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# What does it mean to feel loved: Cultural consensus and individual differences in felt love

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**Abstract**

Cultural consensus theory is a statistical framework (CCT) for the study of individual differences in the knowledge of culturally shared opinions. In this article, we demonstrate how a CCT analysis can be used to study individual differences and cultural consensus on what makes people feel loved, or more generally any social behaviors that are governed by cognitive schemata. To highlight the advantages of the method, we describe a study in which people reported on their everyday experiences of *feeling loved*. Our unique approach to understanding this topic is to focus on people's cognitive evaluations on what feeling loved (both romantically and nonromantically) entails by exploring the shared agreement regarding when one is most likely to feel loved and the individual differences that influence knowledge of these shared agreements. Our results reveal that people converge on a consensus about indicators of expressed love and that these scenarios are both romantic and nonromantic. Moreover, people show individual differences in (1) the amount of knowledge they have about this consensus and (2) their guessing biases in responding to items on love scenarios, depending on personality and demographics—all conclusions made possible by the CCT method.

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Cultural consensus theory, feelings of love, hierarchical Bayesian modeling, individual differences

Consider the following situation: Your partner tells you how much he/she cares about you and forms a habit of texting or calling you frequently during the day, asking where you are and what you are doing. This makes you feel warm and loved inside. However, another person might conceivably experience the same behaviors from their significant other but might not experience felt love but rather feel controlled, even violated. Thus, a question comes to mind: Does everyone agree which everyday life experiences make them and other people feel loved? Would these experiences consistently elicit loving feelings in *everyone*? Are there important individual differences linked to identifying this behavior as an indicator of love? How can we measure the consensus among people on the concept of felt love, in such a way that we account for individual differences? Are any individual differences in consensus awareness systematically associated with personality characteristics?

In this article, we show how cognitive psychometric methodology, built upon cultural consensus theory (CCT; Batchelder & Romney, 1988; Romney & Batchelder, 1999), can simultaneously inform us about the nature of generalized expectations or cognitive schemata governing social behaviors and about the individual's knowledge of these schemata. CCT consists of a family of cognitive response models for various questionnaire formats, for example, True/False, ordered categories (Likert, as in grading essay questions), or continuous responses (as in probability judgments). With CCT models, we can derive shared beliefs and knowledge about content domains by applying a formal model of the decision-making process. CCT is most often used with knowledge domains that have no requirements for a ground truth or scientifically verifiable correct answers, but it is assumed that there exists a cultural consensus in the shared knowledge and beliefs domain. In this framework, *consensus* signifies the general agreement on a certain content domain or an overlap in knowledge and opinion on a theoretical concept, which is shared by all members of a culture. *Culture* can be defined simply as any group who assumedly share knowledge or beliefs, for example, adults in the U.S., or Facebook users.

In order to operationalize and understand a certain concept within a culture or a group of people, we collect responses on series of related items on the content domain from multiple members of the culture and apply CCT models to simultaneously derive the consensus and the participants' knowledge of it. It is not assumed that every member of the group knows all of the consensus answers; therefore, the response models allow individuals to vary in their degree of cultural knowledge as well as their response biases when in doubt. Using CCT, researchers can find an essential, operational, and succinct definition of a concept that are accepted by a group that shares some common knowledge or beliefs. CCT models have been used extensively in a wide variety of domains, for example, in studying medical knowledge and beliefs in anthropology (Weller, Bear, de Alba Garcia, & Rochad, 2012), in extracting information from eye-witness testimonies (Waubert de Puiseau, Aβfalg, Erdfelder, & Bernstein, 2012), in inferring judgment of personality traits in social networks (Agrawal & Batchelder, 2012; Batchelder, Kumbasar, & Boyd, 1997), and have been proposed for evaluating interpersonal agreements on psychological concepts such as behavior (Oravecz, Faust, Levitis, & Batchelder, 2015).

Central to all CCT models is how cultural truth is specified. In models for True/False and True/False/Don't know questionnaires, truth is usually characterized as dichotomous (True or False). However, Batchelder and Anders (2012) present model for a True/False questionnaire where truth lies on a continuum as in fuzzy logic. Also, CCT models for ordinal categories (e.g., Anders & Batchelder, 2015) and CCT models for items requiring continuous (slider) response (e.g., Anders, Oravecz, & Batchelder, 2014) treat truth as on a continuum. For a detailed summary of the CCT framework, please consult Batchelder, Anders, and Oravecz (2018).

The CCT approach is especially important because it allows for exploring group beliefs beyond merely aggregating between responses of individuals. Its methodology is based on quantifying the individual's knowledge of the concept together with the consensus on the related items by weighting the responses of each person by their competency and aggregating responses across people. In general, the overall goal of applying a CCT model is to (1) identify if there are one or more latent "cultural groups" that share a consensus on answers to a set of questions, (2) decide if the data supports the statistical model used to do this, and (3) if so, estimate the parameters of the model. By parameters, we mean the cultural salience or difficulty of each question, the cultural competence or the calibration of each informant, and the response biases of each informant. When identifying the latent cultural groups of informants, if more than one consensus truth/cultural group is estimated, the CCT model would estimate corresponding group membership parameters for each informant (Anders & Batchelder, 2012).

It should also be noted that CCT is designed for questions that address knowledge or beliefs shared by the informants and not informants' opinions or personal beliefs about topics. For example, questions such as "Is Washington the capital city of the United States?" or "Do Canadians like ice skating?" can be appropriate for a CCT approach but questions such as "Do you like ice skating?" are not suitable for CCT. Hence, we think that the study of relationships, where relevant concepts are organized around people's beliefs rather than factual knowledge, would deeply benefit from the CCT approach.

As an example, in the application section, we examine judgments on whether people in general would feel loved by various everyday life scenarios, that is the *cultural consensus on felt love*. To get accurate insights, we have to take into account people's cognitive individual differences in their judgment process. Some people might be more aware of the meaning of interpersonal behaviors: A person who is more in agreement with others knows more about the shared cognitive beliefs on felt love. Moreover, it is reasonable to assume that some people are more inclined to guess when they are uncertain in their decision, while others might not. Moreover, guessing tendencies can differ across people with different backgrounds. Ideally, we would like to derive shared agreement or consensus truth in a way that these cognitive individual differences are taken into account.

In this article, we demonstrate a specific CCT-based research tool, namely the extended Condorcet model (ECM), for studying individual differences and cultural consensus on what makes people feel loved. In the sections below, we first describe how the ECM can be used in relationship research by providing an in-depth explanation of the model parameters and practical guidance on the model fitting. We then compare the CCT approach to more traditional approaches and present its advantages for relationship research. Finally, we demonstrate how the ECM can be used to explore the concept of felt love and how to interpret the findings from this analysis.

## *Exploring consensus and individual differences with the ECM*

The specific consensus model that we propose for addressing questions on shared cognitive schemata governing social behaviors is the ECM. As a CCT model, the ECM allows for individual differences in the degree to which a respondent knows the shared agreement. ECM is also capable of discerning between individual guessing biases. When respondents are asked to answer items in terms of True/False/Don't know, guessing biases occur when a person shows a tendency to guess a True (or False) answer when they are uncertain. For example, it has been shown that men are more willing to guess than women when faced with uncertainty: that is, women use "Don't know" systematically more often than men (Oravecz, Vandekerckhove, & Batchelder, 2014). The ECM accounts for all of these individual differences in the decision-making process when deriving the consensus answer. Specifically, in the study presented below, ECM allowed us to derive the shared agreements on felt love items by accounting for individual differences as well as dependencies in the data (i.e., items centering on the same concepts as well as respondents sharing the same cultural background). Consensus on felt love was already examined with the ECM by Oravecz, Muth, and Vandekerckhove (2016). The current study aims at replicating the findings as well as expounding on that research in terms of looking at individual differences in personality and its relation to knowledge of consensus on felt love.

The core of the ECM is a multinomial processing tree that describes the latent decision process behind the manifest True/False/Don't know responses on the items. Figure 1 shows a decision tree for a single respondent for the item "Most people feel loved when someone is there just to listen" based on the cognitive ECM. According to this decision tree, it is assumed that the consensus answer on an item is either "True" or "False," while "Don't know" answers are also allowed when participants are unsure about a scenario. The ECM captures the decision-making process in terms of three person-specific parameters: participants' ability in knowing the consensus, their willingness to guess when they don't know the answer (as opposed to marking Don't know), and guessing bias toward guessing "True." In order for a respondent to get an item correct, they would either have to know the answer (thick branches) or they would have to guess it correctly (thin branches leading to the "correct" answer). Using the ECM, we can account for the correct answers that come from guessing in addition to answers responded with certainty.

To summarize, CCT infers consensus answers, based on the manifest responses, while proposing an underlying cognitive model of the decision process giving rise to these

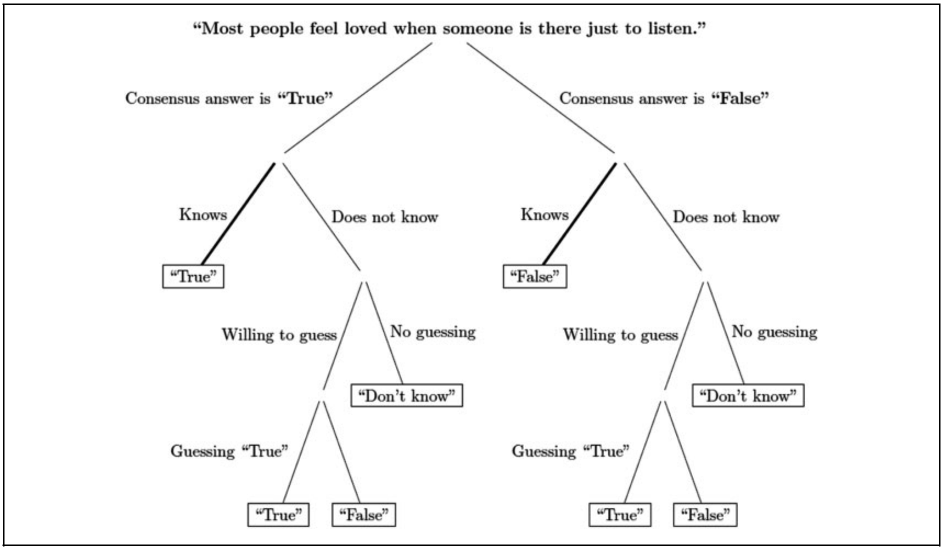


**Figure 1.** Processing tree model based on the ECM. Possible answers appear in rectangles and the decision process leading to them is denoted by the lines. ECM = extended Condorcet model.

observations. Moreover, the ECM also considers inter-item differences. That is, the difficulty level of the items—in our case, how difficult it is to know the consensus answer—is allowed to differ across items (De Boeck & Wilson, 2004). This way, if a person's ability level is higher than the item's difficulty level, then he/she will probably respond correctly to the item (thick branches in Figure 1). On the other hand, if a person's ability level is lower than the item's difficulty level, then he/she will probably not know the correct answer (thin branches in Figure 1). Overall, the person-specific cognitive model parameters in the ECM include ability, guessing bias (probability of guessing true), and willingness to guess and the item-specific parameter the model considers is item difficulty.

The proposed ECM is a complex multilevel latent variable model. The Bayesian statistical framework (Gelman, Carlin, Stern, & Rubin, 2013; McElreath, 2016) offers flexible tools for fitting complex models to fit the ECM in addition to providing principled ways for statistical inference. Bayesian methods have also been recently used to implement consensus models (Anders & Batchelder, 2012; Oravecz, Anders, & Batchelder, 2015; Oravecz, Vandekerckhove, & Batchelder, 2014).

For fitting the model to the data in the Bayesian framework, we need to specify "prior distribution" on each of the model parameters. The prior distribution represents the current knowledge we have about the model parameters expressed by placing a probability distribution on the parameters. In consensus analysis, we generally avoid imposing any researcher's prior belief when analyzing the responses of individuals to their culture. On the other hand, to do Bayesian inference, one has to have a prior, and that is why in this analysis so-called non-informative priors are used to satisfy both needs. This means that prior probabilities are distributed practically equally across the range of possible parameter values. It bears pointing out that our choice of prior—as long as no values are given zero prior weight—in this case is mostly inconsequential, since the large amount of data will dominate the shape of the posterior distribution and overwhelm the shape of the prior.

Once priors are specified, we combine the likelihood function, based on the processing tree model in Figure 1, by using Bayes' Rule (see, e.g., Gelman et al., 2013). As a result of combining prior knowledge with data likelihood, we arrive to a posterior probability distribution of the model parameters. This means all person-specific parameter estimates (e.g., consensus knowledge), item-specific consensus (e.g., consensus answer), as well as regression coefficient estimates have probability distributions, which allow us to make inference about their likely values in a straightforward manner. This is because in the Bayesian framework model parameters are considered random variables with probability distributions, which allows us to make probabilistic statements about the range of likely parameter values.[1] For example, we can say that a standardized regression coefficient, representing the association between consensus knowledge and neurotic personality trait, has a 95% probability to be larger than 0, and we can also quantify the exact effect size in terms of the mean of the posterior distribution.

The ECM allows for heterogeneity in respondent and item characteristics and also assumes that these person and item parameters form a joint level-2 (population) distribution—therefore, it is a multilevel/hierarchical model (Gelman & Hill, 2006). We can learn about sources of heterogeneity in respondents' cognitive attributes by regressing the consensus knowledge level, guessing bias and willingness to guess on personality characteristics and also demographic variables. Implementing model fitting in the Bayesian statistical framework has the crucial advantage of enabling regression type of inference and consensus modeling in a one-step procedure.

The ECM provides us with a unique approach to identifying a population's shared idea of what actions make people feel loved and how much knowledge individuals have of this shared concept of "felt love." Thus, in this article, we will advance the relationship literature by examining common beliefs that people share about actions that generate internal feelings of love by using a novel psychometric approach to aggregating the responses of informants to questions regarding a shared knowledge domain.

## *Comparison between the CCT approach and more traditional approaches*

CCT models work under the assumption that neither the researcher nor any one respondent can define the cultural consensus truth. Prototype analysis (Fehr, 1988; Fehr & Russell, 1991) is similar to CCT in the way that they both search for shared knowledge and beliefs of people about a concept that is unknown a priori to the researcher. Prototype analysis begins by asking laypeople to come up with features that they think define a concept. For this, the participants should be able reliably rate the centrality of each of the features to the concept. Once this verbatim list of features is established, researchers code and place them into categories that are known as the prototypes of that concept. On the other hand, CCT begins with a set of questions that are related to a concept. Then responses are collected, but the "cultural consensus" or "cultural correctness" is unknown a priori to the researcher and is derived based on cognitive models that guide the aggregation of responses in order to estimate the cultural consensus on those questions. These CCT models take into account differences in the respondents' cognitive characteristics (e.g., ability to know the consensus, guessing bias, etc.) in responding to those questions. In other words, CCT explores whether there is enough agreement across people for a set of questions related to a concept.

Statistically, CCT is also comparable with traditional reliability analyses. In traditional reliability analyses, we first estimate the answers to the questions and then estimate the respondents' correspondence to those estimated answers. In contrast, in the CCT model implemented here, we simultaneously estimate respondent knowledge level, decisions characteristics (e.g., propensity to guess True when faced with uncertainty), and consensus-based answers, while also accounting for the possibility that some questions are easier to answer than others (heterogeneous item difficulty).

When comparing ECM to traditional item response theory (IRT; De Boeck & Wilson, 2004) models, an important difference lies in the area of application: IRT models most often presume that the researcher has knowledge of the "correct answers" (as in items scored correct or wrong) to the questions. Sometimes IRT will work with unscored responses like grades from various raters on essay tests. In this case, IRT places an emphasis on the correct grade category for the essay, whereas ECM (and CCT approaches in general) is interested in whether or not the graders are sharing the same viewpoint about the essay. Thus, the "correct" answer in ECM is basically the answer with the most consensus among people. In sum, ECM does not use previously established answers but rather derives the consensus answers together with the respondents' ability (and other cognitive characteristics) and the items' difficulty. Moreover, another difference between traditional IRT models and the ECM is that with the ECM we can account for "Don't know" answers using a latent cognitive model for the decision-making process, whereas in an IRT model, "Don't know" answers would have to be coded as incorrect answers or even as missing data. This is to say that willingness to guess in the decision process is modeled. Moreover, while guessing in the IRT framework is a parameter of the item characteristic curve, in CCT it is a person-specific cognitive characteristic. In other words, the proposed CCT model also focuses on examining the individual differences in cognitive response style, such as the willingness to guess and the guessing bias.

In psychometrics for tests (where items are scored as correct or wrong), factor analysis of the respondent-by-respondent correlations is another traditional approach. However, this also does not provide the kind of information as does factoring item-by-item correlations (R-analysis). CCT approaches use the responses not the scored responses; moreover, they explore if there is a strong signal about whether or not there is a shared consensus. More to the point, the ECM is a cognitive model of the respondent with several parameters of interest. A factor analysis of the respondent-by-respondent correlations is a test of a theorem in the ECM that if there is a single consensus (rather than a mixture of several or just idiosyncratic opinion data), then the factor analysis should reveal a single dominant factor and the rest noise.

## The study of love using cultural consensus theory

In the past, researchers have studied the experience of love in various ways: through creating love taxonomies by grouping different love styles in various categories (e.g., Berscheid, 2006; Sternberg, 1986); by taking a behavioral approach at love from attachment, caregiving, and sexual perspectives (e.g., Hazan & Shaver, 1987); looking at loving acts (Buss, 1988) or through biological assessments of people who are "in love" (e.g., Young, 2009). In addition, there is also the essentialist approach toward the study of love, claiming that there are some features and characteristics of love that need to exist for it to be called love (Hegi & Bergner, 2010). In summary, these studies propose that love can be multi-faceted.

Love can also be structured as a prototype; that is, a concept organized around its clearest and typical cases. Fehr (1988) used prototype analysis to develop a list of 68 features based on people's opinion on attributes of love. Results showed that features like honesty, trust, and caring were prevalent and features like dependency, sexual passion, and physical attraction were not as prevalent. This suggests that laypeople have a comprehensive understanding of love and consider features attributed to the companionate love dimension at the center of the concept of love (Fehr, 2006). Fehr and Russell (1991) also took the prototypical approach to look at common concepts of laypeople of different *types* of love. After running a series of studies, they concluded that familial and friendship kinds of love were the types of love that people considered as the prototypical types of love while romantic, passionate, and sexual love were considered non-prototypical. Furthermore, Fehr and Broughton (2001) found that people's conception and experience of love is related to individual differences such as personality types and gender: For example, men score higher on traits such as "arrogant-calculating" and "cold-heartedness" which were highly correlated with ratings on passionate love. On the other hand, women scored higher on "warm-agreeable" and "trust" scales which were positively correlated with friendship love scores. To pursue this prototype research further, Sprecher and Fehr (2005) developed a compassionate love scale that considered everyday loving acts beyond romantic relationships, focusing on close other (e.g., family and friends) and humanity (e.g., strangers and all humankind) relationships. They found that people who are more religious or spiritual experience more compassionate love toward close others and all humankind in their everyday life. They also found that women experience more compassionate love than men regardless of whether the target of the compassionate love was friends and family or strangers.

Building on this work, in the current study, we aim to pursue the same broad prototype outlook on love and consider feeling loved from the perceiver's point of view when situated in various everyday life contexts. The everyday life scenarios we consider in the current study include both romantic and nonromantic relationship contexts in addition to scenarios such as "their pets are happy to see them" or "the sun is shining" which are everyday life contexts void of the presence of others and are not considered in either romantic or nonromantic relationship categories. Additionally, we focus on people's shared idea (consensus) on love in everyday life by exploring the overlap of their cognitive schemata on loving behaviors and explore the individual differences involved in knowing this consensus.

There are many factors that might influence whether a situation, communication, or behavior is perceived as love. In this study, we will examine a few likely candidates that are known to play a role in relationship-relevant variables. First, personality research has repeatedly shown that personality differences play an important part in the love felt in romantic relationships with higher levels of love associated with higher levels of extraversion and agreeableness (Ahmetoglu, Swami, & Chamorro-Premuzic, 2010; Asendorpf & Wilpers, 1998; Schmitt et al., 2009). Moreover, research has shown that people who are high in nurturance traits (e.g., agreeableness) mostly hold a companionate conception of love, whereas low nurturance traits (e.g., cold-heartedness) are associated with more passionate conception (Fehr & Broughton, 2001). Nonpsychological person characteristics can also be important. For example, individuals currently in a relationship may know more about love signals, simply because they are exposed to them more frequently and have better relational characteristics while maintaining a romantic relationship (Stafford & Canary, 1991). Also, while this project is focused on the American cultural consensus of felt love, even within the country, there may be differences based on race, gender, or even age cohort. For instance, previous research on different ethnic groups in the U.S. has shown that love experiences can differ among multiple cultures within a country (Doherty, Hatfield, Thompson, & Choo, 1994; Gao, 2001). Fehr and Broughton (2001) have shown that there are differences in the way men compared to women conceptualize love. Women tend to think about passionate love as more of a friendship and sisterly love, whereas men conceptualize it as infatuation, puppy love, and sexual love (Fehr & Broughton, 2001). These research studies give us reason to believe that individual differences, specifically demographics and personality types, might play a role in the way people perceive love in everyday life; hence, we have included them in the current study on felt love.

In the current study, we approach felt love by asking people to judge whether selected everyday life scenarios would make most people feel loved. By relying on a cultural consensus model (ECM), we will study the agreement on these loving scenarios. The scenarios cluster around certain topics, and we will specifically examine whether individuals consistently judge certain groups of items as loving, and others as not. The final list of scenarios includes behaviors with controlling or possessive behaviors, next to more typical signals of love, such as trust, acceptance, support in needs and goals, and so on (see more details in Methods section). Besides exploring this cultural consensus, we quantify person-specific cognitive characteristics with respect to how aware people are of the consensus on loving scenarios and how they decide to judge a scenario when uncertain. Individual differences in these cognitive indicators will be explored in terms of participants' personality traits and demographic background. The specific research questions for this study include (1) Do people who share the same cultural background agree on what makes them feel loved? (2) What scenarios make people feel loved, and do systematic themes underlie shared beliefs about indicators of felt love? (3) Are there individual differences in people's decision styles and levels of knowledge on indicators of felt love? (4) Can these individual differences be linked to person-specific predictors?

# Methods

## Participants

Participants were 495 adults (245 men; $M$ age = 51 years, $SD$ = 15.70, range = 18–93) representative of the U.S. population above 18, recruited through Qualtrics Online Sample service (Qualtrics, Provo, UT, USA). Qualtrics implements quality control by including attention filters and by eliminating those who completed the survey faster than some minimal estimated time required to read and respond the questions. Initially, we were provided with 500 participants with equal numbers of men and women but five of the participants were eliminated from the analysis due to responding "Don't know" to all of the questions of the survey.

Out of the remaining 495 participants, 80% ($n$ = 397) of the participants described themselves as White; 10% ($n$ = 49) of the participants described themselves as Black; and 10% ($n$ = 49) as other races. Fifty-six percent ($n$ = 275) of the participants reported as being married, cohabiting, or in stable relationships; 22% ($n$ = 108) reported as being single or single but dating; 22% ($n$ = 109) reported as being divorced, widowed, or separated; and the three remaining participants preferred not to answer. The education level of the participants varied from not graduating from high school to professional or doctorate degrees with 36% ($n$ = 176) of the participants having high school diploma or lower; 52% ($n$ = 259) had at least an associate's degree or a bachelor's degree; and 12% ($n$ = 59) had a master's degree or higher.

# Procedures

Participants were asked to respond to demographic items, to evaluate 60 scenarios where love might be felt, and to complete the Big Five Inventory (Rammstedt & John, 2007). The goal was to examine the role of personality traits in addition to basic demographic information as part of participants' individual differences in knowing the consensus on felt love. These materials are elaborated on in the following section. The current study is part of a larger study on well-being; therefore, participants also responded to well-being items.[2]

## Measures

*Demographics.* Items in this part of the questionnaire asked respondents about their gender, age, primary racial or ethnic group, relationship status, education level, the population of the city they currently live in, and how much religion is important to them.[3] The questions were constructed in a multiple-choice format with the option, "I prefer not to answer" for those who preferred not to respond to some of the items.

*Felt love questionnaire.* This 60-item questionnaire consisted of 53 scenarios used in Oravecz et al. (2016) in addition to seven more scenarios that were added based on feedback derived from the Oravecz et al. (2016) study. In short, the majority of these questions referenced scenarios in which people can feel loved, which were generated by a focus group which align with current theories and studies on love (Feeney, 2004;

Fredrickson, 2013; Gable, Reis, Impett, & Asher, 2004; Hendrick & Hendrick, 2006; Reis, Clark, & Holmes, 2004). We also had a set of items with a negative connotation (controlling/possessiveness theme) in order to balance all the positive scenarios about loving actions and to explore people agreement on these.

A complete description of the items can be found in the Online Supplementary Material. All items started with "Most people feel loved when . . . ," followed by phrases that represent loosely clustered topics including (1) trust and acceptance (e.g., "when somebody confides with them"), (2) support in needs and goals (e.g., "someone celebrates their accomplishments"), (3) symbolic/physical expressions (e.g., "they get gifts"), (4) sharing time with others (e.g., "they spend time with their friends"), (5) other possible sources of love (e.g., religion, pets, nature, patriotism, gratitude, politeness, etc.), (6) controlling behavior from others (e.g., "someone wants to know where they are at all times"), and (7) control scenarios, which had a neutral connotation in terms of loving signals (e.g., the sun is shining).[4]

Participants were asked to make a decision about whether *most people* would feel loved in these scenarios by marking either True, False, or Don't know. This is an important distinction that we ask about most people's experiences in general and not the participants' personal experiences and aligns with the assumptions of the CCT framework: The explored consensus is about shared knowledge and beliefs and not personal opinions. Instructions clarified that answers to this section should reflect what participants think that *most people* interpret as love, not their *own* interpretation. In order to reduce hesitations in answering, instructions also noted: "Because this is a survey about your beliefs about other people, it is important to keep in mind that there are no right or wrong answers."

*Big Five Inventory-10.* The Big Five Inventory-10 (BFI-10; Rammstedt & John, 2007) is a brief version of the 44-item Big Five Personality Inventory (BFI; John, Donahue, & Kentle, 1991). This abbreviated version of the BFI was developed for contexts in which participant time is limited. Two items were selected from the BFI for each of the 5 personality scales (i.e., Extraversion, Agreeableness, Conscientiousness, Neuroticism, Openness), for a total of 10 items. Comparing the reliability and validity of BFI-10 to the original BFI, results indicate that BFI-10 scales capture at least 70% of the full BFI variance and retain 85% of the retest reliability while the discriminant and structural validity of both versions of the BFI remain the same (for more information on these tests, refer to Rammstedt & John, 2007).

## Data analysis

To conduct our analysis, we fitted the ECM described above to the data on felt love in Just Another Gibbs Sampler (Plummer, 2003), interfaced via MATLAB, by running six chains, 4,000 burn-in, and 10,000 iterations.[5] Optionally, the analysis can be carried out with a graphical user interface-based computer program.[6] Convergence criteria was met for all model parameters ($R$ < 1.1), indicating that our model parameters were successfully estimated, and thus estimates can be retained for interpretation (see, e.g., in Gelman et al., 2013). The estimation procedure provides us with a posterior distribution for each model parameter (e.g., person-specific consensus knowledge, guessing bias, willingness to guess, regression coefficients, etc.). This means that we have, for example, 60,000 samples of person-specific consensus knowledge parameter, based on which we can calculate mean, posterior standard deviation, interval estimates, and so on.

## Results

### *Model fit: Do people converge toward a one-cultured consensus on felt love?*

In order to check whether the proposed model provides a good description of the observed data, we first perform a posterior predictive model check (PPC) in the Bayesian framework. This procedure involves generating a hundred new data sets based on random samples from the posterior distribution of the parameter estimates (described above) and comparing these data sets to the observed data. If observed data and generated data sets are consistent, then we can conclude that the proposed model fits well.

The three panels in Figure 2 represent the model fit for each of the possible responses to the felt love items (True, False, and Don't know, respectively, from left to right). The horizontal axes of these graphs indicate the frequency of the observed data and the vertical axes represent the frequency of the generated data sets predicted by the model. Each circle corresponds to these measures (observed vs. mean of a 100 generated data sets) for one person. The lines extending from each circle depict the 95% percentile around the mean, representing the uncertainty in the prediction. As can be seen, there is an almost perfect correlation between the generated and observed data: The circles overlap very well with the straight diagonal line in the graphs. Overall, PPC indicates that our model appropriately fits all three response options and does not misrepresent the data we have observed.

### *Consensus estimates on felt love items*

By using Bayesian methods to fit the ECM to the felt love data, we can summarize model-based agreements on love scenarios in terms of consensus estimates for each item. Table 1 summarizes these estimates along with a subset of the felt love scenarios; the comprehensive results table can be found in the Online Supplementary Material. In Table 1, the third column shows the observed mean of the True/False responses with False responses coded as 0 and True coded as 1. Therefore, when respondents see an item more as an indicator of love and responded True, the mean would be closer to 1 and vice versa. The fourth column is based on the posterior medians where consensus "labels" were derived from (labeled as False for 0 and True for 1). These labels indicate whether the majority of the general population agreed upon the item to be an indicator of felt love (True) or not (False). The amount of uncertainty in these posterior median estimates (i.e., consensus labels) is quantified by the posterior standard deviations (column five of Table 1). The last column shows the item difficulty estimate for each love scenario. We used this estimate to rank the items from 1, which is the hardest item (only people with high levels of knowledge about the shared consensus on felt love can respond correctly), to

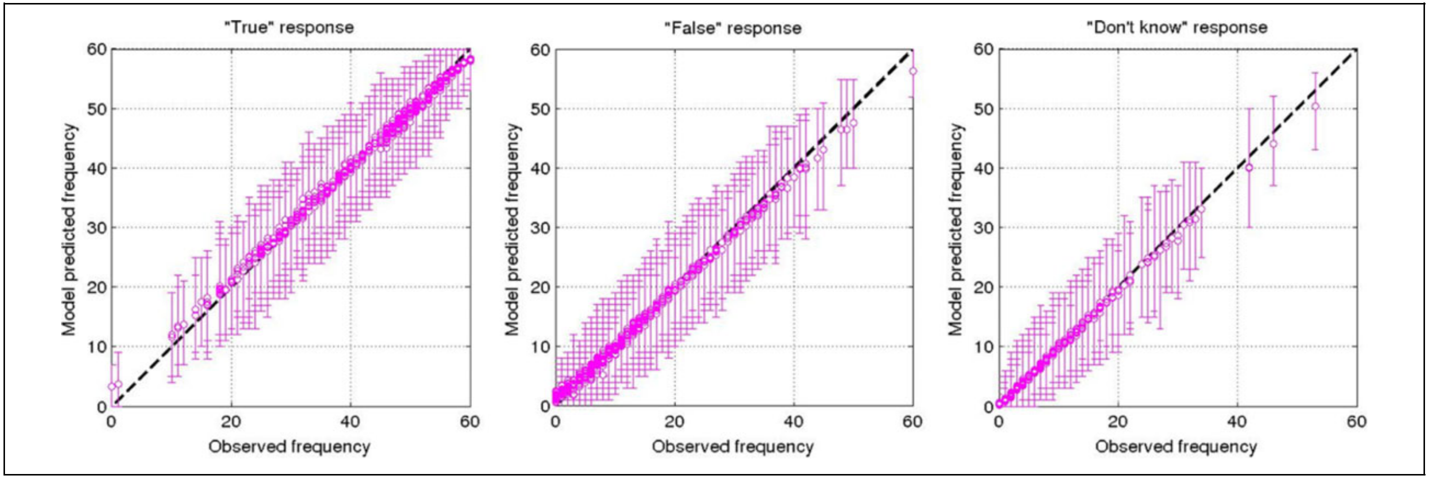


**Figure 2.** Posterior predictive check of model fit. The three panels summarize the number of True, False, and Don't know responses, respectively, for every person: Each circle corresponds to one person's observed True, False, or Don't know response frequency (*x*-axis), plotted against the mean observed True, False, or Don't know response frequency from 100 generated data sets (*y*-axis). The lines extended from each circle depict the 95% percentile around the mean.

**Table 1.** Raw data means and estimates on selected felt love items.

| Item # | Most people feel loved when . . . | T/F Mean | Consensus label | Consensus PSD | Item difficulty rank |
|---|---|---|---|---|---|
| 41 | someone shows compassion toward them in difficult times. | .98 | True | .00 | 60 |
| 34 | a child snuggles up to them. | .97 | True | .00 | 59 |
| 24 | their pets are happy to see them. | .96 | True | .00 | 57 |
| 38 | someone tells them “I love you.” | .95 | True | .00 | 54 |
| 28 | someone wants to know where they are at all times. | .29 | False | .00 | 18 |
| 9 | someone tells them what is best for them. | .32 | False | .00 | 12 |
| 47 | someone is possessive about them. | .35 | False | .00 | 15 |
| 37 | someone insists to spend all of their time with them. | .49 | False | .00 | 9 |
| 19 | someone gives them positive feedback on the internet. | .50 | True | .00 | 5 |
| 20 | they get a compliment from a stranger. | .43 | True | .00 | 4 |
| 8 | the sun is shining. | .45 | True | .13 | 2 |
| 54 | they feel close to nature. | .59 | True | .00 | 9 |

*Note.* The second column shows the mean of the responses to items with *“True” coded as 1 and “False” coded as 0. PSD = posterior standard deviation.*

60, which is the easiest item (minimal knowledge of the consensus is necessary to get this item correct).

It is important to reiterate that the raw data summaries (third column) are based on aggregating over the observed data (respondents’ raw responses to items), one scenario at a time. This is an improvement upon simple summary statistics such as whether there are dominantly True or False answers (majority rule), which would neglect the dependence of all other responses in the matrix (all items similarly focus on the concept of felt love). Moreover, aggregate measures simple statistics would not account for differences in people’s knowledge-level, ignoring the fact that different people can differentially contribute to the “majority” based agreement indicator. Moreover, simple aggregate measures simple statistics would also ignore the possibility that some of the True/False responses come from guessing. And finally, when, for example, trying to count the number of responses per category to derive that the majority of them is True or False, the Don’t know responses would most often be treated as missing data. This is problematic since most likely it is not missing at random; therefore, it contains important information on how people handle uncertainty. In contrast, the consensus model works with the full person-by-item matrix of trichotomous responses and has a substantively guided model on how people make decisions to account for the underlying processes that give rise to the observed response. Furthermore, heterogeneity in item difficulty is also taken into account. For example, with ECM, we derive the posterior median (consensus label) by considering every participants’ knowledge about the consensus on felt love, the possibility of participants guessing for each item, and item difficulties. ECM then intricately models how people make decisions on each felt love scenario based on their responses and then comes up with the consensus label of whether the consensus on a scenario is that it makes the majority of people feel loved or not.

Table 1 contains three sections that reflect three levels of outcomes. The top section includes example scenarios for which people demonstrated high convergence toward a consensus, and these estimates had no uncertainty in and their items were among the easiest for which to know the consensus. Even the raw data summaries of these items, the T/F mean shown in column 3, show a clear trend: means are close to 1 (True coded as 1, False as 0). The consensus estimate was "True" for these items as shown in "Consensus label" (column 4). The "Consensus posterior standard deviation column" (column 5) shows value of 0 for all the items, which indicates practically no uncertainty in these posterior point estimates. Interestingly, these scenarios in which people expressed that they felt loved varied in terms of both the context (e.g., romantic relationships, parent-child relationships, nature, internet, etc.) and the type of behavior (e.g., compassion, feedback, care, patriotism, etc.). Based on the last column (to remind the reader, higher ranks are equivalent to easier items), all four of these items were ranked high, indicating easy items for which people needed less knowledge of the consensus to get the item correct.

The middle section of Table 1 contains felt love scenarios which were highly divisive on the raw data level: here people were divided in choosing whether a scenario can elicit loving feelings in most people or not, but the ultimate consensus was False. As seen in the "T/F mean" column (to remind the reader, this column shows the ratio of True responses to the total number of responses), the number of True and False responses were very close. The model-based estimates found in column 4 predict a False label, and column 5 shows that there is practically no uncertainty in the estimates, with 0 posterior standard deviations presented in that column. Unlike the items in the top section, these items rank low in terms of item easiness, meaning only people with high consensus knowledge would get them right. An interesting observation based on these middle section scenarios is that most of the items that the consensus labeled False center on the theme of controlling behavior. For example, people have indicated in this survey that they do not feel loved when someone wants to know where they are all the time (item #28), when someone tells them what is best for them (item #9), someone is possessive about them (item #47), and someone insists to spend all of their time with them (item #37). All of these scenarios portray a type of controlling behavior that people do not deem as signaling loving feelings.

Lastly, the bottom set of scenarios are the items that again show a large division in answers, but consensus ultimately agreed on True. Similar to the items in the top section, these items have no uncertainty in their posterior estimates (posterior standard deviation [PSD] = .00) from the model, meaning that the model was able to borrow enough information from sources other than the raw answers to this particular item. Moreover, these item difficulty rankings were very low, indicating that few people knew the correct answer to these questions. Here, we have highlighted the items with the largest split in the raw data in order to demonstrate the range of division in people's opinions on scenarios, note that additional items in the Online Supplementary Material illustrate the full range of division in opinions.

Consider two specific items in Table 1, which both have a noteworthy split in people's opinions about whether these scenarios make them feel loved or not. The scenario "someone gives them positive feedback on the internet" shows the highest split based on the raw data ($M = .50$). The item "someone insists to spend all of their time with them" also shows an almost complete split among people ($M = .49$). Despite the split in the first scenario, the consensus indicates that people feel loved when someone gives them positive feedback on the internet, whereas the consensus estimate on the second item indicates that people do not feel loved when someone insists on spending all of their time with them. Both these items have posterior standard deviations of 0, indicating no uncertainty and that the model was able to borrow enough information from other sources than the raw answers—for example, the ability level of the respondents—to derive the consensus estimate. On the other hand, on another split item, although respondents are divided on the item "the sun is shining," the posterior standard deviation also shows some uncertainty in terms of the consensus estimate the model has developed (PSD = .13). This item was intended as a control and we did not expect strong consensus in terms of loving signals about this item.

### *Individual differences in convergence toward consensus*

Fitting the consensus model (ECM) on our data allows us to consider participants' individual differences in their responses of felt love. This method provides summary statistics for three cognitive parameters: a latent person-specific ability, a person-specific guessing bias (probability of guessing true), and willingness to guess. Our sample had noteworthy variability in cognitive characteristics, illustrated in Figure 3's histograms of person-specific posterior mean parameter estimates.

Figure 3 includes three histograms for person-specific parameter estimates (posterior means): ability (knowing the consensus on the love items), guessing bias (propensity of guessing "true" when a respondent does not know the consensus on love items), and willingness to guess; and one histogram for the item-difficulty estimate (posterior means). Item difficulty in our case represents how difficult it is for people to know the consensus answer on a specific item. Starting with the histogram on the top left, this person-specific plot presents the 495 person-specific ability estimates, demonstrating respondents' knowledge of the consensus on felt love. This figure can be interpreted in relation to item difficulty spread figure—the top right histogram of Figure 3. The item difficulty histogram shows that all 60 items covered a satisfactory range of easy, medium, and difficult items ($M = -.14$, $SD = 1.95$). The average item difficulty is fixed to 0 and the scale ranges approximately from –4 to 4, with –4 being the easiest items, 0 being the medium, and 4 being the hardest items. Our items demonstrated a considerable amount of variability in difficulty in this set. Accordingly, people with an estimated ability of 0 would get a medium difficulty item correct about half of the time. By getting an item "correct" in this setting, we mean being able to respond with the answer that matched the model-based consensus answers. On the other hand, people whose ability estimates are around 2 would get a medium difficulty item correct most of the time and also have a better chance at knowing the response to the more difficult items. In other words, people who portrayed high ability in knowing the consensus on felt love were

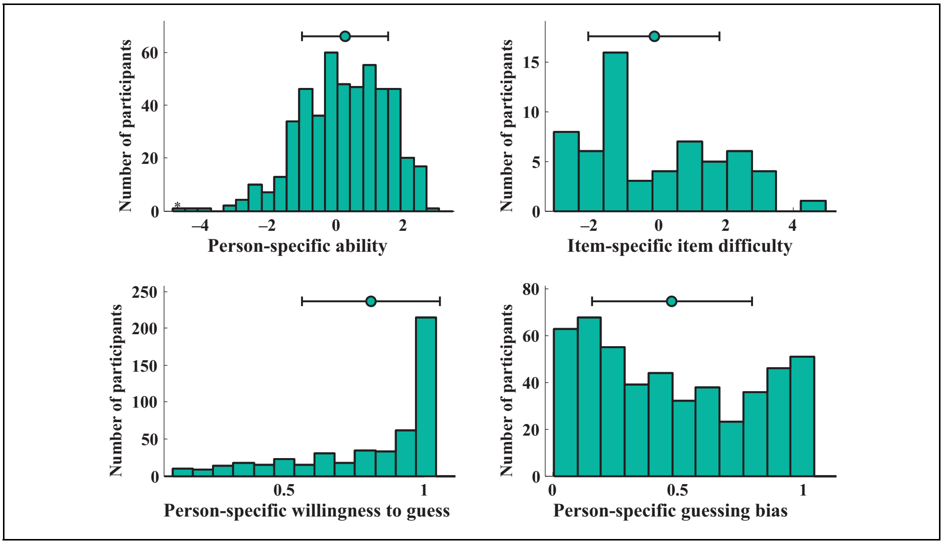


**Figure 3.** Distribution of item-specific and person-specific ECM parameter estimates. Histograms depict the frequency of posterior mean estimates. The middle of the bar on top of each graph indicates their mean and the end points are one standard deviation above and below the mean. ECM = extended Condorcet model.

much better at saying whether a scenario was an indicator of felt love for most people or not. This trend continues for people higher and lower than 0 ability in terms of their knowledge of consensus for easy versus difficult items. As demonstrated in the top left graph, most people in our study had a higher than average ability (ability levels larger than 0) and thus have a considerable amount of knowledge of the consensus on what makes people feel loved. This means we have sufficiently informative data to derive the consensus answers. The bar above the person-specific ability graph shows the mean of the plotted values ($M$ = .26) and one standard deviation above and below the mean ($SD$ = 1.28).

With the ECM, we were able to capture individual differences in cognitive response styles in terms of ability, guessing bias, and willingness to guess. The bottom graphs of Figure 3 illustrate the range of person-specific parameter estimates of cognitive response styles of our sample. These parameter probabilities range between 0 and 1, where higher values are more likely. Probability values in the bottom left histogram in Figure 3, estimated willingness to guess, are close to 1 ($M$ = .81, $SD$ = .25), meaning that most people were willing to guess whether an item was an indicator of felt love when they were unsure of the response. The observed data also confirmed this finding with the limited number of "Don't know" responses to items. Moreover, this graph captures people with low willingness to guess tendencies, indicating that individual differences indeed exist in cognitive responses. In other words, this graph shows that although most people were inclined to guess rather than select "Don't know" on whether an item was an indicator of felt love or not, there were still some individuals who did not want to guess and selected "Don't Know."

**Table 2.** Summary of selected explanatory variables in terms of cognitive individual differences.

| Parameter | Predictor | Mean | PSD | $p$(<0) |
|---|---|---|---|---|
| Ability | Gender (1: Male) | −.28 | .07 | 1 |
| | Relationship | .17 | .07 | .01 |
| | Race (Black) | −.17 | .07 | .99 |
| | Neuroticism | .19 | .09 | .02 |
| | Agreeableness | .27 | .08 | .00 |
| Guessing "True" | Race (Black) | .30 | .16 | .00 |
| | Race (Asian) | .37 | .13 | .00 |
| | Age | −.25 | .14 | .97 |
| | Openness | .31 | .13 | .01 |
| Willingness to guess | Relationship | .37 | .18 | .02 |

*Note*. PSD = posterior standard deviation.

The bottom right histogram of Figure 3 describes person-specific guessing bias estimates. This distribution shows that our sample had heterogeneous levels of bias for guessing; the majority of participants were more likely to guess False when they did not know the consensus answer ($M = .48$, $SD = .32$). To clarify, values close to 1 correspond to person profiles with a tendency of guessing True most of the time, values in the middle represent no systematic guessing tendency, and values close to 0 mean tendency of guessing False most of the time. Moreover, consider that estimates close to 0—guessing false—have higher probability (a dense area of the distribution). In summary, this means that when our participants were not sure of whether an item was an indicator of felt love, the majority of the participants were biased toward guessing that the item was not an indicator of felt love (guessing False).

## *Individual differences and explanatory variables*

A prime advantage of the Bayesian framework is that we can explore the relationship between the cognitive parameters and explanatory variables about the individuals (i.e., personality factors, age, gender, relationship, and race) in the same model. Table 2 summarizes the results for our regression analyses, with person-specific latent variables of consensus knowledge—guessing bias and willingness to guess—regressed on a set of predictors. In the Bayesian approach, all regression coefficients have posterior probability distributions. Consequently, drawing inference on the regression coefficients in this framework requires that we compute the probability that the coefficient is plausibly different from 0. In other words, we measure how much posterior mass falls on either side of 0. Here, we selected the explanatory variables that were at least 95% likely that their estimated value is above or below 0. Thus, in Table 2, all the explanatory variables (column 2) either had a probability value below .5 or above .95 ($p$ (< 0); column 5) when regressed with each of the cognitive individual differences (column 1).

Results in the top section of Table 2 indicate trends in people's ability to know consensus. Firstly, these results suggest there is a gender effect on a person's ability to know the consensus. Male participants seem to know less about the consensus on felt love compared to women ($M = -.28$, PSD = .07). Secondly, individuals who are in a relationship seem to know more about the consensus than individuals who are not ($M = .17$, PSD = .07). Thirdly, in terms of racial and ethnic groups—we chose White as baseline, due to the majority of our participants identifying themselves as White—individuals identified as Black had less knowledge about the White-dominated cultural consensus compared to other racial and ethnic groups ($M = -.17$, PSD = .07). Finally, two personality traits were related to individual's knowledge of the consensus of felt love as well. Based on these findings, people who are more agreeable ($M = .27$, PSD = .08) and neurotic ($M = .19$, PSD = .09) seem to know the consensus of felt love more than people who do not have these traits.

In the middle section of Table 2, results indicate that belonging to either a Black ($M = .30$, PSD = .16) or Asian ($M = .37$, PSD = .13) racial and ethnic group makes a difference in the guessing bias for answering items. This suggests that Black or Asian individuals are more likely to respond True to the felt love items when they are unsure of the consensus response compared to other races. Moreover, these results also indicate that individuals with an openness trait have a guessing bias toward responding True for items when they are unsure ($M = .31$, PSD = .13). Conversely, the tendency to respond True to felt love items when unsure decreases with increase in age ($M = -.25$, PSD = .14).

Finally, the bottom section in Table 2 shows variables related to individuals' willingness to guess when they don't know the answer to a felt love item. Here, the only variable that relates to willingness to guess is the relationship variable. This suggests that people in relationships are more willing to guess True or False, as opposed to Don't know, when unsure ($M = .37$, PSD = .18).

## Discussion

In this study, we explored the concept of felt love from a person-centered perspective. We examined different romantic and nonromantic scenarios that occur in daily life and asked people if they perceived those scenarios as loving signals and if they aligned with the cultural agreement. We extended a previous study by Oravecz et al. (2016) in several ways: We used a larger sample size, an extended item bank, and systematically explored specifically how cognitive individual differences in felt love can be tied to explanatory variables (e.g., personality characteristics) beyond merely demographic background. More specifically, we investigated the relationship between people's cognitive characteristics and their personality factors, relationship status, age, gender, and race. Our analysis resulted in some interesting findings, summarized below, about what makes people feel loved and the individual differences in cultural consensus of the indicators of felt love.

### *What makes us feel loved and what doesn't?*

Our findings confirmed that people see loving signals in a wide variety of contexts and scenarios, including both romantic and nonromantic settings. This supports Fredrickson's (2013) claim that love can present itself anytime and anywhere, even between two strangers over a shared positive emotion. For example, although people had strong consensus on the loving feelings communicated by scenarios with romantic connotations like “they make love,” “they are hugged,” “someone tells them ‘I love you’,” and “they are holding hands,” people also had strong consensus on nonromantic scenarios like “a child snuggles up to them,” “their pets are happy to see them,” or “someone shows compassion toward them in difficult times” as indicators of felt love. It is interesting to note that all the scenarios listed above had an interpersonal (even between people and pets) aspect to them. On the other hand, people were mostly split on items that did not have an interpersonal context (e.g., “the sun is shining” or “they eat their favorite food”), demonstrating a higher degree of uncertainty about these scenarios. This split in consensus agreement was predicted because the neutral items mentioned above were intended as control items in this list of scenarios.

It should also be noted that not all interpersonal scenarios were viewed as indicating love. As can be seen in Table 1, people agreed strongly that scenarios like “someone tells them what is best for them,” “someone wants to know where they are at all times,” “someone is possessive about them,” and “someone insists to spend all of their time with them” did not make them feel loved. If examined closely, all these scenarios—although interpersonal—contained a controlling theme. These scenarios were phrased in a way that one person was either imposing his/her opinion on another person (“someone tells them what is best for them”) or he/she was trying to control the other’s behavior (e.g., “someone wants to know where they are at all times”). These may be an example of social control interactions between network members that entail regulation, influence, and constraint. While lovingly intended to encourage health and wellness, they often result in distress in the receiver (Lewis & Rook, 1999; Umberson, 1992). Controlling behaviors can also come from insecure attachment style (Hazan & Shaver, 1987), a common predictor of negative relationship characteristics (Carnelley, Pietromonaco, & Jaffe, 1994; Hazan & Shaver, 1990). Although the link between controlling behavior and insecurity in a relationship may be one reason why people do not see these scenarios as loving signals, unfortunately, attachment style was not assessed in this study and future research is needed to investigate this topic.

Lastly, another possible explanation for the negative interpretation of “controlling” items is that controlling behavior has a largely negative connotation in U.S. culture. For example, a more interdependent or communal culture might have a completely different consensus. For example, research has shown that in China, inhibiting a child’s behavior is associated with mother’s warm and accepting attitudes, whereas in Canada, similar behavior is negatively associated with motherly love (Chen et al., 1998). Therefore, based on our results, it is feasible to infer that generally, the individualistic Western culture does not view controlling behavior as indication of love, and this belief is consensually agreed upon among people in the U.S. With that in mind, it would be interesting to further investigate whether presenting the same scenarios that were voted as False (non-loving signs) in the U.S. would be voted as indicators of love in other cultures or even U.S. cultures that include people from different races (e.g., Latino population with a communal nature).

## *Does everyone know equally about the consensus on felt love?*

In our exploration of relationships between people’s ability in knowing the consensus on felt love and their demographic background, we found that depending on people’s gender, race, personality traits, and relationship status, they have differential ability of knowing the consensus on felt love. More specifically, we found that male participants show less knowledge of the consensus on felt love than female participants. This gender difference about experiences of love aligns with many of the past research on this topic (Fehr & Broughton, 2001; Hendrick, Hendrick, Foote, & Slapion-Foote, 1984; Sprecher & Toro-Morn, 2002). Specifically, research has shown that men and women differ in their thought process about the concept of love. Men are more likely to think about sexual commitment and the pleasure of intercourse when thinking about love, whereas women are more prone to thinking about love as emotional commitment and security (Buss, 2000; Cimbalo & Novell, 1993; Hazan & Shaver, 1987). This distinction between male and female perceptions of romantic love, not to be confused with love experienced in casual day-to-day interactions, could partially explain why men displayed less knowledge of the consensus in the scenarios of love presented in this study. Our items on felt love were less centered on sexual and intimate relationships and behaviors and more centered on emotional support and supportive behavior from others during everyday momentary experiences. Thus, an everyday nonsexual approach to love could be more in line with the cognitive framework of women than men.

In terms of relationship status, we also found that people in relationships know more about the consensus on felt love than people who are single. Since love is defined as an interpersonal connection between two people who share a micro-moment of positivity in the midst of their daily life (Fredrickson, 2013), people who are in a relationship and have more chances of experiencing and receiving these signals of love may have more knowledge of what makes them feel loved than those who are not in a relationship. Moreover, based on previous research, people who have maintained a good quality relationship show better relational characteristics (Stafford & Cannary, 1991) and higher emotional intelligence (Brackett, Warner, & Bosco, 2005) than people who have not and thus could be an explanation why these people know more about the shared belief about love among people.

In terms of racial demographics, using the White racial group as baseline in our analysis, results indicated that in this U.S. sample Black people showed less knowledge about the consensus on felt love than other racial and ethnic groups. This finding is expected because the majority of the U.S. sample recruited is of White racial/ethnic background and thus this majority (White) mostly influences the consensus on the indicators of love. Consequently, other racial groups such as Black people might have less knowledge of what the White majority considers as indicators of felt love. Like the plausible cultural differences discussed above (i.e., individualistic vs. interdependent cultures), future research should investigate whether different racial groups also have different norms as to what feeling love means. Assumed norms found here may not be norms at all, and instead, norms may be differentiated based on important individual differences.

Our results also demonstrated personality differences in people's ability to know the consensus on felt love. Based on our findings, people who were higher in agreeableness and/or higher in neuroticism showed more knowledge about the consensus on felt love. Previous research on the five dimensions that comprise the Big Five and love has shown agreeableness and extraversion being closely related to individual differences in love

(Caralis & Haslam, 2004; Gurtman & Pincus, 2003; Heaven, Da Silva, Carey, & Holen, 2004; Schmitt, 2004; Wiggins, 1979). Our finding on the agreeableness trait is in line with previous findings showing it to be related to positive relationship characteristics (e.g., relationship satisfaction, marital stability; Karney & Bradbury, 1995; Kwan, Bond, & Singelis, 1997; Shaver & Brennan, 1992). Thus, it is reasonable for people who are more agreeable and experience more positive relationships to know more about what makes people feel loved. The finding that neuroticism is related to *more* knowledge of the consensus on felt love is surprising when considering the literature which typically links neuroticism to problematic relationship outcomes, such as divorce, low relationship satisfaction, marital instability, and shorter relationships (Eysenck, 1980; Karney & Bradbury, 1995; Shaver & Brennan, 1992). This association between neuroticism and felt love consensus knowledge may be possible due to the fact that individuals high in neuroticism still *experience* love, they simply do not have lasting love experiences (not tested here). For example, facets of neuroticism like impulsivity are related to manic love experiences (Lester & Philbrick, 1988; Middleton, 1993; Woll, 1989), and thus, possibly *more* love experiences. Thus, the common characteristic of both agreeableness and neuroticism could be the amount of *experience* with love. Consequently, people with higher neuroticism or agreeableness scores both have an understanding of the consensus of what makes people feel loved. Further research on this finding is warranted to investigate the effect of personality on people's understanding of felt love.

### *Do people differ in their guessing bias and being willing to guess on indicators of felt love?*

People indeed have differential inclinations toward guessing when unsure of the correct response on felt love indicators depending on their demographic background and personality. Our results revealed that people in relationships are more willing to guess an answer of True/False to the felt love items when they don't know the answer rather than picking the "Don't know" response. This propensity to guess could be due to the fact that people who are in relationships may consider their relationship as a knowledge base for understanding what makes people feel loved and thus would rather express this relationship knowledge by giving an opinion on those indicators as opposed to stating they don't know.

Moreover, we found that as adults age, they are less inclined to guess True when unsure of the correct response to indicators of felt love. In other words, when unsure if a scenario makes people feel loved, older adults are more prone to indicate that people do not feel loved by a scenario than younger adults. This could be due to the fact that across the life span adults experience a decline in life satisfaction (Neto & da Conceicao Pinto, 2015) and prevalence of depressive symptoms (Kennedy, 1996), which might lead to an increase in social isolation and loneliness (Halmos, 1952; Jylha, 2004; Sheldon, 1948), increased risk of mortality (Bruce, Seeman, Merrill, & Blazer, 1994), and increased difficulties with activities of daily living (Penninx et al., 1998) resulting in older adults being more pessimistic about scenarios that make people feel loved in everyday life. Hence, as age increases, individuals become biased toward guessing that scenarios are not loving. Another possible explanation for why older adults are less prone to consider a scenario as a loving experience when they are uncertain could be that the scenarios presented in this study may be more relevant to younger adults and less relevant to older ones (e.g., playing sports, being a part of a group, etc.) and thus older adults could not relate to them as much as younger adults did. This idea would be a great hypothesis to test in future research on aging and felt love experiences in daily life.

On the other hand, we found that people who identify themselves as black and Asian are more likely to guess True when unsure of their response on indicators of felt love. Previous research has shown that depending on the culture in which people were raised, they acquire differential levels of emotional investment tendencies and experience different levels of love (Gangestad & Simpson, 2000). It is possible that black and Asian individuals were raised in cultural environments that fostered more communal tendencies and experiences of love and consequently are more likely to see everyday scenarios as loving even if others do not.

Finally, a similar trend in guessing bias was seen with people who score high on the personality trait openness. Our findings indicated that people who show openness to experience tend to guess True when they are unsure of their response to felt love items. This finding is unsurprising since the trait openness in the BFI framework is conceptualized as “receptivity to many varieties of experiences and a fluid and permeable structure of consciousness” (McCrae, 1994). Receptivity to a range of experiences may explain why people with high openness would be more willing to state a scenario would make people feel loved (picking True) when they are unsure rather than picking False as they are more apt to seeing various experiences in everyday life as loving moments.

### *Are there cultural differences in what makes people feel loved?*

A notable strength of this study is that we utilized a novel cultural consensus tool via the Bayesian statistical framework that enabled us to derive a single culture consensus on felt love, while simultaneously measuring people’s differential abilities for knowing the consensus. Although the current model assumes a single underlying consensus agreement on felt love, using racial background helped us incorporate some interesting differences. In future studies, consensus on indicators of felt love could be studied within subgroups in the U.S. or even samples from different countries. We believe cultural differences could greatly impact which scenarios are considered as indicators of felt love. Previous research has revealed that cultural factors both on the societal and the psychological level contribute to personal relationships, specifically those pertaining to love (Dion & Dion, 1991, 1993; Inman & Sandhu, 2002; Rodriguez, Montgomery, Pelaez, & Salas, 2003; Wan, Luk, & Lai, 2000). More specifically, cultural differences impact various dimensions of love such as how it feels to love, the thoughts that come to mind when in love, and the behaviors that are deemed appropriate and pleasing in our love lives (Landis & O’Shea, 2000; Schmitt, 2004; Sternberg, 1998). These distinct love experiences are not only seen among different cultures across countries (e.g., collectivism vs. individualism in Asian compared to Western countries; Dion & Dion, 1996; Hofstede, 2001; Triandis, 2001) but can also be found among multiple cultures within the U.S. (e.g., different love experiences among various ethnic groups; Doherty et al., 1994; Gao, 2001). Although cultural differences have been considered in many studies on love, a cross-cultural study on factors that make people *feel* loved—from the perspective of the receiver of loving signals—has yet to be conducted.

## Conclusion

This study provided a strong foundation for studying the concept of *felt* love; looking at love from the receiver's perspective on what factors contribute to love. Using a novel methodological approach to analyzing cultural consensus in a national subset, we provided evidence that there is a cultural agreement among people about indicators of felt love in a U.S. subset. We found that people feel loved in a range of settings much wider than just romantic relationships, which included momentary everyday interactions and experiences with friends, pets, and family. Moreover, people in the U.S. consider scenarios that have an underlying "controlling" nature as non-loving signals, which could be a sign of cultural trends.

This study closely replicated previous findings from Oravecz et al. (2016) in addition to advancing the previous study by exploring further individual differences in people's consensus on felt love. Similar to Oravecz et al. (2016), we found gender and relationship effects in the current study as well. More specifically, based on our findings, men compared to women seem to know less about the general consensus on felt love. In addition, individuals who are in a relationship show more knowledge about the consensus on felt love and are also more willing to guess an answer as opposed to say Don't know when they are unsure of their response.

Extending the previous study, when we explored personality types in terms of cognitive individual differences on felt love consensus, results indicated that agreeable and neurotic people seem to be more knowledgeable of the consensus on felt love. Overall, although knowledge of love can differ between people, there is a consensus within the U.S. culture about which scenarios elicit love in most people.

We acknowledge that our study is limited with regard to our selection of individual differences that we examine with regard to consensus on indicators of felt love. We believe that other individual differences such as attachment styles and communal orientations would also be interesting variables to consider with respect to what makes people feel loved. Future research is needed to look at consensus on indicators of felt love with relation to such relationship-related variables. Moreover, it would be interesting to consider consensus on felt love internationally, in order to examine cross-cultural beliefs about what makes people feel loved, but also to look at a more diverse sample within the U.S. Conclusively, these findings highlight the importance of looking at the experience of love from the perspective of the receiver: the person receiving loving signals. This study advances the literature by assessing felt love beyond the context of romantic relationships, to include momentary everyday life interactions and experiences.

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## Supplemental material

Supplementary material for this article is available online.

## Notes

1. In the classical or sometimes called “frequentist” statistical framework model, parameters are fixed quantitates, estimated with error, and we cannot talk about their likely values in terms of probabilities.
2. These items were based on Meaning in Life Questionnaire, Steger, Frazier, and Oishi, 2006; Scale of Positive and Negative Experience, Diener et al., 2010; Flow Short Scale, Rheinberg, Vollmeyer, and Engeser, 2003; PERMA profiler positive relationships scale, Butler and Kern, 2015; Interpersonal Support Evaluation List, Cohen, Mermelstein, Kamarck, and Hoberman, 1985.
3. The data used in the current study is from a larger study that used a wider range of demographic questions. For the purpose of our research questions, we only used age, gender, relationship status, and racial/ethnic group information.
4. All felt love scenarios are listed in the Online Supplementary Material based on the category they belong to.
5. Computer script is available from the second author.
6. You can download the program from https://git.psu.edu/zzo1/HierarchicalCondorcetModeling Toolbox

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