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Research Article

An information theory account of preference prediction accuracy

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Abstract

Knowledge about other people's preferences is essential for successful social interactions, but what exactly are the driving factors that determine how well we can predict the likes and dislikes of people around us? To investigate the accuracy of couples' preference predictions we outline and empirically test three hypotheses: The positive valence hypothesis predicts that predictions for likes are more accurate than for dislikes. The negative valence hypothesis predicts the opposite, namely that dislikes are predicted more accurately than dislikes. The base rate hypothesis predicts that preference knowledge critically depends on the base rates of likes and dislikes within a given domain. In a series of studies we show that predicting likes over dislikes has relatively little effect compared with base rates. That is, accuracy is greater for relatively rare events regardless of whether they are liked or disliked. Our findings further suggest that when predicting preferences, people seem to rely on a combination of general, stereotypical knowledge of common preferences on the one hand and specific, idiosyncratic knowledge of rare preferences on the other.

Keywords: Preferences; Prediction accuracy; Positivity effect; Negativity effect; Base rate

Knowing about the likes and dislikes of friends and acquaintances is an important aspect of our social lives. Accurate predictions of preferences are particularly important in close relationships, where couples often make important and consequential decisions on behalf of each other (Fagerlin, Ditto, Danks, & Houts, 2001). Despite this importance, it has been found that the accuracy of such predictions is often rather low even though couples have the opportunity of getting ample feedback over time (Lerouge & Warlop, 2006; Pollmann & Finkenauer, 2009; Scheibehenne, Mata, & Todd, 2011; Swann & Gill, 1997). We test accuracy in more detail by distinguishing between general accuracy (e.g., my partner does not like romantic comedies) and specific accuracy (e.g., although my partner does not like romantic comedies, he does like the movie "When Harry met Sally") and by investigating how accuracy relates to the base rates of preferences. From a statistical point of view, accuracy further depends on the reliability or consistency of the to-be-predicted person's preferences (Cronbach, 1955). To help people make better predictions it is important to gain a better understanding of the diverse factors that drive accuracy in preference predictions. Two factors that may be particularly relevant here are the internal cognitive processes underlying preference predictions and the external environmental structures that people face (Anderson & Schooler, 1991; Gigerenzer, Todd, & the ABC research group, 1999).

To investigate the accuracy of preference predictions in more detail, here we focus on three research hypotheses that have been proposed in the literature. The positive valence hypothesis predicts that predictions for likes are more accurate than for dislikes. The negative valence hypothesis predicts the opposite, namely that dislikes are predicted more accurately than dislikes. Next to these two valence-based accounts there is

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the base rate hypothesis, which predicts that preference knowledge critically depends on the prevalence of likes and dislikes within a given domain. Even though these different accounts are closely related, they have not yet been considered in concert. Below, we provide a theoretical outline of all three hypotheses, followed by a series of three experiments that put them to an empirical test.

Positive valence hypothesis

In support of the positive valence hypothesis, Gershoff, Mukherjee, and Mukhopadhyay (2003) found that, when given the opportunity to learn about a person's preferences, people often seek out information about liked alternatives, presumably because there is less ambiguity in likes as compared to dislikes (Gershoff, Mukherjee, & Mukhopadhyay, 2007) For example, if someone likes a movie, chances are that they will like all of its attributes (actors, plot, genre) at least a little. If the movie is disliked, it may not be clear if this is due to one particular attribute of the movie, a combination of attributes, or all of them. From this perspective, likes are more informative than dislikes because they provide one with more definite information. Besides this, people may often prefer to communicate likes rather than a dislikes, because they want to make a cheerful impression (Leary & Kowalski, 1990; Zhao, Grasmuck, & Martin, 2008). In turn, positive information may also be better remembered, which would increase the chances of making accurate predictions (Matt, Vázquez, & Campbell, 1992). In line with this, Mata, Scheibehenne, and Todd (2008) found that parents knew likes better than dislikes when predicting the preferences of their children for school lunch dishes.

Negative valence hypothesis

In contrast to the positive valence hypothesis, there are also arguments suggesting that dislikes will be better predicted than likes. Dislikes are more likely to be communicated (Eisenhower, Mathiowetz, & Morganstein, 1991) and negative information has been shown to attract more attention than positive information (Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001), providing more opportunity for learning. In a consumer context, negative product information is often regarded as more diagnostic and more important than positive information (Ahluwalia, 2002; Herr, Kardes, & Kim, 1991).

In many social situations, giving something that is disliked will be the more costly error as compared to not giving something that is liked as the former will lead to negative feedback, which can improve the encoding and memory of negative preferences (Baumeister et al., 2001; Ito, Larsen, Smith, & Cacioppo, 1998; Pratto & John, 1991; Taylor, 1991). Empirical support for the negative valence hypothesis stems from a study by Liem, Zandstra, and Thomas (2010) who found that parents who predicted the food flavor preferences of their children were more accurate for dislikes than for likes.

Base rate hypothesis

In difference to the previous valence-based accounts, the base rate hypothesis predicts that accuracy depends on the proportion of likes and dislikes within a given domain. From the perspective of information theory, rare events or exceptions are more informative than more frequent events (Shannon, 1948). Formally, the informational value I of an item x can be expressed as the negative logarithm of its probability *p:* $I_x = -\log(p_x)$ (Shannon & Weaver, 1949). As a simple example, imagine a waitress serving drinks to a table of five customers, four of whom ordered a beer and one a glass of wine. To remember who ordered which drink, it will be much easier for the waitress to remember the single person who ordered the wine rather than what each of them ordered separately.

As in the example of the waitress, trying to memorize each individual preference for every single person around us would tax our limited cognitive resources and thus be biologically costly (Dukas, 1999). Here, a more efficient way of encoding would be to memorize the general tendency plus exceptions. With respect to preference prediction, this suggests that people will be more accurate when predicting rare idiosyncratic or uncommon preferences of their partner within a given domain, and that they have a general understanding of the respective common or default preferences.

While there is an ongoing debate regarding the extent to which decision makers consider or neglect base-rate information (e.g. Kahneman & Tversky, 1973; Kruglanski & Gigerenzer, 2011), past research consistently found that people's predictions are strongly influenced by base-rates (see Ajzen, 1977, for an early demonstration). With respect to preference prediction, an empirical study by West (1996) provides further support for the base rate hypothesis. In her experiment, participants who predicted preferences for abstract quilt patterns paid more attention to rare preferences during learning. Similarly, people also seem to pay more attention to rare events in real-word contexts, for example when forming social judgments (Skowronski & Carlston, 1987). The importance of base rates is further supported by research showing that people are sensitive to the diagnosticity of preferences, for example by paying more attention to extreme likes and dislikes (Gershoff et al., 2003). In addition, Scheibehenne et al. (2011) found that people often seem to possess some sort of general knowledge about the stereotypical or common preferences within a given domain. To our knowledge, it has not yet been tested, however, whether increased attention to rare preferences leads to more specific knowledge about rare preferences.

Measuring prediction accuracy

Testing these three hypotheses on empirical grounds requires a solid and interpretable measure of prediction accuracy. Here, one possible measure is to calculate the proportion of correct predictions separately for all liked and all disliked items within a given set. While feasible, this measure systematically depends on the base rates of the predictions, that is, the number of items that are predicted as likes relative to the number of items predicted as dislikes. To illustrate this, assume that of a list of 100 dishes, Ann likes 90. Betty wants to predict Ann's preferences but does not have any specific knowledge about Ann's idiosyncratic likes and dislikes. Betty does know however that most dishes are generally liked, so she randomly predicts that Ann will like 60 of them. In this scenario, Betty will on average correctly identify 54 likes and 4 dislikes. These scores represent 60% accuracy for likes and 40% accuracy for dislikes, suggesting a positive valence effect such that Betty has a better knowledge for likes than for dislikes. However, in this example the higher accuracy for likes is driven entirely by Betty's general knowledge about common preferences or base rates. In other words, here a positivity effect is to be expected simply because Betty predicts more likes than dislikes.

A measure of Betty's specific knowledge about Ann (which she does not possess in this example) requires controlling for base rates. One way of doing this is by calculating the observed to expected ratio (O/E ratio; c.f. Norén, Hopstadius, & Bate, 2013). The O/E ratio indicates how much better the observed accuracy (54 and 4 in the example above) is compared to the expected random accuracy from base rates alone. For likes, the expected accuracy is calculated as the number of predicted likes (here: 60) times the number of actual likes (here: 90), divided by the total number of items (100). For dislikes the calculation proceeds analogously. Dividing Ann's observed score by the expected score leads to an O/E ratio of 1 for both likes and dislikes, correctly revealing that Ann did not have any specific knowledge about Betty's preferences. The O/E ratio thus indicates how much better a person's predictions are relative to base rate guessing (i.e., an O/E ratio of 2 indicates that predictions are twice as accurate relative to guessing).

The correction for base rates is related to the idea that accuracy has many components, including stereotypical and specific knowledge, which can be disentangled (Cronbach, 1955). Such corrections are common among person perception researchers (Kenny, Kashy, & Cook, 2006) but have rarely been applied in research on preference prediction even though they can provide novel insights into the factors that drive prediction accuracy. In particular, O/E scores allow disentangling accuracy due to possible general knowledge about base rates of likes and dislikes from specific knowledge that goes beyond base rates. This is important for testing the base rate hypothesis according to which prediction accuracy depends on how common or rare certain likes and dislikes are. When controlling for such base rates, the hypothesis predicts a higher accuracy for rare preferences because rare preferences carry more informational value.

The current studies

Given the importance of making accurate preference predictions in many situations in our daily lives, it is interesting to test empirically how people's preference knowledge is structured to improve our understanding of when and why people's preference knowledge is accurate. To this end, we will present a series of three studies with diverse samples in which we investigate what couples know about their partner's preferences.

Study 1

We start our investigation of people's knowledge about their partner's preferences by assessing married couples' knowledge in the food domain. As married couples are likely to eat together on a regular basis, this provides us with a suitable real-world environment to explore the accuracy of their preference predictions. The positivity hypothesis predicts that likes are predicted more accurately than dislikes while the negativity hypothesis predicts the opposite. Assuming that most food items are liked by most people, the base rate hypothesis predicts that most items are predicted as being liked (resulting in higher accuracy for likes based on uncorrected scores) and that people should have more specific knowledge about dislikes (resulting in higher accuracy for dislikes after controlling for base rates).

Method

Participants. The sample consisted of 199 newlywed couples who participated in the first wave of a larger study on couple well-being in exchange for 15 Euros and a book (see Pollmann & Finkenauer, 2009 for a detailed description of the sample). Husbands on average were 32 years old (SD = 4.86) and wives 29 (SD = 4.28). The average time the couples had been romantically involved was 5 years and 9 month (SD = 3.03). Two individuals failed to answer the question about their own food preferences and two others failed to answer both the questions about their own and their partner's food preferences, thereby also making their partner's score unusable. As a result, six individuals are not included in the analyses reported below. Additionally, 47 people liked all dishes, so that a percentage of correct dislikes could not be calculated and 42 people predicted that their partner would like all dishes so that O/E ratios could not be calculated (Table 1).

Procedure and materials. Both members of each couple filled out a set of questionnaires at home in the presence of a research assistant who made sure that they did not discuss their answers with each other. Embedded in a battery of questionnaires was a menu with 12 food dishes selected from typical menus served in Dutch restaurants (e.g., Grilled scampi (8

Table 1
Observed and expected (in parentheses) number of correct and incorrect predictions for likes and dislikes in Study 1.

Agents' predictions	Targets' preferences		
	Likes	Dislikes	Sum
Likes	6.19 (5.02)	1.46 (2.64)	7.65
Dislikes	1.66 (2.83)	2.64 (1.49)	4.30
Sum	7.86	4.13	12

pieces) with a garlic chili sauce). For each dish, participants indicated whether they would or would not order that item in a restaurant (dichotomous scale). Later in the package they were asked to predict which of these 12 dishes their partner would or would not order. At the end of the questionnaire, participants were asked how often they eat out. It turned out that they all eat out sometimes, the median response being 3–11 times a year, indicating that participants were probably familiar with the presented dishes (see the online appendix for more details on the materials).

Dependent variables. In determining the accuracy of people's predictions we first calculated the uncorrected *percentage of correct likes and dislikes* for each participant. Thus, for instance, if one partner liked ten items and the other predicted four of these correctly, the percentage of correct likes would be 40%. To control for base rates and to investigate specific knowledge, we also calculated the O/E ratio by dividing the number of actual correct likes and correct dislikes by the number of correct likes and correct dislikes chance would predict, as outlined in the introduction. Note that, because the O/E ratios are not normally distributed but have a theoretical range from 0 to ∞, throughout the manuscript we performed the comparative analyses of these ratios on log-transformed scores. The means presented in the result sections are the original O/E ratios.

Results

Participants liked most of the items (66%). Thus, dislikes represent the less common preference. In this case, the base rate hypothesis predicts that the percentage of correct likes (the more common preference) will be larger than the percentage of correct dislikes (the less common preference) and that the O/E ratio will be larger for dislikes than for likes. By contrast, the positive valence-based hypotheses predict that accuracy should be higher for likes and the negative valence hypothesis predicts that it should be higher for dislikes, both irrespective of base rates.

Percentage of correct likes and dislikes. On average, people correctly predicted 78% of the items the partner liked (SD = 21%) as compared to only 62% (SD = 34%) of all items the partners disliked. A comparison of these percentages shows that people are better (i.e., more accurate) at predicting likes (the common preference) than dislikes (the rare preference) $t(345) = 6.79$, $p < .001$, $d = .57$.

O/E ratios. The O/E ratios for likes ($M = 1.34$, $SD = 0.78$) and for dislikes ($M = 1.87$, $SD = 1.36$) are significantly larger than 1 ($t_{\text{correct likes}}(391) = 8.71$, $p < .001$; $t_{\text{correct dislikes}}(317) = 11.35$, $p < .001$), indicating that predictions are better than chance and that people do have specific knowledge beyond base rates. Results further show that the O/E ratios for dislikes are significantly larger than the O/E ratios for likes, $t(296) = 7.63$. $p < .001$, $d = 0.44$. Thus, when controlling for base rates, prediction accuracy is higher for the less common dislikes than the more common likes.

Discussion

The results are in line with the base rate hypothesis according to which people have more general knowledge about their partner's common preferences and at the same time more specific knowledge about their partner's rare preferences. These results underline the need to take base rates into account when investigating whether people know more about other people's likes or dislikes.

To further disentangle the effect of a possible positive or negative valence effect and the base rates, an experimental design is needed where the base rates (i.e., the prevalence of likes and dislikes) varies between prediction domains. To this end we conducted another study where romantic couples were asked to predict likes and dislikes across different domains.

Study 2

If preference prediction depends on base rates, prediction accuracy should vary with the proportion of likes and dislikes within a given domain. To test this idea, we investigated preference knowledge in three different domains (food, vacations, and movies) which were based on earlier research on preference knowledge (Gershoff & Johar, 2006; Scheibehenne et al., 2011), and on the expectation that the proportions of likes and dislikes will vary across these three domains.

Method

Participants. Two research assistants recruited romantic couples from among their friends and acquaintances to take part in this study. Twenty heterosexual couples who had been romantically involved for an average of 6.8 years (SD = 9.45) participated in exchange for 10 Euros. The men on average were 30 years old (SD = 11.75), the women 28 (SD = 10.20).

Procedure and materials. As in Study 1, participants filled out a questionnaire in their homes in the presence of a research assistant who made sure that partners did not discuss their answers with each other. After answering demographic questions about age, gender, relationship length and relationship status, participants indicated for 10 restaurants, 10 vacations, and 10 movies whether they liked them or not and whether or not they thought their partner liked them. Restaurants included different cuisines like "Japanese (sushi)" and "Italian." The movies were recent and well-known and represented different genres, ranging from romantic comedy ("Music and lyrics") to thriller ("Sunshine"). Each movie was presented with a picture and a short summary of the content. The vacations included a wide range of options from city trips and cruises to skiing vacations and were also presented with a picture.

Results

Overall, participants liked the majority of the items. The proportions of liked items varied between prediction domains. On average, participants liked 79.5% of the cuisines, 74.0% of the vacations, and 60.0% of the movies (see Table 2 for details about the number of correct and incorrect predictions within each domain). The percentages differed significantly ($F(2, 38) = 17.88$, $p < .001$, $\eta_p^2 = .485$). Based on these percentages, the base rate hypothesis predicts that the percentage of correctly predicted likes will be higher for movies as compared to cuisines and vacations, whereas when controlling for base rates by calculating O/E ratios, the reverse pattern will emerge.

Percentage of correct likes and dislikes. To compare the percentage of correctly identified preferences across domains, we conducted a repeated measure ANOVA. Six people liked all 10 cuisines, so a percentage of correct dislikes could not be calculated for these cases and they are not included in this analysis. The ANOVA indicates a main effect of type of preference (likes vs. dislikes), $F(1, 33) = 17.45$, $p < .001$, $\eta_p^2 = .35$, no main effect of domain $F(2, 66) = 1.37$, $p = .26$, $\eta_p^2 = .04$, and an interaction between type and domain, $F(2, 66) = 5.20$, $p = .008$, $\eta_p^2 = .14$. Further comparisons with Bonferroni correction indicated that participants were more accurate at predicting likes (the common preference) in all three domains, but that the difference between correctly predicted likes and correctly predicted dislikes differed across domains. Specifically, for cuisines, which were mostly liked, the accuracy for likes was much higher than for dislikes ($M_{dif} = 0.49$, $p < .001$). For vacations, the difference was smaller but still significant ($M_{dif} = 0.14$; $p = .042$). Finally, for movies, the difference was small and not significant ($M_{dif} = 0.05$, $p = 1.00$). Together, these results show that prediction accuracy varied systematically with the base rates of likes and dislikes.

Fig. 1 provides a graphical representation of the relationship between prediction accuracy (y-axis) and the proportion of items that were liked (x-axis), separately for each domain. In the figure, prediction accuracy is plotted as the percentage of correct likes minus the percentage of correct dislikes. Thus, positive values indicate a higher proportion of correct likes while negative values indicate a higher proportion of correct dislikes. The figure also shows the main results of Studies 1 and 3.

O/E ratios. Across all three domains, O/E ratios for likes and dislikes were higher than chance (all t's > 4.5, all p's < .001), indicating that prediction accuracy was not just driven by base rates. For example, for liked cuisines, the number of expected correct answers based on chance was 6.28 and the number of observed correct likes was 7.10; thus the number of observed correct likes was 1.13 times higher than the number of expected correct likes (see Table 2).

To test whether the O/E ratios differed depending on how common or rare likes and dislikes are, as predicted by the base rate hypothesis, we conducted a repeated measure ANOVA across all three domains. In addition to the six targets who indicated no dislikes for restaurants, this analysis excluded six participants who predicted no dislikes for either vacations or restaurants or had no correct dislikes, so the (log-transformed) O/E ratios could not be calculated, leaving 21 cases with complete data. Results indicate that overall, the O/E ratios for likes (the common preference) were smaller than those for dislikes (the rare preference); $F(1, 20) = 52.08$, $p < .001$, $\eta_p^2 = .72$ and that accuracy differed across the different domains $F(2, 40) = 5.37$, $p = .009$, $\eta_p^2 = .21$. Importantly, results show an interaction effect indicating that the difference between likes and dislikes varied across the three prediction domains; $F(2, 40) = 15.46$, $p < .001$, $\eta_p^2 = .44$. Further analyses show that for cuisines and vacations, where most items were liked, the O/E ratios for likes were much smaller than for dislikes (cuisines: $M_{dif} = -1.79$; vacations: $M_{dif} = -1.68$, both $p < .001$). For movies, where the proportion of likes was only slightly larger than the proportion of dislikes, the difference was much smaller and not significant ($M_{dif} = -0.23$, $p = .243$).

Discussion

These results show that the observed prediction accuracy was higher than would be expected in the case of random guessing. The empirical evidence further indicates that accuracy within each domain mirrors the proportions of likes and dislikes, as predicted by the base rate hypothesis. For example, for movies, the proportion of likes versus dislikes was about 60:40, indicating that dislikes where only slightly more informative than likes. Accordingly, there were only small accuracy differences in this category. For vacations and restaurants, the differences were more pronounced (74:26 and 80:20, respectively) and so was the difference in accuracy for likes and dislikes. In summary, as the difference between the number of liked items and the number of disliked items increased, so did the difference between the correctly predicted likes and the dislikes, indicating an influence of base rates on preference prediction accuracy.

In a domain where most items are liked, prediction accuracy can be easily achieved by using base rate knowledge (e.g. "my partner likes most cuisines"), whereas the dislikes must be

Table 2
Observed and expected (in parentheses) number of correct and incorrect predictions for likes and dislikes across the three domains in Study 2.

Agents' predictions	Targets' preferences								
	Cuisines			Vacations			Movies		
	Likes	Dislikes	Sum	Likes	Dislikes	Sum	Likes	Dislikes	Sum
Likes	7.10 (6.28)	0.80 (1.62)	7.90	6.43 (52.5)	0.68 (1.85)	7.10	4.45 (3.40)	1.23 (2.28)	5.68
Dislikes	0.85 (1.67)	1.25 (0.43)	2.10	0.98 (2.15)	1.93 (0.75)	2.90	1.55 (2.60)	2.78 (1.73)	4.33
Sum	7.95	2.05	10	7.40	2.60	10	6.00	4.00	10

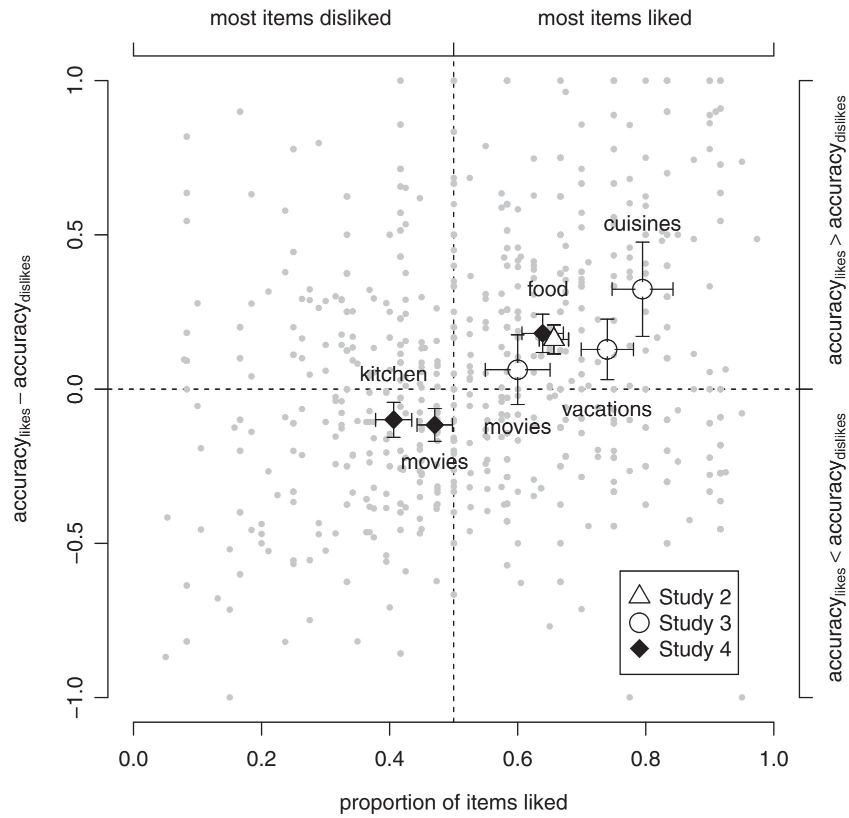

Fig. 1. Proportion of items the to-be predicted partner likes plotted against the difference between the prediction accuracy for likes and dislikes, separately for each domain in Studies 1, 2, and 3. Points in the upper half of the figure depict cases where likes were better predicted than dislikes. Points on the right depict cases in which participants liked most of the items. Gray dots indicate individual data. As can be seen from the figure, the relative accuracy for predicting likes and dislikes depends on the proportion of liked versus disliked items, indicating a systematic influence of base rates.

predicted based on specific knowledge (e.g. "my partner does not like Japanese food"). The O/E ratios suggest that, when controlling for base rates, the specific accuracy for dislikes was higher than the accuracy for likes. This is in line with the base rate hypothesis according to which rare or uncommon preferences (here: a dislike for a specific cuisine) are more informative, which would lead to more specific knowledge.

In difference to the base rate hypothesis, the two valence-based hypotheses predict that either likes or dislikes are better predicted, regardless of the relative frequency of dislikes and likes. Contrary to this, we found that accuracy did depend on the proportions of likes and dislikes for both measures of accuracy.

In the data on hand, the base rates of likes and dislikes varied between domains, which provided the basis for testing the base rate hypothesis. However, in all three domains likes were more frequent than dislikes, such that the dislikes always carried more informational value than likes. To further test the scope of the base rate hypothesis, it would be desirable to extend the analysis to cases where the majority of the items are disliked, because then the base rate hypothesis predicts that the direction of prediction accuracy reverses. To test this prediction, we re-analyzed data of an existing study that also included a domain where most items were disliked.

Study 3

To test the base rate hypothesis in a domain where most items were disliked, we re-analyzed data from a previous study conducted by Scheibehenne et al. (2011). When dislikes are more frequent than likes, both valence accounts still predict higher prediction accuracy for either likes or dislikes while the base rate hypothesis predicts that prediction accuracy reverses.

Method

In the original study by Scheibehenne et al., 38 younger couples (mean age 24, range 19–32 years old) and 20 older couples, (mean age 69, range 62–78 years old) predicted each other's likes and dislikes across several domains, including 40 food dishes, 40 movies, and 38 kitchenette designs on a scale from 1 ("don't like it at all") to 4 ("like it very much"); the intermediate scale labels were "somewhat dislike it" (2) and "somewhat like it" (3). As a criterion for accuracy, each partner also stated his or her own preferences on the same scale. In the original study, analyses on the difference between younger and older couples and more extreme preferences were reported. For more details of the experimental design and more results, see Scheibehenne et al. (2011). Based on these data, prediction accuracy within each domain could be estimated. For the purpose of the analysis on hand, we reduced the original answer scale to "likes" (values of 1 and 2) and "dislikes" (values 3 and 4). While this rendered the answers less nuanced, it did not systematically bias the results and it allowed for a direct comparison between the previous two studies that relied on a dichotomous answer scale.

Results

Participants in the experiment liked 63.9% (SD = 17.8%) of the food items, 47.0% (SD = 15.2%) of the movies, and 40.6% (SD = 15.6%) of the kitchenettes (see Table 3 for details). The difference between these proportions were statistically significant ($F(1.89, 217.38) = 65.89$, $p < .001$, $\eta_p^2 = .36$).

Percentage of correct likes and dislikes. When comparing the percentages of correctly predicted likes and dislikes across domains, there was no main effect of valence (likes vs. dislikes), $F(1, 115) = 0.25$, $p = .62$, a main effect of domain $F(2, 230) = 74.66$, $p < .001$, $\eta_p^2 = .39$, and an interaction between valence and domain, $F(1.856, 219.47) = 86.05$, $p < .001$, $\eta_p^2 = .43$. Similar results emerged when taking the whole range of the original rating scale into account by using the mean (squared) distance between the predicted and the actual ratings as independent variable. Pairwise comparisons with Bonferroni correction showed that for food items, accuracy was higher for likes (the common preference) than for dislikes ($M_{dif} = 0.27$, $p < .001$). For movies and kitchenettes, where most items were disliked, it was the other way round. Here, accuracy was higher for dislikes (the common preference) ($M_{dif\ movies} = -0.09$; $p = .001$; $M_{dif\ kitchenettes} = -0.16$; $p < .001$). As shown in Fig. 1, these findings provide a consistent pattern that is in line with the results of the previous studies: As the proportion of likes increases, so does the accuracy for predicting likes.

O/E ratios. Three subjects predicted no (dis)likes in a given domain and an additional five subject had no correct (dis)likes in a given domain, so the (log-trasformed) O/E ratios could not be computed. For the remaining data, mean prediction accuracy in all three domains was higher than chance (all t's > 4.9, all p's < .001), indicating that accuracy was not just driven by base rates but also involved specific knowledge.

A comparison of the O/E ratios for likes and dislikes based on a repeated measures ANOVA showed that, overall, the O/E ratios for likes were smaller than for dislikes, $F(1, 107) = 8.38$, $p = .005$, $\eta_p^2 = .07$ and they differed across domains, $F(1.82, 194.86) = 80.10$, $p < .001$, $\eta_p^2 = .43$. There was also an interaction between valence and domain $F(1.49, 159.68) = 43.05$, $p < .001$, $\eta_p^2 = .29$. For food, O/E ratios were smaller for likes (the common preference) than for dislikes ($M_{dif} = -0.56$, $p < .001$); for movies, the ratios were larger for likes than for dislikes, but not significantly so ($M_{dif} = 0.08$, $p = .12$); for kitchenettes, the ratios were clearly larger for likes than for dislikes ($M_{dif} = 0.17$, $p < .001$). These results again show that rarer preferences were predicted with more specific accuracy.

Discussion

Results indicate that prediction accuracy varied along the proportion of likes and dislikes, irrespective of which indicator of accuracy (percentages or O/E ratios) one looks at. In a domain where most items were liked (food), predictions for dislikes were more accurate after controlling for base rates whereas in the domain where most items were disliked (kitchenettes), this pattern reversed. These results are difficult to explain based on either the positive or negative valence hypothesis but they are in line with the predictions of the base rate hypothesis according to which people have more specific knowledge about rare preferences. Thus, after controlling for base rates, rare preferences were predicted more accurately, irrespective of valence. When base rates were not controlled for, prediction accuracy was higher for more common preferences.

General discussion

To gain a better understanding of the factors that determine how well people know and predict each other's preferences, we outlined and empirically tested three hypotheses: Two valence-based accounts suggesting that prediction accuracy is higher for items that are either liked (positive valence hypothesis) or disliked (negative valence hypothesis) and a base rate hypothesis according to which accuracy critically depends on the base rates, i.e., the proportion of likes over dislikes. Past research provides theoretical rationales and empirical support for all three hypotheses. In support of the positivity hypotheses,

Table 3
Observed and expected (in parentheses) proportions of correct and incorrect predictions for likes and dislikes across all three domains in Study 3 (Scheibehenne et al., 2011).

Agents' predictions	Targets' preferences								
	Cuisines			Movies			Kitchenettes		
	Likes	Dislikes	Sum	Likes	Dislikes	Sum	Likes	Dislikes	Sum
Likes	50.6% (40.5%)	12.9 % (22.9%)	63.4%	30.1% (20.7%)	13.8% (23.2%)	43.9%	21.2% (17.6%)	22.2% (25.8%)	43.4%
Dislikes	13.3% (23.4%)	23.2% (13.2%)	36.6%	16.9% (26.4%)	39.2% (29.7%)	56.1%	19.4% (23.0%)	37.1% (33.6%)	56.6%
Sum	63.9%	36.1%	100%	47.0%	53.0%	100%	40.6%	59.4%	100%

it has been argued that information about likes is often encoded more deeply and thus more accessible in memory (Gershoff, Mukherjee, & Mukhopadhyay, 2006; Matt et al., 1992). In contrast to this, researchers also argued that dislikes are communicated more consistently (Liem et al., 2010) and that negative information is more diagnostic (Herr et al., 1991), hence fostering the negative valence hypothesis. Notwithstanding these theoretical justifications, it has also been suggested that prediction accuracy may not be driven by valence but rather by the informational value of an item (e.g. Gershoff et al., 2003; Skowronski & Carlston, 1987). As the informational value of an item critically depends on the probability of its occurrence (Shannon, 1948), this points towards the base rate hypothesis.

Across three consecutive studies, our results consistently showed that partners' knowledge about each other's food, movie, vacation, and furniture preferences depends more strongly on base rates than on the valence. Whether a like or a dislike is predicted more accurately depends on how many other likes and dislikes there are, hence supporting the base rate hypothesis. Apparently, participants in our studies possessed knowledge about rare events or exceptions in combination with general knowledge about base rates, i.e. whether items in a given domain are mostly liked or disliked.

Past research on preference knowledge suggests that in absolute terms, prediction accuracy for preferences often tends to be rather low (Davis, Hoch, & Ragsdale, 1986; Lerouge & Warlop, 2006; Mata et al., 2008; Pollmann & Finkenauer, 2009; Scheibehenne et al., 2011). Our results provide a more nuanced picture indicating that accuracy systematically varies depending on the structure of the environment that people face. While we did not directly assess the cognitive processes underlying preference predictions, our results fit well with West's (1996) findings that people pay more attention to information about rare preferences. This behavior may reflect an adaptive strategy of preference prediction that relies on knowledge of general tendencies or base rates, in combination with specific knowledge of exceptions, thus making efficient use of potentially scarce memory resources (Anderson & Schooler, 1991; Dukas, 1999). Such a strategy would also be advantageous for maintaining relationships because it allows communicating to the other person that his or her special preferences are recognized. If Ann knows that Betty likes puppies, this is not very special, but if Ann knows that Betty likes sharks, this indicates that Ann really knows Betty. Thus, even though people's overall preference knowledge may at times be low, it may nevertheless be based on a very functional and adaptive structure.

Our results contribute to the literature on preference predictions in several ways and they point to new directions for future research. First, our findings indicate that it is important for researchers to take base rates into account. This is particularly relevant with respect to the question whether there is a general positivity effect or general negativity effect in people's knowledge about other people's preferences. While both effects are well justified on theoretical grounds, empirical evidence for both effects seems rather mixed, even within the same domain. For example when parents predict the food preferences of their children, some results indicate that likes are better predicted than dislikes (e.g. Mata et al., 2008) while others using a similar task find the opposite pattern (e.g. Liem et al., 2010). Our results provide a possible explanation for these discrepancies as they indicate that valence-based explanations may often be overshadowed or even biased by differences in the base rates of likes and dislikes. As a consequence, researchers analyzing accuracy data are well-advised to also consider base-rates.

Second, our results suggest that preference predictions result from a combination of general or stereotypical knowledge together with specific knowledge about one's partner. As the two factors may contribute in varying degrees and they may both be more or less accurate, it seems worthwhile for future research to further specify and disentangle these sources (see Mata et al., 2008 for a similar argument).

Third, our findings are in line with a growing number of studies showing that people often take base rate information into account when making predictions (Zukier & Pepitone, 1984) and thus contribute to the continuous debate on base-rate neglect (Kahneman & Tversky, 1973; Kruglanski & Gigerenzer, 2011).

Fourth, the prediction accuracies that we observed were consistently above chance level and also exceeded the accuracy expected from just utilizing knowledge about base rates. To better understand peoples' prediction strategies requires finding additional factors that influence this accuracy. Based on past literature on what people think are informative preferences when they are to judge the similarity between themselves and others (Gershoff et al., 2003, 2006, 2007), one could predict that people's specific knowledge is influenced by how extreme the preferences are. Our design did not enable us to disentangle the effect of rare and extreme preferences, because the extreme preferences in Study 3 were also rarer, but a controlled study could bring these ideas together and investigate them in concert.

By the same token, the valence hypotheses and the base rate hypothesis are not mutually exclusive. For example, one could be sensitive to rare items and at the same time also pay more attention to positive or negative items. Disentangling the relative influence of base rates and valence requires a more controlled study where both factors vary independently, ideally in a within-subject design. It should also be noted that in the current set of studies, participants were not given a neutral response option. This forced our participants to state a preference where they might not actually have had a strong preference thus inducing error variance or noise but no systematic bias. While we deem it unlikely that leaving out the neutral option influenced our conclusions, future research might benefit from using a more refined answer scale.

An alternative explanation for our finding that base rates influence how much people know about other people's likes and dislikes could be that it is more costly for people to get a 'rare event' wrong than a 'common' one. In that case, people would know more about rare events not because they are carry more informational value, but because the costs of getting them wrong would be higher. For example, if your partner will eat almost anything except tomatoes, they might be more disappointed if you forgot about this special dislike than they would be if you forgot that they dislike a more commonly disliked food like anchovies. In analogy to a signal-detection framework, future studies should disentangle these two accounts by measuring the respective costs and benefits involved when making correct or incorrect predictions (McNicol, 2005).

If people's preference knowledge is influenced by the costs of certain mistakes, prediction accuracy may further depend on personal dispositions or goals. Someone who is more prevention-focused (Higgins, 1998) or who has a strong affiliation goal may be more concerned about avoiding a costly mistake and therefore pay even more attention to particular preferences. Looked at from this perspective, one would also expect individual differences due to aspects such as personality traits, motivation, or experience. As a first step in this direction, additional exploratory analyses for Study 1 indicate enhanced knowledge of rare preferences (dislikes) for partners who prepare dinner more often. In particular, the interaction effect between how often someone prepares dinner (four levels: 0–11 times per year, 1–3 times a month, 1–2 times a week, 3–7 times a week) and the type of correctly identified preference (correct like, correct dislike) was significant, $F(3, 341) = 2.97$, $p = .032$. Those who prepare dinner 3–7 times a week know almost as many likes as dislikes (mean difference = 0.11), whereas those who prepare dinner 0–11 times a year clearly know the likes better than the dislikes (mean difference = 0.30). Thus, it seems that those who have more experience preparing dinner rely less on base rates and have more specific knowledge.

For most people, an important indication of a good relationship is the feeling that the other person knows them well (Pollmann & Finkenauer, 2009). People who are more involved in a friendship have more of a tendency to overestimate their friend's knowledge about their preferences than those who are less involved (Gershoff & Johar, 2006) and receiving a bad gift from one's partner (indicating low preference knowledge) can lead to negative evaluations of the relationship (Dunn, Huntsinger, Lun, & Sinclair, 2008).

Given its importance for interpersonal relations, it is of great value to understand how people make predictions about what others around them want and what they do not want. Our results suggests that understanding these prediction strategies benefits from taking into account both the underlying psychological processes and the structure of the environment in which these predictions are made. Towards the goal of predicting other people's preferences, relying on a combination of both, general and specific knowledge can be an efficient and adaptive strategy.

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Appendix A. Methodological details

Methodological details of this article can be found online at http://dx.doi.org/10.1016/j.jcps.2014.10.002.

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