual level, investigating their accuracy in different social environments (e.g., changing number of people with different properties, availability of valid cues), and predicting group-level patterns that these strategies can produce.

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Table 1

Notation, Strategy Equations, and Constraints on Parameters

Notation			
$p_{i,est\_oneself}$	Individual i's estimate of whether a peer is like oneself.		
$\hat{p}_{i,est\_oneself}$	Model prediction of i's estimate of whether a peer is like oneself.		
$p_{i,true\_oneself}$	True proportion of peers like oneself for individual i.		
$\bar{p}_{true\_oneself}$	Mean of the true proportion of peers like oneself across all individuals in the population, that is: $\frac{1}{n}\sum_{i=1}^{n} p_{i,true\_oneself}$.		
r	Parameter describing one's hypothesis that a peer is like oneself.		
w	Parameter describing reliance on knowledge about peer's actual behavior.		
Strategies	$\hat{p}_{i,est\_oneself} =$	r constraints	w constraints
General model	$r \times (1-w) + w \times p_{i,true\_oneself}$	$r \in [0\ 1]$	$w \in [0\ 1]$
Ego projection	r	$r \in [.5\ 1]$	$w = 0$
Probability matching	$p_{i,true\_oneself}$	$r = 0$	$w = 1$
Ego-common memory	$1 \times (1-w) + w \times p_{i,true\_oneself}$	$r = 1$	$w \in [0\ 1]$
Ego-rare memory	$0 \times (1-w) + w \times p_{i,true\_oneself}$	$r = 0$	$w \in [0\ 1]$
Population memory	$\bar{p}_{true\_oneself} \times (1-w) + w \times p_{i,true\_oneself}$	$r = \overline{p}$	$w \in [0\ 1]$

Table 2

Participants' (N=239) Characteristics

	Mean (SD)
Age	21.3 (2.1)
	N (%)
Male gender	164 (68.9)
Race/Ethnicity	
White	95 (39.6)
Black	61 (25.8)
Latino/a	38 (15.8)
Other	44 (18.8)
Heterosexual orientation	182 (76.7)
High school degree/GED	155 (64.6)
Currently enrolled in school	31 (12.9)
Past 30 days substance use	
Alcohol (heavy drinking)	118 (49.8)
Marijuana	183 (76.6)
Methamphetamine	76 (31.8)
Prescription drugs	57 (23.9)
Heroin	28 (11.7)
Cocaine	40 (16.7)

Table 3

Model weights for VBMC, BIC, and AIC for All Strategies Fitted Separately for Nonusers and Users, with Highest Values for Each Substance and Model Selection Criterion in Bold and the Second Highest in Italics

		Substance					
Groups	Strategy	Alcohol	Marijuana	Meth	Prescription drugs	Heroin	Cocaine
n		117	56	162	179	208	195
	General model	**0.68,0.59,0.85**	**0.94,0.90,0.96**	*0.15,0.16,0.47*	*0.05,0.07,0.28*	*0.11,0.31*,**0.71**	*0.12,0.15,0.46*
	Ego projection	*0.32,0.41,0.15*	*0.06,0.1,0.04*	**0.85,0.84,0.53**	**0.95,0.93,0.72**	0.10,0.25,0.10	**0.87,0.85,0.53**
Nonusers	Prob. matching	0,0,0	0,0,0	0,0,0	0,0,0	0,0,0	0,0,0
	Ego-common	0,0,0	0,0,0	0,0,0	0,0,0	**0.84,0.44**,*0.19*	0.01,0,0
	Ego-rare	0,0,0	0,0,0	0,0,0	0,0,0	0,0,0	0,0,0
	Population memory	0,0,0	0,0,0	0,0,0	0,0,0	0,0,0	0,0,0
n		118	181	75	57	28	40
	General model	**0.77,0.55,0.83**	**0.86,0.73,0.93**	*0.41,0.19,0.42*	*0.41*,0.36,**0.61**	0.20,0.10,0.18	*0.22,0.15,0.03*
	Ego projection	*0.17,0.37,0.14*	*0.07,0.16,0.04*	0,0,0	0,0,0	0,0,0	0,0,0
Users	Prob. matching	0,0,0	0,0,0	0,0,0	0,0,0	0,0,0	0,0,0
	Ego-common	0,0,0	0,0,0	0,0,0	0,0,0	0,0,0	0,0,0
	Ego-rare	0,0,0	0,0,0	0,0,0	0,0,0	**0.46,0.52,0.48**	0,0,0
	Population memory	0.06,0.08,0.03	*0.07*,0.12,0.03	**0.59,0.81,0.58**	**0.59,0.64**,*0.39*	*0.35,0.38,0.35*	**0.78,0.85,0.70**

Note: The model weights for Variable Bayesian Monte Carlo (VBMC) were estimated from the estimated lower bound (ELBO) of the model evidence. The model weights for the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) were calculated according to established procedures (see e.g., Wagenmakers & Farrell, 2004).

Table 4

Best Fitting Maximum Likelihood Parameter Estimates and Constrained Parameter Values for Nonusers for All Strategies

Strategy	Alcohol	Marijuana	Meth	Prescription drugs	Heroin	Cocaine
			r			
General model	0.85	0.79	0.97	0.96	1	0.99
Ego projection	0.8	0.62	0.95	0.96	0.99	0.98
Prob. matching*	0	0	0	0	0	0
Ego-common memory*	1	1	1	1	1	1
Ego-rare memory *	0	0	0	0	0	0
Population memory*	0.57	0.32	0.73	0.75	0.89	0.84
			w			
General model	0.22	0.42	0.08	0.02	0.1	0.06
Ego projection*	0	0	0	0	0	0
Prob. matching*	1	1	1	1	1	1
Ego-common memory	0.37	0.55	0.13	0.11	0.1	0.08
Ego-rare memory	0.92	0.91	0.98	0.98	1	0.99
Population memory	0.32	0.4	0.23	0.07	0.43	0.28

Note: The asterisk * indicates a fixed parameter. For the population memory strategy $r = \bar{p}_{true\_oneself}$ (see Table 1). These maximum likelihood parameter estimates correspond well with the estimates obtained from VBMC by taking the mean of the posterior distributions (not shown).

Table 5

Best Fitting Parameter Maximum Likelihood Parameter Estimates and Constrained Parameter Values for Users for All Strategies

Strategy	Alcohol	Marijuana	Meth	Prescription drugs	Heroin	Cocaine
			r			
General model	0.48	0.74	0.20	0.23	0	0.20
Ego projection	0.52	0.78	0.50	0.50	0.50	0.50
Prob. matching*	0	0	0	0	0	0
Ego-common memory*	1	1	1	1	1	1
Ego-rare memory*	0	0	0	0	0	0
Population memory*	0.65	0.86	0.41	0.37	0.22	0.26
			w			
General model	0.27	0.31	0.79	0.24	0.89	0.43
Ego projection*	0	0	0	0	0	0
Prob. matching*	1	1	1	1	1	1
Ego-common memory	0.75	0.56	0.96	0.86	1	0.9
Ego-rare memory	0.67	0.84	0.84	0.46	0.89	0.57
Population memory	0.26	0.22	0.8	0.27	0.9	0.45

Note: The asterisk * indicates a fixed parameter. For the inference strategy $r = \bar{p}_{true\_oneself}$, the overall proportion of people like themselves. These maximum likelihood parameter estimates correspond well with the estimates obtained from VBMC by taking the mean of the posterior distributions (not shown).

Table 6

Mean (SD) Proportion of Accurate Estimates of Peers' Substance Use

Substance	All participants	Nonusers	Users
Alcohol	.63 (.38)	.66 (.37)	.61 (.39)
Marijuana	.75 (.39)	.65 (.44)	.78 (.36)
Methamphetamine	.79 (.33)	.76 (.34)	.86 (.29)
Prescription drugs	.72 (.36)	.74 (.35)	.65 (.39)
Heroin	.91 (.22)	.91 (.21)	.89 (.25)
Cocaine	.84 (.29)	.86 (.27)	.75 (.36)

Note: Proportion correct is calculated as the mean proportion correct across participants.

Table 7

Mean (SD) True Proportion of Peers Like Oneself

Substance	All participants	Nonusers	Users
Alcohol	.62 (.40)	.61(.39)	.63 (.40)
Marijuana	.74 (.39)	.39 (.44)	.84 (.30)
Methamphetamine	.66 (.40)	.76 (.34)	.44 (.43)
Prescription drugs	.67 (.39)	.76 (.34)	.40 (.40)
Heroin	.84 (.31)	.91 (.22)	.35 (.44)
Cocaine	.77 (.36)	.86 (.26)	.30 (.40)

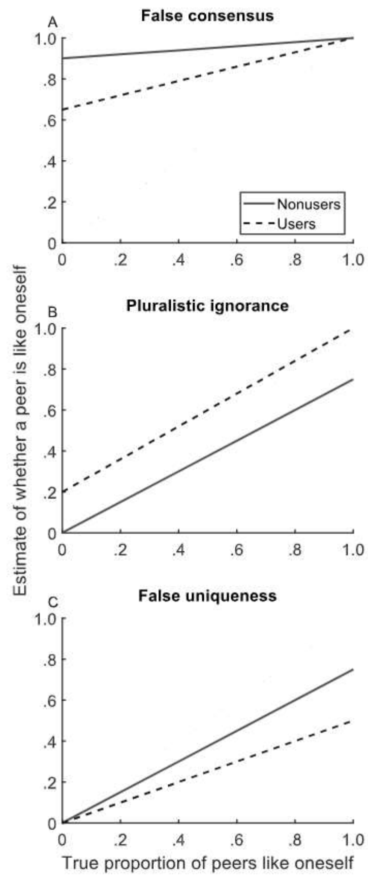

Figure 1. Illustrations of different group-level patterns of estimates of peers' substance use. A. False consensus: both nonusers and users overestimate peers like oneself, B. Pluralistic ignorance: both groups overestimate users among their peers (vice versa also possible), C. False uniqueness: both groups underestimate peers like oneself.

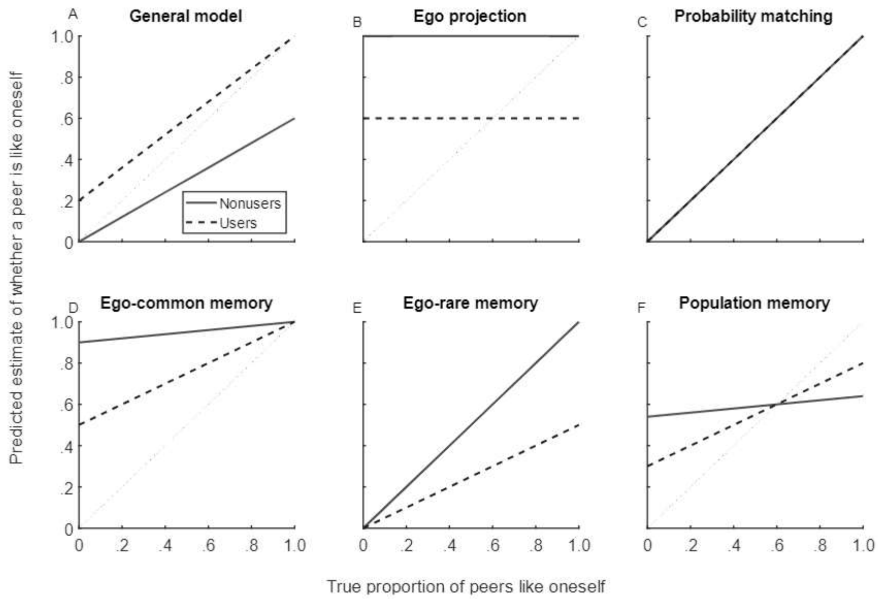

Figure 2. Illustrative model predictions ($\hat{p}_{i,est\_oneself}$, on y-axes) for estimates of whether a peer is like oneself, for different true levels of proportion of peers like oneself ($p_{i,true\_oneself}$, on x-axes). Panels show predictions for different strategies: A. General model, B. Ego projection, C. Probability matching, D. Ego-common memory, E. Ego-rare memory. F. Population memory. The values of the parameters for nonusers and users are: 1.0 and .6 for ego projection (Panel A), 1.0 and 0.5 for the ego-rare memory strategy, and .1 and .5 for the population memory, and ego-common memory strategies. The dotted line indicates perfect correspondence between the predicted estimate and the true proportions.

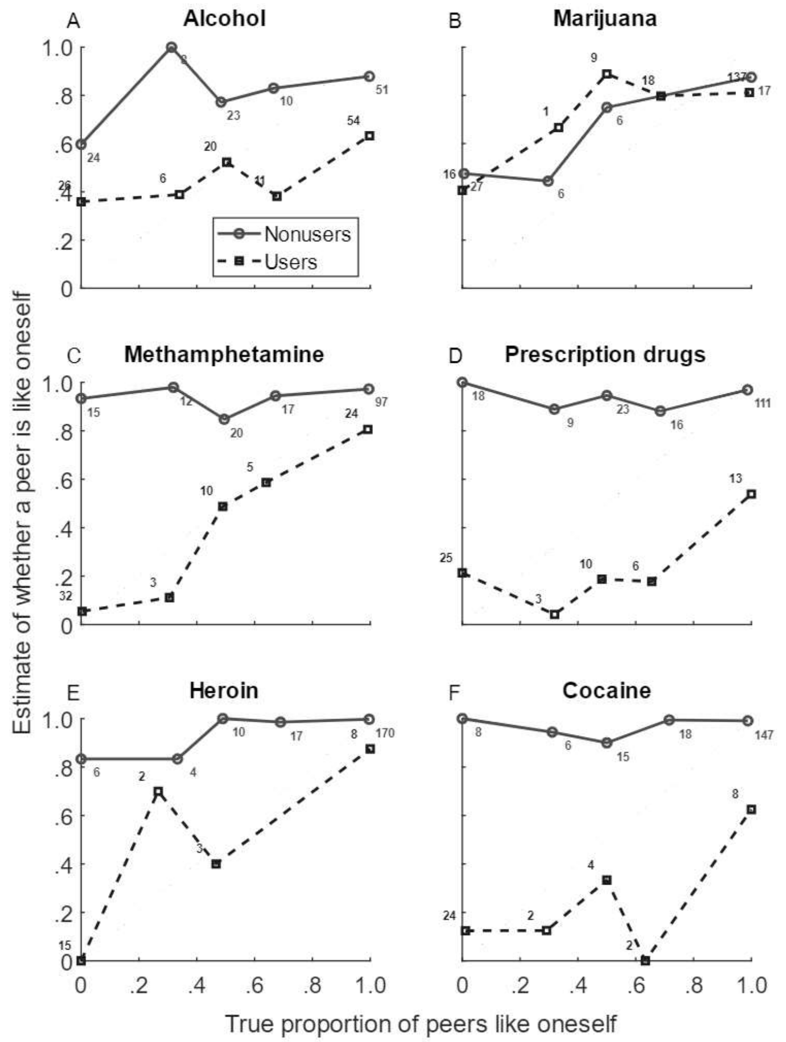

Figure 3. Average of participant *i*'s estimates of whether a peer is like oneself (average $p_{i,est\_oneself}$ across peers, on *y*-axes), for participants with different true levels of proportion of peers like oneself ($p_{i,true\_oneself}$, on *x*-axes), separately for the six substances. The numbers at each data point indicate the number of participants.

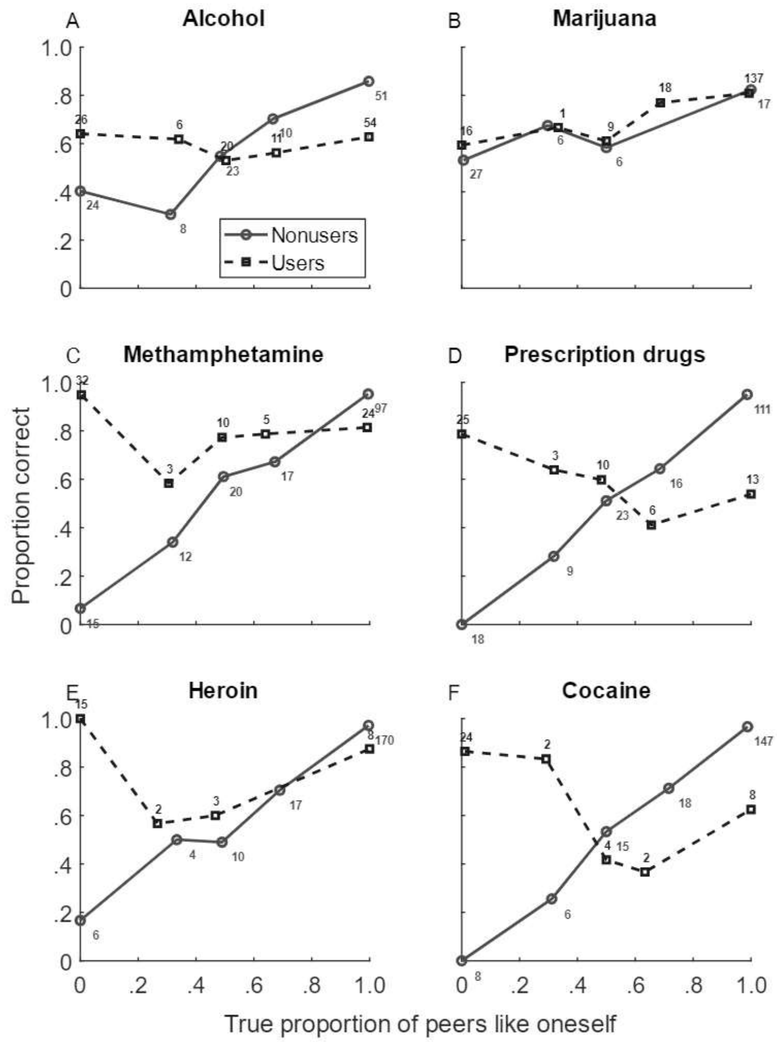

Figure 4. Mean proportion correct estimates of whether peers are like oneself or not (*y*-axes), for participants with different true levels of proportion of peers like oneself ($p_{i,true\_oneself}$, on *x*-axes).

Supplemental Online Materials

Cognitive Strategies for Peer Judgments

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In this Supplemental Online Materials, we present tables with fit indices for different ways of fitting the strategies to data, figures with predictions based on fitted parameter values from the different strategies, and a figure that shows the results of an analysis of the potential impact of underreported substance use.

Table S1

Mean Squared Error for All Strategies Fitted Separately for Nonusers and Users, with Lowest Mean Squared Error Values for Each Substance in Bold and the Second Lowest in Italics

		Substance					
Groups	Strategy	Alcohol	Marijuana	Meth	Prescription drugs	Heroin	Cocaine
Nonusers							
	General model	**0.150**	**0.203**	**0.046**	**0.041**	**0.011**	**0.017**
	Ego projection	0.163	0.236	0.052	*0.041*	0.012	0.022
	Prob. matching	0.278	0.321	0.183	0.190	0.056	0.091
	Ego-common memory	0.278	0.320	0.183	0.190	0.056	0.091
	Ego-rare memory	0.199	0.277	0.095	0.083	0.020	0.036
	Population memory	*0.156*	*0.208*	*0.047*	0.042	*0.011*	*0.017*
Users							
	General model	**0.238**	**0.163**	**0.125**	**0.185**	**0.083**	**0.150**
	Ego projection	*0.250*	0.173	0.250	0.250	0.250	0.250
	Prob. matching	0.334	0.209	0.136	0.286	0.087	0.202
	Ego-common memory	0.272	0.191	*0.126*	0.198	0.084	0.156
	Ego-rare memory	0.255	*0.169*	0.127	*0.196*	*0.083*	*0.151*
	Population memory	0.316	0.187	0.136	0.283	0.086	0.199

Table S2

Model weights for VBMC, BIC, and AIC for All Strategies Fitted Separately for Nonusers and Users with Only One Peer, with Highest Values For Each Substance and Model Selection Criterion in Bold and the Second Highest in Italics

		Substance					
Groups	Strategy	Alcohol	Marijuana	Meth	Prescription drugs	Heroin	Cocaine
n		117	56	162	179	208	195
	General model	*0.23*,0.14,*0.39*	**0.58**,**0.44**,**0.68**	*0.12*,*0.09*,*0.32*	*0.03*,*0.07*,*0.27*	*0.02*,*0.06*,*0.26*	0.01,0.03,0.16
	Ego projection	0.13,*0.17*,0.12	*0.33*,**0.44**,*0.25*	**0.86,0.90,0.67**	**0.97,0.93,0.73**	0.01,0.05,0.04	*0.18*,**0.48**,**0.42**
Nonusers	Prob. matching	0,0,0	0,0,0	0,0,0	0,0,0	0,0,0	0,0,0
	Ego-common memory	0,0,0	0,0,0	0,0,0	0,0,0	**0.96,0.87,0.69**	**0.81**,**0.48**,**0.42**
	Ego-rare memory	0,0,0	0,0,0	0,0,0	0,0,0	0,0,0	0,0,0
	Population memory	**0.64,0.69,0.48**	0.09,0.12,0.07	0.03,0.01,0.01	0,0,0	*0.02*,0.01,0.01	0,0,0
n		118	181	75	57	28	40
	General model	*0.18*,0.08,*0.25*	**0.62**,*0.33*,**0.71**	*0.39*,*0.12*,*0.31*	*0.22*,0.09,0.21	*0.31*,0.11,0.2	*0.41*,*0.23*,*0.41*
	Ego projection	0.17,*0.24*,0.20	0.03,0.12,0.05	0,0,0	0.13,*0.29*,*0.25*	0,0,0	0,0.01,0.01
Users	Prob. matching	0,0,0	0,0,0	0,0,0	0,0,0	0,0,0	0,0,0
	Ego-common memory	0,0,0	0,0,0	0,0,0	0,0,0	0,0,0	0,0,0
	Ego-rare memory	0,0,0	0,0,0	0,0,0	0,0,0	**0.40,0.60,0.54**	0,0,0
	Population memory	**0.65,0.68,0.56**	*0.34*,**0.55**,*0.24*	**0.61,0.88,0.69**	**0.65,0.62,0.53**	0.29,*0.28*,*0.26*	**0.59,0.76,0.58**

Note: The model weights for Variable Bayesian Monte Carlo (VBMC) were estimated from the estimated lower bound (ELBO) of the model evidence. The model weights for the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) were calculated according to established procedures (see e.g., Wagenmakers & Farrell, 2004).

Table S3

Model weights for VBMC, BIC, and AIC for All Strategies Fitted Separately for Nonusers and Users with More Than One Peer, with Highest Values For Each Substance and Model Selection Criterion in Bold and the Second Highest in Italics

		Substance					
Groups	Strategy	Alcohol	Marijuana	Meth	Prescription drugs	Heroin	Cocaine
n		117	56	162	179	208	195
	General model	*0.31.19*,*0.48*	*0.30*,*0.11*,*0.25*	*0.15*,*0.14*,*0.43*	*0.13*,*0.10*,0.35	0.09,0.11,*0.38*	*0.14*,*0.12*,*0.40*
	Ego projection	**0.69**,**0.81**,**0.52**	0.06,0.07,0.06	**0.75**,**0.79**,**0.52**	**0.85**,**0.89**,**0.64**	**0.62**,**0.79**,**0.54**	**0.85**,**0.88**,**0.60**
Nonusers	Prob. matching	0,0,0	0,0,0	0,0,0	0,0,0	0,0,0	0,0,0
	Ego-common memory	0,0,0	**0.64**,**0.81**,**0.68**	0.10,0.07,0.05	0.02,0.01,0.01	*0.29*,0.11,0.07	0,0,0
	Ego-rare memory	0,0,0	0,0,0	0,0,0	0,0,0	0,0,0	0,0,0
	Population memory	0,0,0	0.01,0.01,0.01	0,0,0	0,0,0	0,0,0	0,0,0
n		118	181	75	57	28	40
	General model	**0.75**,*0.35*,**0.68**	0.13,0.05,0.22	*0.39*,0.18,**0.42**	***0.80***,***0.82***,***0.93***	0.10,0.05,0.08	*0.24*,*0.14*,*0.27*
	Ego projection	*0.20*,**0.59**,*0.29*	**0.51**,**0.63**,**0.52**	0,0,0	0,0,0	0,0,0	0,0.01,0.01
Users	Prob. matching	0,0,0	0,0,0	0,0,0	0,0,0	**0.48**,**0.24**,**0.23**	0,0,0
	Ego-common memory	0,0,0	0,0,0	0,0,0	0,0,0	0.05,**0.24**,**0.23**	0.02,0.06,0.05
	Ego-rare memory	0,0,0	0,0,0	0.16,*0.26*,0.19	0,0,0	*0.19*,**0.24**,**0.23**	0,0,0
	Population memory	0.05,0.06,0.03	*0.49*,*0.32*,*0.26*	**0.46**,**0.55**,*0.39*	*0.20*,*0.17*,*0.07*	0.18,**0.24**,**0.23**	**0.74**,**0.79**,**0.67**

Note: The model weights for Variable Bayesian Monte Carlo (VBMC) were estimated from the estimated lower bound (ELBO) of the model evidence. The model weights for the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) were calculated according to established procedures (see e.g., Wagenmakers & Farrell, 2004).

Table S4

Best Fitting Maximum Likelihood Parameter Estimates and Fixed Parameter Values for Nonusers with One Peer for All Strategies

Strategy	Alcohol	Marijuana	Meth	Prescription drugs	Heroin	Cocaine
			r			
General model	0.82	0.79	0.96	0.97	1	1
Ego projection	0.79	0.68	0.95	0.97	0.99	1
Prob. matching*	0	0	0	0	0	0
Ego-common memory*	1	1	1	1	1	1
Ego-rare memory*	0	0	0	0	0	0
Population memory*	0.72	0.47	0.83	0.81	0.93	0.9
			w			
General model	0.27	0.33	0.05	0	0.17	0
Ego projection*	0	0	0	0	0	0
Prob. matching*	1	1	1	1	1	1
Ego-common memory	0.40	0.47	0.09	0	0.17	0
Ego-rare memory	0.87	0.86	0.96	0.97	1	1
Population memory	0.30	0.30	0.11	0	0.38	0

Note: The asterisk * indicates a fixed parameter. For the population memory strategy $r = \bar{p}_{true\_oneself}$ (see Table 1). These maximum likelihood parameter estimates correspond well with the estimates obtained from VBMC by taking the mean of the posterior distributions (not shown).

Table S5

Best Fitting Maximum Likelihood Parameter Estimates and Fixed Parameter Values for Users with One Peer for All Strategies

Strategy	Alcohol	Marijuana	Meth	Prescription drugs	Heroin	Cocaine
			r			
General model	0.52	0.64	0.35	0.44	0	0.18
Ego projection	0.53	0.69	0.50	0.50	0.58	0.50
Prob. matching*	0	0	0	0	0	0
Ego-common memory*	1	1	1	1	1	1
Ego-rare memory*	0	0	0	0	0	0
Population memory*	0.57	0.79	0.51	0.50	0.67	0.40
			w			
General model	0.23	0.37	0.84	0.25	0.87	0.54
Ego projection*	0	0	0	0	0	0
Prob. matching*	1	1	1	1	1	1
Ego-common memory	0.60	0.60	0.94	0.67	1	0.92
Ego-rare memory	0.63	0.77	0.89	0.58	0.87	0.62
Population memory	0.22	0.29	0.84	0.25	0.82	0.57

Note: The asterisk * indicates a fixed parameter. For the population memory strategy $r = \bar{p}_{true\_oneself}$ (see Table 1). These maximum likelihood parameter estimates correspond well with the estimates obtained from VBMC by taking the mean of the posterior distributions (not shown).

Table S6

Best Fitting Maximum Likelihood Parameter Estimates and Fixed Parameter Values for Nonusers with More Than One Peer for All Strategies

Strategy	Alcohol	Marijuana	Meth	Prescription drugs	Heroin	Cocaine
			r			
General model	0.89	1	0.98	0.97	0.99	0.98
Ego projection	0.81	0.54	0.95	0.94	0.99	0.97
Prob. matching*	0	0	0	0	0	0
Ego-common memory*	1	1	1	1	1	1
Ego-rare memory*	0	0	0	0	0	0
Population memory*	0.53	0.25	0.7	0.74	0.88	0.83
			w			
General model	0.21	0.65	0.11	0.1	0.06	0.08
Ego projection*	0	0	0	0	0	0
Prob. matching*	1	1	1	1	1	1
Ego-common memory	0.35	0.65	0.15	0.18	0.07	0.11
Ego-rare memory	0.97	1	0.99	0.99	1	0.99
Population memory	0.2	0.55	0.15	0.06	0.29	0.27

Note: The asterisk * indicates a fixed parameter. For the population memory strategy $r = \bar{p}_{true\_oneself}$ (see Table 1). These maximum likelihood parameter estimates correspond well with the estimates obtained from VBMC by taking the mean of the posterior distributions (not shown).

Table S7

Best Fitting Maximum Likelihood Parameter Estimates and Fixed Parameter Values for Users with More Than One Peer for All Strategies

Strategy	Alcohol	Marijuana	Meth	Prescription drugs	Heroin	Cocaine
			r			
General model	0.41	0.83	0.1	0.11	0	0.18
Ego projection	0.51	0.83	0.50	0.50	0.50	0.50
Prob. matching*	0	0	0	0	0	0
Ego-common memory*	1	1	1	1	1	1
Ego-rare memory*	0	0	0	0	0	0
Population memory*	0.67	0.87	0.38	0.34	0.11	0.22
			w			
General model	0.37	0.09	0.67	0.09	1	0.02
Ego projection*	0	0	0	0	0	0
Prob. matching*	1	1	1	1	1	1
Ego-common memory	0.90	0.49	0.98	0.95	1	0.89
Ego-rare memory	0.69	0.87	0.72	0.28	1	0.41
Population memory	0.31	0.06	0.69	0.17	1	0.03

Note: The asterisk * indicates a fixed parameter. For the population memory strategy $r = \bar{p}_{true\_oneself}$ (see Table 1). These maximum likelihood parameter estimates correspond well with the estimates obtained from VBMC by taking the mean of the posterior distributions (not shown).

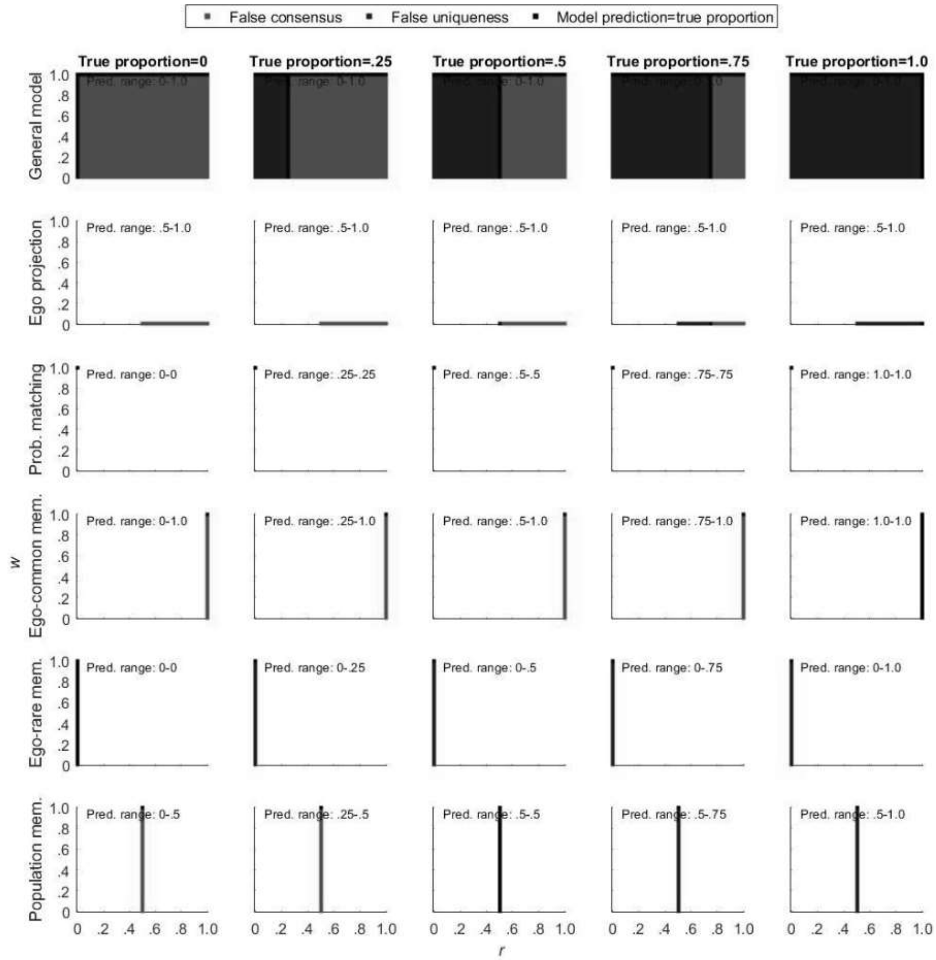

Figure S1. Group level patterns produced by different strategies. Parameter space (r on x-axis and w on y-axes) and prediction ranges of whether a peer is like oneself for the models of five different strategies ($\hat{p}_{i,est\_oneself}$, rows) and five different levels of true proportion of peers like oneself ($p_{i,true\_oneself}$, columns). For example, prediction range ".5-1.0" means that the model only predicts estimates that between 50% and 100% of one's peers are like oneself. Some prediction ranges include just a single value (e.g. "1.0-1.0"), meaning that these models predict that an individual will always give this estimate given a specific true proportion of peers like oneself. The population memory model (last row) is constrained to r=$\bar{p}_{true\_oneself}$, where $\bar{p}_{true\_oneself}$ is the mean of all people like oneself. Here $\bar{p}_{true\_oneself}$ is assumed to be 0.5.

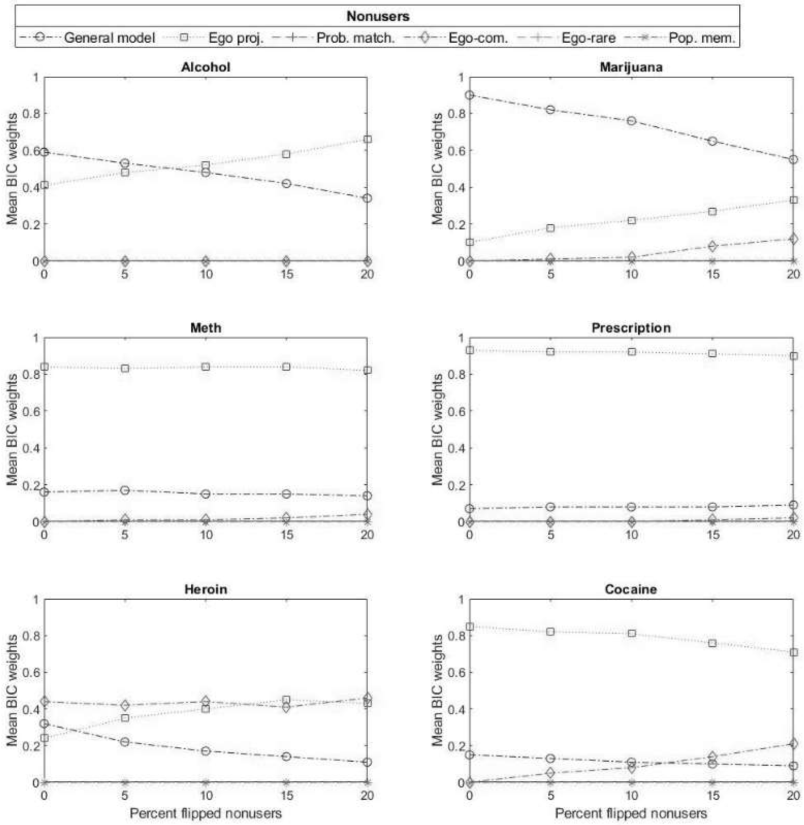

Figure S2. Mean BIC weights for nonusers for the different models across different percentages of flipped nonusers (i.e., percentages of nonusers that were recoded as users) across 200 simulation runs. All models were fitted on each run and the BIC weights were then averaged.

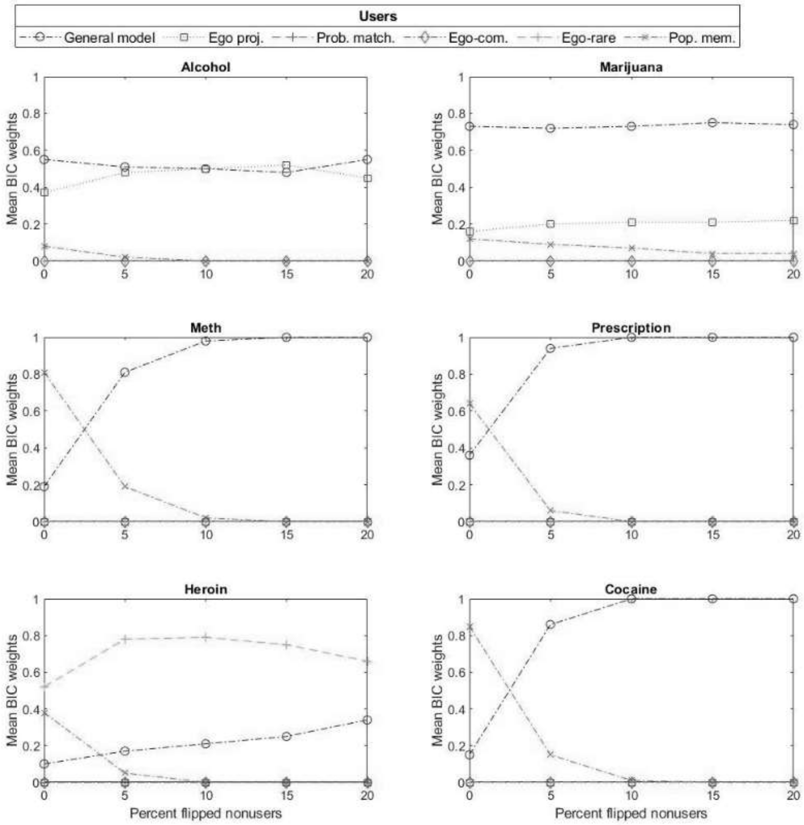

Figure S3. Mean BIC weights for users for the different models across different percentages of flipped nonusers (i.e., percentages of nonusers that were recoded as users) across 200 simulation runs. All models were fitted on each run and the BIC weights were then averaged.

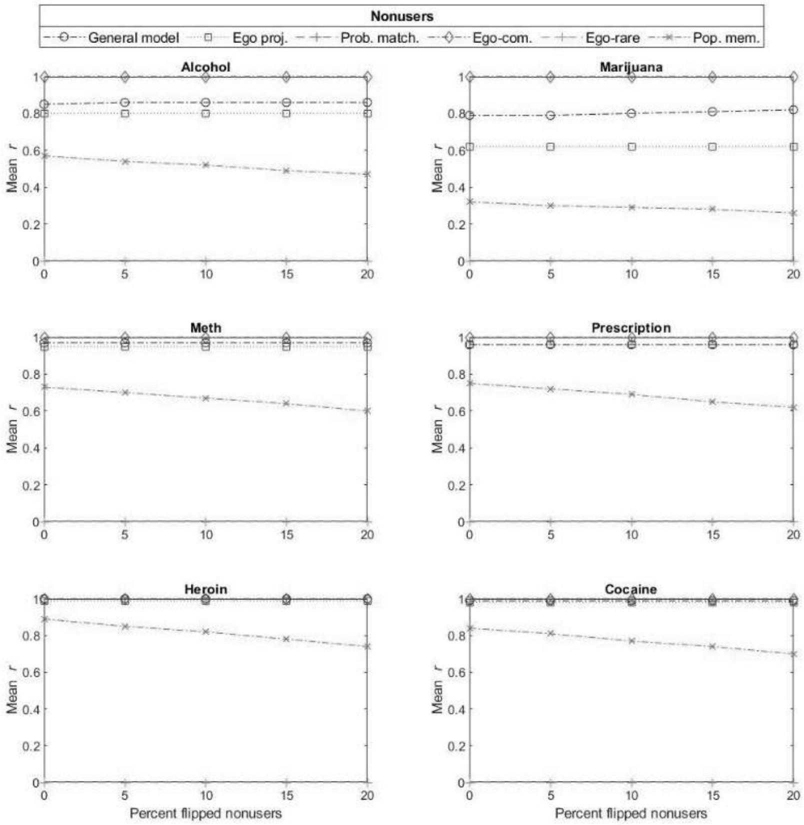

Figure S4. Mean parameter r values for nonusers for the different models across different percentages of flipped nonusers (i.e., percentages of nonusers that were recoded as users) across 200 simulation runs. All models were fitted on each run and the parameter values were then averaged.

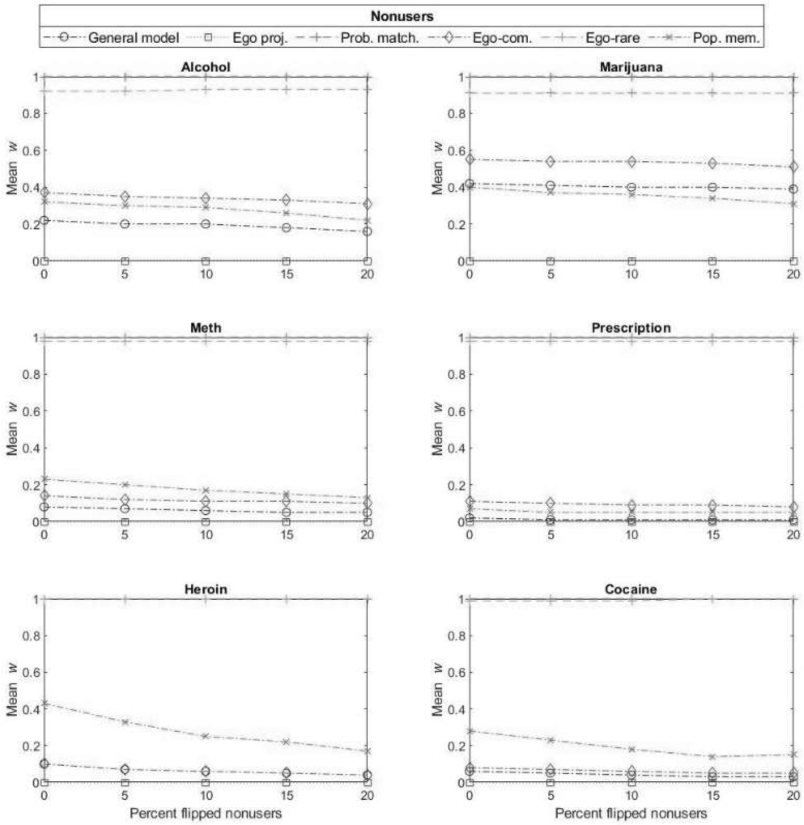

Figure S5. Mean parameter w values for nonusers for the different models across different percentages of flipped nonusers (i.e., percentages of nonusers that were recoded as users) across 200 simulation runs. All models were fitted on each run and the parameter values were then averaged.

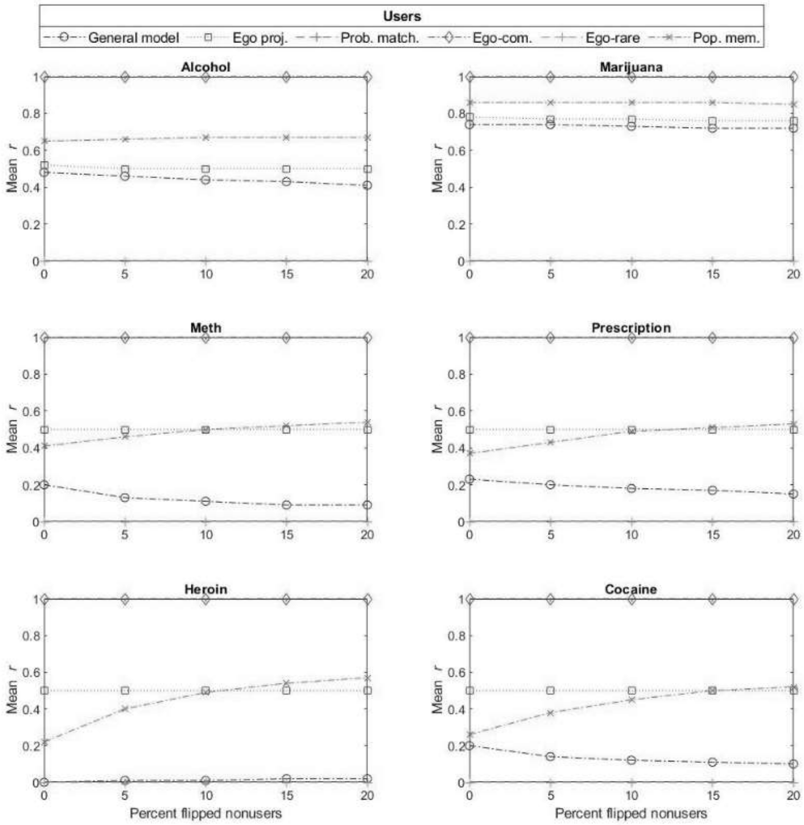

Figure S6. Mean parameter *r* values for users for the different models across different percentages of flipped nonusers (i.e., percentages of nonusers that were recoded as users) across 200 simulation runs. All models were fitted on each run and the parameter values were then averaged.

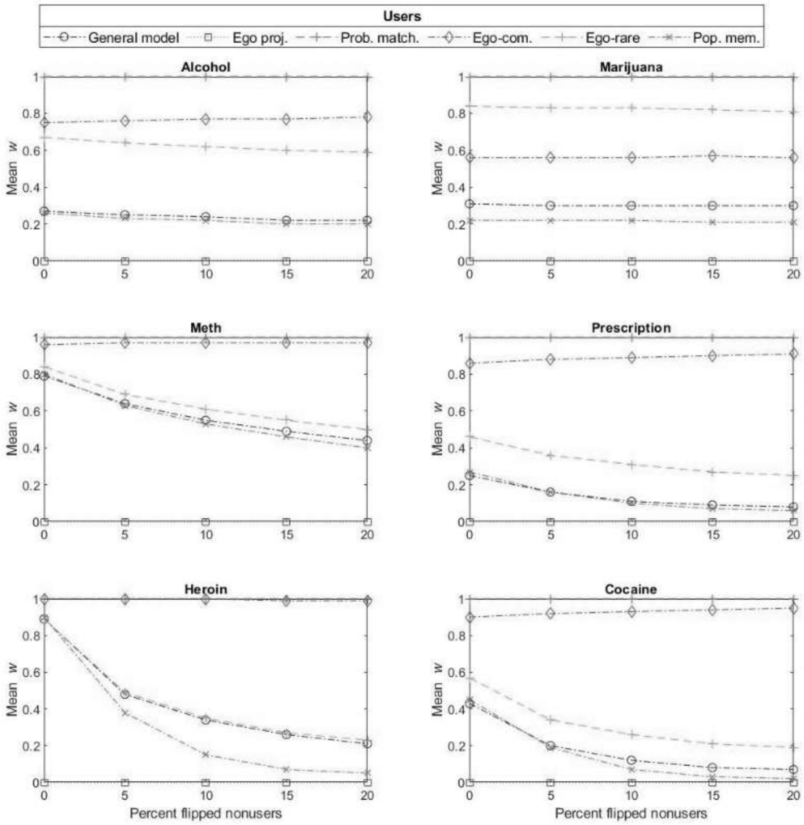

Figure S7. Mean parameter w values for users for the different models across different percentages of flipped nonusers (i.e., percentages of nonusers that were recoded as users) across 200 simulation runs. All models were fitted on each run and the parameter values were then averaged.

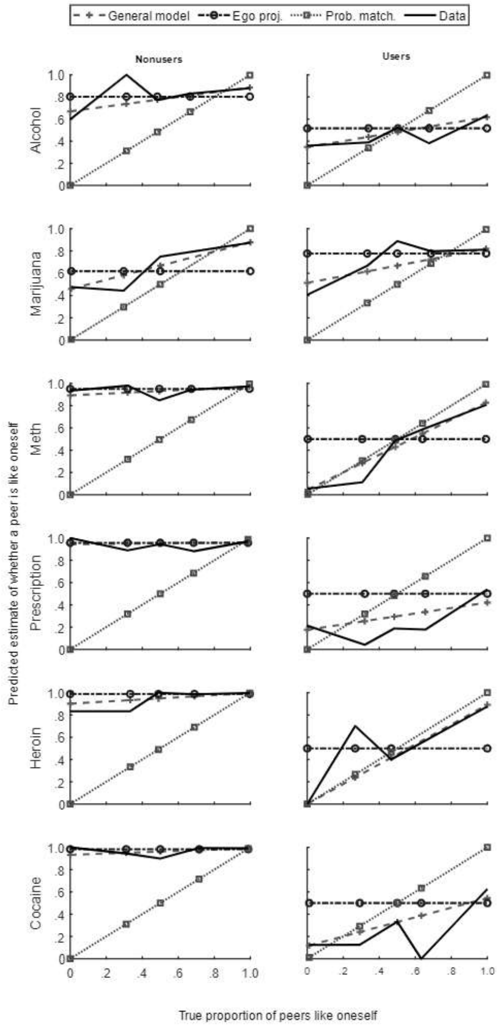

Figure S8. Actual (black lines) and predicted (colored lines) average individual estimates of whether a peer is like oneself (average $p_{i,est\_oneself}$, on *y*-axes), for different true levels of proportion of peers like oneself ($p_{i,true\_oneself}$, on *x*-axes). Predicted estimates are based on the general model, ego projection and probability matching. Rows show results for the six different substances. The left column shows results for nonusers, and the right column for users of these substances.

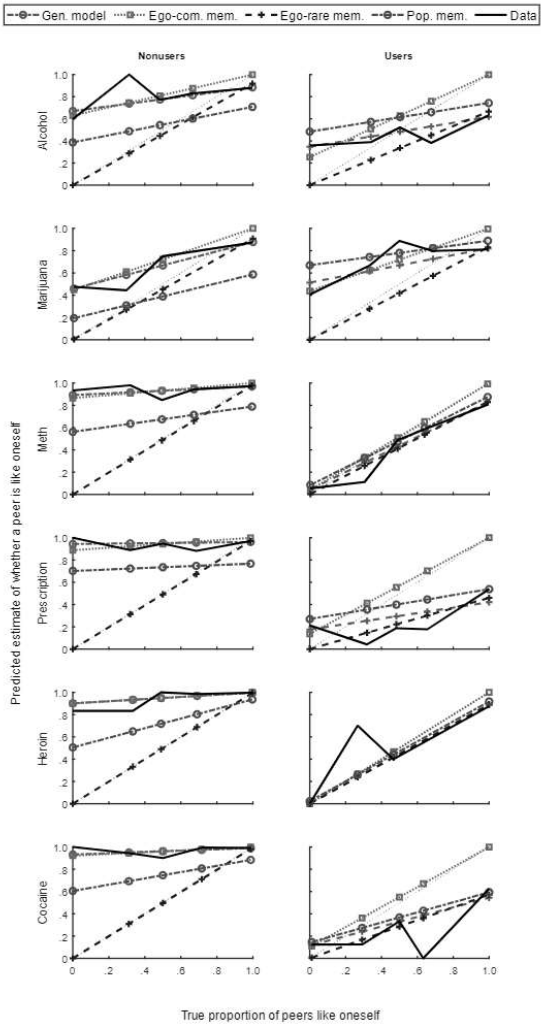

Figure S9. Actual (black lines) and predicted (colored lines) average individual estimates of whether a peer is like oneself (average $p_{i,est\_oneself}$, on y-axes), for different true levels of proportion of peers like oneself ($p_{i,true\_oneself}$, on x-axes). Predicted estimates are based on the general model, ego-common memory, ego-rare memory, and population memory. Rows show results for six different substances. The left column shows results for nonusers, and the right for users of these substances.

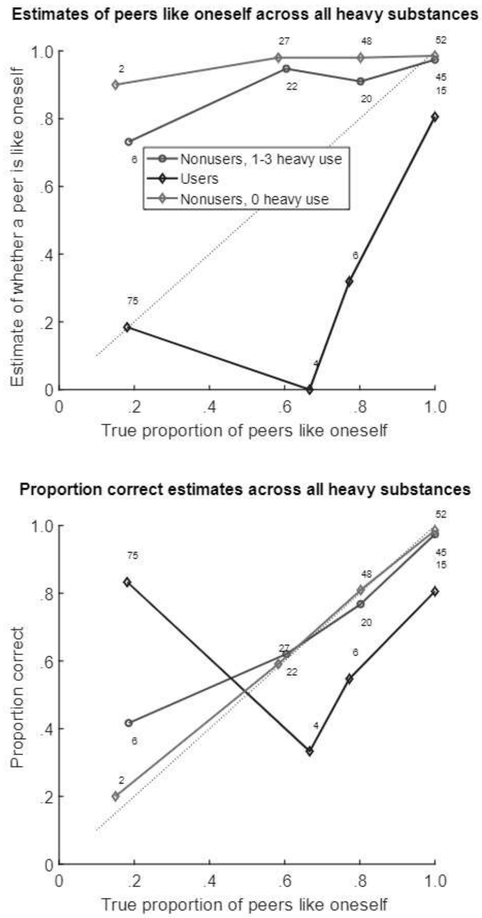

Figure S10. Top panel: Average estimate of whether a peer is like oneself (average $p_{i,est\_oneself}$, on *y*-axes) for different levels of true proportion of peers like oneself ($p_{i,true\_oneself}$, on *x*-axes). Bottom panel: Mean proportion correct estimates of whether peers are like oneself or not (*y*-axes) for different levels of true proportion of peers like oneself ($p_{i,true\_oneself}$, on *x*-axes). The data is shown separately for stated users of either of the four heavy substances (meth, prescription drugs, heroin, or cocaine; blue diamonds) and two groups of stated non-users: those who reported that they did not use a specific heavy substance buy that they did use 1 to 3 other heavy substances (red circles) and those who reported that they did not use any heavy substance (green diamonds).