Uncovering the Most Important Factors for Predicting Sexual Desire using Explainable Machine Learning

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Abstract

Background: Low sexual desire is the most common sexual problem reported with 34% of women and 15% of men reporting lack of desire for at least three months in a 12-month period. Sexual desire has previously been associated with both relationship and individual well-being highlighting the importance of understanding factors that contribute to sexual desire as improving sexual desire difficulties can help improve an individual's overall quality of life.

Aim: The purpose of the present study was to identify the most salient individual (e.g., attachment style, attitudes toward sexuality, gender) and relational (e.g., relationship satisfaction, sexual satisfaction, romantic love) predictors of dyadic and solitary sexual desire from a large number of predictor variables.

Methods: Previous research has relied primarily on traditional statistical models which are limited in their ability to estimate a large number of predictors, non-linear associations, and complex interactions. We used a machine learning algorithm, random forest (a type of highly non-linear decision tree), to circumvent these issues to predict dyadic and solitary sexual desire from a large number of predictors across two online samples (N = 1846; includes 754 individuals forming 377 couples). We also used a Shapley value technique to estimate the size and direction of the effect of each predictor variable on the model outcome.

Outcomes: The outcomes included total, dyadic, and solitary sexual desire measured using the Sexual Desire Inventory.

Results: The models predicted around 40% of variance in dyadic and solitary desire with women's desire being more predictable than men's overall. Several variables consistently predicted dyadic sexual desire such as sexual satisfaction and romantic love, and solitary desire such as masturbation and attitudes toward sexuality. These predictors were similar for both men and women and gender was not an important predictor of sexual desire.

Clinical Translation: The results highlight the importance of addressing overall relationship satisfaction when sexual desire difficulties are presented in couples therapy. It is also important to understand clients' attitudes toward sexuality.

Strengths & Limitations: The study improves on existing methodologies in the field and compares a large number of predictors of sexual desire. However, the data were cross-sectional and there may have been variables that are important for desire but were not present in the datasets.

Conclusion: Higher sexual satisfaction and feelings of romantic love toward one's partner are important predictors of dyadic sexual desire whereas regular masturbation and more permissive attitudes toward sexuality predicted solitary sexual desire.

Keywords: Close Relationships; Sexual Desire; Machine Learning; Random Forests; Shapley Values

Uncovering the Most Important Factors for Predicting Sexual Desire using Explainable Machine Learning

Across time sex and sexual desire have been sources of inspiration for art, music, literature, and media. Understanding the nature of desire and factors affecting sexual desire have also been of interest to researchers, clinicians, and educators across multiple disciplines [1–4]. Sexual desire is a motive, drive, or wish to engage in sexual activity either with oneself or with a partner [5]. In a recent systematic review of 64 studies, the authors created a conceptual model of factors associated with sexual desire in long-term relationships [2]. These factors were divided into individual (e.g., attachment style, expectations, cognitive focus), interpersonal (e.g., relationship length, satisfaction, communication), and societal variables (e.g., sexual attitudes, egalitarianism). While the review provided a comprehensive model including potentially important predictors of sexual desire, no studies to date have attempted to quantify which variables might be the most predictive of sexual desire.

Identifying which factors are the most likely to contribute to sexual desire is important in order to design interventions for when sexual desire discrepancy (i.e., when one partner's sexual desire is higher or lower than their partner's) or low sexual desire is a problem. Sexual desire has been robustly associated with sexual and relationship satisfaction [6–9] and individual well-being [10,11]. Therefore, individuals who experience sexual desire difficulties are also likely to experience poor outcomes individually as well as interpersonally. This is especially important given the high prevalence of low sexual desire; 34% of women and 15% of men report lack of interest in having sex for at least three months in a 12-month period [12]. Therefore, the present study aims to add to the existing literature by attempting to identify the most important and robust predictors of sexual desire using machine learning.

Previous research has shown that sexual desire ebbs and flows over time due to a variety of factors often leading to instances of sexual desire discrepancy in couples [13–15]. While the fluctuations in desire are not always distressing, sexual desire difficulties rank among the most frequently reported reasons for people to seek sex and couples therapy [16]. There have been a large number of factors associated with sexual desire in the literature [2,17]. A great deal of research has focused on examining gender differences in sexual desire with some studies showing that women, on average, report lower levels of sexual desire compared to men [18–21]. However, other studies have found that there is more variation within than between genders[22]. Similarly, some studies have found differences in sexual desire for different sexual identity groups (e.g., lesbian women report lower levels of sexual desire compared to bisexual and straight women) whereas others have found no consistent differences [21,23–25].

Factors such as hormonal contraceptives[26], medications such as antidepressants[27], mood[28], and attachment style[21] have all been linked to sexual desire in previous research. Recent research into interventions for low sexual desire have found mindfulness to be an effective treatment for improving sexual desire [29–31]. Therefore, it may also be that being higher in mindfulness is associated with increased sexual desire. Couple dynamics in a relationship also play a role in sexual desire. As described above, sexual and relationship satisfaction both predict sexual desire [6–9]. Previous research has also shown that sexual desire tends to wane in relationships over time with most couples reporting high sexual desire at the start of their relationship but a decline in desire over time [32]. Some of this may also be explained by age; younger people tend to report higher levels of sexual desire compared to older adults [32]. Furthermore, more restrictive attitudes toward sexuality have been associated with lower sexual desire[33,34].

Using Machine Learning to Predict Sexual Desire

Existing research into sexual desire has exclusively relied on linear regression models to estimate associations between variables. However, traditional linear models are ill-equipped to address a large number of predictors simultaneously [35] and, perhaps surprisingly, do not provide reliable or meaningfully interpretable estimates for the effect that variables have on the outcomes due to issues such as suppression and cancellation effects, and multicollinearity [36,37]. The reliability of the linear model coefficients are highly sensitive to choice of control variables which means that both the size and direction of the effect can change depending on which variables are controlled for [36–40].

Furthermore, while non-linear associations and complex interactions often occur in nature, traditional linear models are not able to adequately model such complexity without explicitly specifying these relationships *a priori*. For example, if one suspects a quadratic relationship, or an interaction between two variables, then one has to pre-specify x^2 or an *xy features*, respectively. However, these examples are inherently restrictive; unless such additional features are correctly specified *a priori*, the linear model will be unable to accurately fit non-linear associations and complex interactions in the data [41]. Because of the problems associated with more traditional models, there has been a call recently to move toward more flexible and powerful machine learning models which learn non-linear and complex interactions from the data themselves [35].

In order to circumvent the problems using linear models, we employ a random forest algorithm [42], which is a form of explainable decision tree. Random forests can estimate a large number of predictor variables and highly non-linear relationships while minimizing overfitting to the data thus aiding generalizability of the results beyond a single sample. A small number of studies in relationship science have used the random forest algorithm to predict a variety of outcomes such as romantic attraction [43], relationship satisfaction [44], and commitment [44]. A landmark study by Joel et al.[44] examined the most important individual and relational predictors of relationship satisfaction and commitment across 43 studies and found they could predict 40% of the variance in the outcomes on average. Unfortunately, owing to its powerful non-parametric form, the random forest algorithm does not readily provide effect sizes or specify whether each variable is positively or negatively associated with the outcome. While the random forest can be readily interrogated to identify important predictors, the associated *importance weights* have been found to be unreliable and inconsistent [37]. Inconsistency means that importance weights can indicate that a predictor is important even if it is not. Therefore, while prior studies have used importance weights to assess which factors seem to be contributing to the model's prediction, the assessment may itself be unreliable. Furthermore, prior work has not been able to provide information about the size or the direction of the effects [44].

A great deal of work has been conducted recently in order to make machine learning algorithms more explainable [45,46]. This work is particularly exciting because social scientists are interested in being able to not only predict an outcome but to also explain which factors are associated with the outcome of interest. In the present study, we take advantage of this new development in machine learning by using Shapley values [37,45,46] to estimate the direction and size of the effect of each predictor variable on the outcome. The Shapley value approach involves systematically evaluating changes in model performance in response to including or restricting the influence from different combinations of predictors. It produces estimates that show both how much and in which direction each variable changes the model outcome. It can also model any interactions in the predictor variables.

Research into predictors of sexual desire to date has been limited due to its reliance on traditional linear models. However, in order to move the field forward and to design effective interventions, it is important to understand which variables are the most likely to change the outcome. The aim of the present study was to compare a number of different predictors to understand which explain the most change in the model outcome. We used data from a sample of individuals (Sample 1) and a sample of couples (Sample 2). In the latter sample, we also estimated both actor and partner effects on sexual desire. Given that women are twice as likely to report low sexual desire as a problem compared to men [12], we examined the models for men and women separately as well as together.

Method

Sample 1

Participants and Procedure

The data were collected as part of a larger cross-sectional study. Participants were recruited through mTurk and were asked to complete an online survey and were paid 30 cents for the task. Recruitment was also conducted through social networking sites (e.g., Facebook, Twitter), email listservs, and targeted recruitment for sexual minority participants on online forums. Participants recruited from these mediums were entered into a draw to win one of four $40 Amazon gift cards. Participants were eligible for the study if they were over 18 years of age and had experience with at least one romantic relationship. Ethical approval was obtained from the [blinded for peer-review] institutional review board and all participants received a written informed consent at the start of the baseline survey. Details of the procedure can be found from [blinded for peer review].

A total of 1,097 participants consented to participate. Participants who had not completed the study (n = 198) or were missing the outcome variable (n = 8) were removed from the analyses[1]. Therefore, the final sample consisted of 891 participants; 557 (62.5%) cis-gender women, 279 (31.3%) cis-gender men, and 25 (2.8%) genderqueer. Most of the

[1] Little's MCAR test showed that the data were not missing completely at random ($\chi^2 = 1191.82$, p = .019). Nineteen percent of the participants who began the survey dropped out before the end of the study. Half the participants who did not complete the study finished before they reached half way on the survey and the rest of the excluded participants completed around 75% of the study.

participants were straight (n = 483; 53.9%), 189 (21.2%) identified as bisexual, 101 (11.3%) gay, and 60 (6.7%) lesbian. Majority of the participants were White (88.4%), married or cohabiting (62.7%), had no children (75.5%), had at least some level of college (95.8%), and did not identify with any religion (54.5%). The average age of the participants was 32.7 years (*SD* = 9.63) and the average relationship length for those who were in a relationship was 6.21 (*SD* = 7.12).

Measures

Because the variables included in the study were selected for their relevance to sexual desire, we included all measures as predictor variables that were collected in the study, which included a total of 95 variables after recoding all categorical variables into dummy variables. The full list of the variables including the dummy coding of the categorical variables can be found in the codebook on the OSF project page. These included demographic questions on age, race/ethnicity, gender, partner's gender, sexual orientation, relationship status, children, country, religion, and education. Participants also completed questions around their contraceptive use (which type of contraception they or they partner used), sexual behaviors (i.e., types of sexual behaviors such as masturbation, oral sex, intercourse participants had engaged in either in the past week or ever in the current or most recent relationship), desire discrepancy, whether they wanted sex or communication more or less than they were currently engaging in, and mental and physical health ("Would you say in general your mental/physical health is", scored from 1 = excellent to 5 = poor). The following constructs were assessed using previously validated questionnaires:

Sexual desire was assessed using the Sexual Desire Inventory (SDI[5]). The scale was used as both a single scale (13 items) as well as divided into dyadic (nine items; α = .77) and solitary desire (four items; α = .91) and assesses an individual's interest sexual activity over the past month with higher scores being indicative of higher sexual desire. Sexual satisfaction was assessed using the General Measure of Sexual Satisfaction Scale (GMSEX; α = .95[47]). The GMSEX is a 5-item measure used to assess satisfaction with the sexual relationship. Relationship satisfaction was assessed using the General Measure of Relationship Satisfaction (GMREL; α = .97[47]). Both GMREL and GMSEX are scored on a 7-point semantic differential scale and higher scores are indicative of greater sexual satisfaction. Dispositional mindfulness was measured using the Five Facet Mindfulness Questionnaire – short form (FFMQ-SF[48]). The scale comprises of a total of 24 items that are divided into five subscales: being non-reactive (α = .80), observant (α = .74), acting with awareness (α = .85), describing feelings (α = .86), and non-judgmental attitude (α = .83). The items are scored on a 5-point Likert scale with higher scores indicating participants' agreement with the statement. Attitudes Toward Sexuality Scale (ATSS; α = .84[49]) was used to assess participants' attitudes toward sexuality. The scale comprises of 13 items that are measured on a 5-point Likert scale with higher scores indicating the participant is more liberal, lower more conservative. The Perception of Love and Sex Scale (PLSS[50]) measures one's perception of love and sex comprising of four subscales: love is most important (six items; α = .76), sex demonstrates love (four items; α = .79), love comes before sex (four items; α = .81), and sex is declining (three items; α = .67). The items are measured on a 5-point Likert scale with higher scores indicating lower agreement. Attachment style was assessed using the Experience in Close Relationships Scale – Short form (ECR-S[51]). The ECR-S consists of two 6-item Likert scales: one for anxiety (α = .75) and one for avoidance (α = .80). Higher scores indicate higher levels of insecure attachment.

Sample 2

Participants and Procedure

The second sample used a combined dataset across two studies on mixed-sex couples. The couples for both studies were recruited through various listservs, websites, and social media (e.g., Facebook, Twitter). Participants who were 18 years of age or older, in a mixed sex relationship for a minimum of three years to capture couples who have formed attachment bonds and are beyond the passionate stage of love, currently living with that partner, with no children under the age of one, and not pregnant (or with a pregnant partner) at the time, met the inclusion criteria and were directed to provide their partner's email address. For the second dataset, in addition to the above criteria, one member of the couple had to be bisexual in order to be eligible to participate due to a broader aim of that study to examine the dynamics of bierasure in mixed sex relationships (see [blinded for peer review]). The respondent first completed the online survey in which they provided an email address for their partner who was then contacted to complete the survey. Ethical approval was obtained from the [blinded for peer-review] institutional review board and all participants received a written informed consent at the start of the baseline survey. Details of the procedure can be found in [blinded for peer review] and [blinded for peer review].

Participants who had not completed the study (n = 14)[2] or were missing the outcome variable (n = 6) were removed from the analyses. The final sample consisted of 955 participants (377 intact mixed-sex couples and 201 individuals); 538 (56.3%) cis-gender women, 405 (42.4%) cis-gender men, and 12 (1.3%) genderqueer. The participants were either straight (n = 534; 55.9%) or bisexual (n = 397; 41.3%). The majority of the participants were White (87.4%), married (60.4%), had at least some level of college (90.8%), and did not identify with any religion (51.9%). The average age of the participants was 30.50 years (*SD* = 8.01) and the average relationship length was 7.41 (*SD* = 6.22).

Measures

Sample 2 had a total of 72 variables. The full list of the variables including the dummy coding of the categorical variables can be found in the codebook on the OSF project

[2] None of the 14 people had completed the survey beyond basic demographic variables.

page. These included demographic questions on age, race/ethnicity, gender, sexual orientation, married or cohabiting, religion, attendance in religious services, and education. Participants also completed questions around their contraceptive use (which type of contraception they or they partner used), sexual behaviors (i.e., types of sexual behaviors such as masturbation, oral sex, intercourse participants had engaged in either in the past 30 days or ever in the current or most recent relationship), desire discrepancy, whether they wanted sex or communication more or less than they were currently engaging in, and mental and physical health (“Would you say in general your mental/physical health is”, scored from 1 = excellent to 5 = poor).

The measures for sexual desire, sexual satisfaction, and relationship satisfaction were the same in Sample 2 as in Sample 1. The following questionnaires were not available in the sample: attachment styles (ECR-S), attitudes toward sexuality (ATSS), trait mindfulness (FFQM-SF), and perception of love and sex (PLSS). The study had an additional scale measuring romantic love, the Romantic Love Scale (α = .89)[52]. The scale consists of 13 items that are meant to measure affiliative and dependent need, a predisposition to help, and orientation of exclusiveness and absorption. The scale is scored on a 9-point scale with higher scores indicating higher romantic love. For dyadic analyses, both dyad members’ scores were included as predictors. The outcome measures were the same as in Sample 1.

Data Analysis

Data Preparation. All categorical variables were dummy coded (0 and 1) with each option included in the models (e.g., ethnicity was coded into “Asian”, “black”, “white”, and “multiracial”). Any variables that would have been exact copies of one another (e.g., no children vs. children) were excluded from the analyses. Any variables that were essentially the same as the outcome variable were removed from the analyses (e.g., total desire when dyadic or solitary desire were outcome variables). Less than 0.1% of the data were missing, and any missing data points were imputed using the *scikit-learn* package *Iterative Imputer* [53] with a Bayesian ridge estimator.

Analyses. We ran three models for each outcome variable (total desire, dyadic desire, solitary desire) for each sample (Sample 1 and Sample 2): Model 1 included data from all participants, Model 2 included data from men only, and Model 3 included data from women only. In Sample 2 (dyads only), we also ran models in which both actor and partner effects were included: Model 4 included data from men as the actor and women as the partner and Model 5 included data from women as the actor and men as the partner[3].

The results were analyzed using Python 3.7 and the code can be found here: [blinded for peer-review]. Each dataset was analyzed using a random forest regressor [42]. A random forest is a type of decision tree that trains on bootstrapped sub-samples of the data in order to avoid overfitting. By selecting multiple random subsets of predictors, the algorithm recursively partitions the input space in order to maximize its predictive power on a randomly selected *out of bag* sample (i.e., a sample that the model has not seen before). The use of this out of bag sample is what helps to mitigate overfitting during the training process. By undertaking this partitioning and out of bag sample testing thousands of times (i.e., by bootstrapping), the random forest is able to derive the best 'average' decision tree for the training data. The tree can model highly non-linear relationships in the data, and therefore represents a significantly more flexible model than a linear regressor.

In general, random forest models are sensitive to hyperparameter settings (such as the number of estimators, or the maximum depth of the decision tree). However, tuning hyperparameters requires a separate validation data split which reduces the effective sample size available for training and testing. Therefore, we use the default "scikit learn" random

[3] Because the random forest algorithm does not assume independence between participants, modeling the interdependence between dyad members is unnecessary and does not affect the results.

forest regressor with k-fold cross-validation [53]. The out-of-bag error is a built-in metric frequently used to estimate the performance of random forests [43,44], but in some circumstances this metric has been shown to be biased above the true error [54,55]. By using a k-fold cross-validation approach, instead of the out-of-bag error, we were able to test the model over the entire dataset, and to acquire estimates for the standard error (see below).

A ten-fold cross-validation scheme was used to train and test the model. This means the total dataset is randomly split into ten equally sized folds. The model is trained on nine out of ten folds, tested on the tenth, and the test fold performance is recorded. This is repeated until all ten folds have been used as a test set. The average performance, as well as the standard error across the ten folds, provide an estimate of model performance on unseen data. The metrics for test data model performance are the mean-squared error (which is the averaged squared difference between the prediction and the observed value), the R^2, and the variance explained. The last model to be trained is then saved, and interpreted using the "SHapley Additive exPlanations" package (SHAP) [37,45,46].

Traditional approaches (e.g., using the coefficients from a linear model, or importances from a random forest) are unreliable and inconsistent, and the Shapley approach has been shown to provide interpretations with theoretic guarantees which are coherent with human intuition (Lundberg et al., 2020). The SHAP package is a unified framework for undertaking model interpretation, and derives from the seminal game theoretic work of Lloyd Shapley [56]. By combining powerful and flexible machine learning algorithms like the random forest with the SHAP method, we are able to *project* the predictors into an interpretable space for subsequent explanation. Similarly to how researchers might design *features* of the predictors according to their prior knowledge (such as the incorporation of an x^2 term), the random forest is able to learn these from the data themselves. Assuming the random forest has been fit, the Shapley value effectively conceives of each predictor (and each combination of predictors) as a collaborative agent striving to maximize the model's predictive performance.

More concretely, SHAP starts with the average model prediction across the dataset, and then systematically measures the impact (i.e., the change in the predicted outcome) that all combinations of an individual's information have on this average prediction, on a per-individual basis. For example, starting with the average model output, if the inclusion of an individual's age into the model results in +0.70 in predicted output, the impact of this variable for this individual is +0.70 on the prediction. This variable can then be removed, and the impact of a different variable (e.g., relationship satisfaction) can be measured. This process continues across all combinations of predictors. Owing to possible interactions between predictors, it is also important to note that the order of inclusion matters, so SHAP also accounts for differences in the ordering. It thereby produces estimates that show how much impact and in which direction each variable, and each interaction, has on the model outcome, for each individual (i.e., it provides per-individual, per-predictor estimations of impact).

Specifically, we used the SHAP *TreeExplainer* package, which provides estimations of the per-individual, per-predictor impact on model output, as well as the average predictor impacts. For the analysis the default settings of the SHAP package *TreeExplainer* were used, and the entire dataset was fed to the model for explanation. The combination of the powerful function approximation capabilities of random forests with the consistent and meaningful estimations of per-individual, per-predictor impact on model output enables a reliable and informative exploration of predictor importance, as well as a means to identify key predictor interactions.

Results

The descriptive statistics for sexual desire for men and women can be found in Table 1. We used a total of 91 variables in Sample 1 and 68 variables (137 variables in dyadic analyses) in Sample 2 to predict sexual desire. In Sample 2, we performed the analyses first at the individual level (N = 955) and then at the dyadic level (N = 377). We performed the individual-level analyses for the total sample as well as for men and women separately. In the dyadic analyses, we only performed the analyses for men and women separately including both actor and partner effects [57] in the model. We also completed models for total desire, dyadic desire, and solitary desire separately. The results can be found in Table 2 including the percentage of variance explained by the model predictors for each outcome for each sample as well as the mean squared error (MSE) and R^2. A full list of variables included in each model with descriptions of the variables as well as all results (including Top-20 variables) can be found on the OSF project page: https://osf.io/ehzkm/?view_only=f9232534d9f84541a38a2fec228fc72d.

Total Variance Explained

In Sample 1, the model's predictive performance was similar across the different outcome variables for desire. The model was better at predicting both dyadic and solitary desire separately compared to when combining the dyadic and solitary desire into total desire in Sample 2. For total desire, the results showed that the model could predict between 31.8% (Sample 2) and 41.9% (Sample 1) of the variance. The model was better at predicting women's (Sample 1: 45.1%; Sample 2: 32.3%) total level of desire compared to men's (Sample 1: 22.7%; Sample 2: 13.1%). Adding partner effects into the model for Sample 2 did not explain additional variance for women (32.3% vs. 32.0%) but explained additional 4% of the variance for men (13.1% vs. 17.4%).

For dyadic desire, the model explained 43.4% of the variance in Sample 1 and 41.1% of the variance in Sample 2 for all participants. The model was better at predicting women's

(Sample 1: 43.7%; Sample 2: 40.9%) dyadic desire compared to men's (Sample 1: 28.5%; Sample 2: 22.3%). Adding partner effects into the model for Sample 2 explained additional 2% of the variance for women (40.9% vs. 42.9%) and additional 6% of the variance for men (22.3% vs. 28.1%). Finally, the model explained 41.6% of the variance in solitary desire in Sample 1 and 41.1% of the variance in Sample 2 for all participants. The model was better at predicting women's (Sample 1: 44.9%; Sample 2: 37.7%) dyadic desire compared to men's (Sample 1: 20.5%; Sample 2: 28.6%). Adding partner effects into the model for Sample 2 explained additional 4% of the variance for women (37.7% vs. 41.9%) but no additional variance for men (28.6% vs. 28.7%). Partner effects explained a small amount of additional variance for some outcomes but the majority of the variance came from actor variables.

Most Predictive Variables

In the majority of the models, the predictive importance of the variables decreased after only a small number of predictors. The rest of the predictors contributed only a small amount of variance into the model individually. Therefore, we only present the top-10 variables for each model in the figures. In the figures, the left side provides the mean effect of each variable on the model outcome. The right side of the figure provides the estimates for each individual participant. Red indicates a higher value of the predictor variable and blue indicates a lower value. For example, red is equal to 1 and blue is equal to 0 for binary variables. It is important to note that the two samples differed somewhat in the predictor variables that were available and therefore the results for the most important predictors vary somewhat across the two samples. For the sake of brevity, we have not discussed each predictor variable in the top-10 in detail as all of the results can be found in the figures. We have provided examples of interpretation and discussed the most interesting and/or consistent predictors below.

In Sample 1 (see Figure 1), sexual satisfaction and solitary desire predicted an increase in dyadic desire across participants for both men and women. For example, participants who scored low in sexual satisfaction, however, reported up to over a 10-point decrease in dyadic desire compared to average. In contrast, participants who reported higher sexual satisfaction, reported up to a 5-point increase in dyadic desire compared to average. Participants who had been in a relationship for longer reported lower levels of dyadic desire compared to participants who had been in a relationship for shorter duration. Higher scores on variables “love is most important”, “sex equals intimacy”, and “sex brings closer” all predicted an increase in dyadic desire. This means that participants who believed that love was not the most important aspect of their relationship (sex was also important) and saw sex as a way to improve intimacy and bring them closer reported higher levels of dyadic desire. For all of these variables, the results showed that lower scores generally had a two to three times larger impact on the model output compared to higher scores. Furthermore, individuals higher in attachment anxiety reported higher levels of dyadic desire compared to those lower in attachment anxiety.

Some of the top-10 predictor variables were similar in Sample 2 (see Figure 2). However, Sample 2 did not include perceptions of love and sex or attachment. Solitary desire, sexual satisfaction, and relationship length were all among top-10 predictors of dyadic desire in Sample 2. Higher levels of romantic love also predicted an increase in dyadic desire. Furthermore, participants who reported that their partner’s desire was higher than theirs reported lower levels of dyadic desire on average. At the dyadic level, both actor and partner effects were found in the top-10 predictor variables. Actor’s sexual satisfaction, solitary desire, romantic love, and report that their partner’s desire was higher were among the top-10 predictors for both men and women. Partner’s sexual satisfaction and dyadic desire also predicted actor’s dyadic desire.

For solitary desire, having masturbated recently was the strongest predictor cross all datasets. In Sample 1 (Figure 4), more liberal attitudes toward sexuality also predicted an increase in solitary desire as did many aspects of mindfulness as well as dyadic desire. Women higher in attachment avoidance also reported higher solitary desire compared to those lower in attachment avoidance. In Sample 2 (Figure 5), romantic love, having engaged in infidelity, age, and relationship length were all among top-10 predictors for solitary desire. At the dyadic level, both actor and partner variables were present with actor's masturbation, dyadic desire, and relationship satisfaction all predicting solitary desire. Partner's sexual satisfaction and solitary desire predicted both men and women's own solitary desire.

Moderator Variables

In addition to the most important predictor variables, we also examined which interactions may have contributed to the overall prediction. Figures with all possible interactions can be found on the OSF project page for each analysis. In the supplemental figures, purple indicates no interaction and yellow indicates the strongest interaction. We have provided figures for the strongest interactions in Figures 7-10. Instead of providing a detailed interpretation of each interaction, we have provided two examples below to aid interpretation of the figures.

Across all participants in Sample 1, an interaction between sexual satisfaction and wanting more sex predicted a change in dyadic desire. Participants who did not want more sex and reported lower sexual satisfaction, also reported lower levels of dyadic desire whereas those higher in sexual satisfaction reported higher levels of dyadic desire. In contrast, participants who wanted more sex and reported a low level of sexual satisfaction reported higher dyadic desire whereas participants who wanted more sex but were sexually satisfied, reported lower dyadic desire. In Sample 2, an interaction between sexual satisfaction and partner's desire being higher also predicted changes in dyadic desire.

Participants who reported that their partner's desire was higher and were low on sexual satisfaction, reported low levels of dyadic desire whereas those who reported higher levels of sexual satisfaction reported lower dyadic desire. An opposite pattern was shown for those who reported that their partner's desire was lower: participants who were low in sexual satisfaction reported high levels of dyadic desire whereas participants who reported high sexual satisfaction reported lower dyadic desire. There were also several predictive interactions for solitary desire.

Discussion

Much of social sciences research has focused solely on explainability which has resulted in models that have limited predictive ability and are therefore of limited utility in practice [35]. Furthermore, an over-reliance on linear models has meant that any potential non-linear relationships and complex interactions may have gone unnoticed. A limited number of studies have begun to use machine learning algorithms that focus on prediction to estimate the predictability of different psychological constructs [43,44,58]. However, these studies have not been able to estimate the relative importance of different constructs or the size and direction of the effects. In the present study, we used random forests [42] with Shapley values [37,45,46], which allowed us to not only estimate the overall predictive power of the model but to also explain which factors the algorithm used to predict the outcome.

We found that overall, the models could predict around 40% of the variance in sexual desire. Dyadic and solitary desire were equally predictable by the model variables. However, in Sample 2, the model was less able to predict total desire compared to dyadic and solitary desire. This may be because different variables explained dyadic and solitary desire. This suggests that it may be better to separate dyadic and solitary desire in studies rather than to look at sexual desire as a single construct. Furthermore, the model was able to explain more variance in women's sexual desire compared to men's sexual desire. Many previous studies have focused solely on women's sexual desire and men's sexual desire has received less attention in the literature [59]. It may be that we were unable to capture variables that are associated with men's sexual desire as these may be less well known. Therefore, future research is needed to better understand what predicts men's sexual desire levels.

The strongest predictors of sexual desire varied somewhat across the two samples most likely because they had somewhat different variables. For dyadic desire, sexual satisfaction and solitary desire were consistently among the strongest predictors. Interestingly, relationship satisfaction was not consistently associated with dyadic desire. However, romantic love in Sample 2 and perception of love and sex in Sample 1 predicted higher levels of dyadic desire. Therefore, the results suggest that simply improving the relationship may not be sufficient to improve a couple's desire for each other. Instead, it may be more beneficial to focus any potential interventions on changing perceptions of love and desire or improving partners' feeling of romantic love toward each other, potentially through self-expanding activities in which partners can see each other in a new light [3]. Consistent with previous research [21], higher attachment anxiety also predicted higher dyadic desire in both men and women. Interestingly, highly anxious women reported higher levels of dyadic desire only when they were low in sexual satisfaction whereas they reported lower levels of dyadic desire when their sexual satisfaction was high. The opposite pattern was true for individuals low in attachment anxiety. This finding is consistent with the idea that attachment-anxious individuals often have sex to gain closeness and seek reassurance [60] and they base the relationship quality on their sexual experiences [61]. Finally, the interaction between sexual satisfaction and wanting more sex showed that wanting more sex does not necessarily equate to higher level of dyadic desire. Therefore, the amount of sex one wants or has should not be used as a proxy for their level of sexual desire.

Furthermore, masturbation was consistently the strongest predictor of solitary desire with those who had masturbated recently reporting higher levels of solitary desire. In Sample 1, more liberal attitudes toward sexuality predicted increased solitary desire whereas more conservative attitudes predicted a decrease in solitary desire. Individuals who were more mindful also reported experiencing higher levels of solitary desire. Therefore, practicing mindfulness at the individual-level and changing societal attitudes toward sexuality at the societal-level may improve solitary desire.

The study has a number of strengths including the use of explainable machine learning and cross-validation in which the model performance is tested on unseen data to avoid overfitting. We also used data from two large samples and estimated both actor and partner effects in a sample of dyads. However, there are also several limitations that should be considered when interpreting results. First, while we estimated the models using a large number of predictors, there are other variables that we did not account for that may influence one's sexual desire (e.g., partner responsiveness, gendered attitudes, partner's attractiveness). Therefore, future research should be conducted in which a greater number of individual, relational, and societal factors are considered. Second, we only used cross-sectional data and it would be interesting to evaluate whether any of the variables predict changes in sexual desire over time.

Third, both samples were convenience samples recruited online. While the samples were diverse in terms of sexual orientation and gender, the majority were white, middle class, and well-educated which limits the generalizability of our findings. The Shapley values provide point estimates for each individual data-point for each variable. Therefore, it is possible to evaluate what the impact of having a different dataset with different values on a specific variable might be. For example, if the Sample 2 had more participants with very low sexual satisfaction, the average impact of the sexual satisfaction variable on the model output would be much larger. This would not necessarily change the impact of each data-point or the prediction accuracy but would change the average association. Fourth, while random forests are a powerful tool that will take advantage of any correlations and interactions in the data, no matter how non-linear, they cannot be used to estimate causality. However, in the absence of a means to reliably estimate causality when examining factors relating to sexual desire, we believe that using a predictive model is perhaps the best option.

In conclusion, the present study used a powerful machine learning technique, random forests, to estimate participants' sexual desire and was the first study that we are aware of in social sciences to use explainable machine learning (Shapley values) to interpret the results from a machine learning algorithm. The results showed that we could predict around 40% of the variance in sexual desire with women's sexual desire generally being more predictable than men's. The majority of the variance was explained by actor rather than partner effects. Several factors were consistently associated with individuals' level of dyadic and solitary desire that can be used in the future interventions to improve individuals' sexual well-being.

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Table 1

Means, Standard Deviations, and Range for Sexual Desire for Sample 1 and Sample 2

	Sample 1			Sample 2		
	Mean	SD	Range	Mean	SD	Range
Total desire						
Total	80.84	16.02	20-120	56.70	14.34	5-101
Women	77.79	16.22	21-117	53.24	14.21	5-101
Men	86.54	14.16	20-120	61.45	13.01	8-99
Dyadic desire						
Total	54.85	10.99	9-79	43.35	10.30	5-70
Women	53.72	11.25	9-79	40.97	10.11	5-70
Men	57.37	10.09	9-78	45.56	9.49	8-68
Solitary desire						
Total	21.13	7.97	4-35	13.34	6.70	0-31
Women	19.63	8.28	4-35	12.28	6.68	0-31
Men	23.59	6.64	4-35	14.86	6.40	0-31

Note. The scale items for the two samples were slightly different with Sample 1 range going from 1-9 and Sample 2 from 0-8.

Table 2

The Overall Prediction Results for Total, Dyadic, and Sexual Desire for Study 1 and Study 2

	Study 1 (Individual)			Study 2 (Dyadic)		
	% Variance	MSE	R^2	% Variance	MSE	R^2
Outcome	M (SE)	M (SE)	M (SE)	M (SE)	M (SE)	M (SE)
All						
Total Desire	41.9 (0.03)	145.4 (9.12)	.41 (0.03)	31.8 (0.03)	139.2 (8.43)	.31 (0.03)
Dyadic Desire	43.4 (0.03)	67.6 (4.35)	.43 (0.03)	41.1 (0.02)	61.8 (3.10)	.40 (0.02)
Solitary Desire	41.6 (0.03)	36.2 (1.49)	.41 (0.03)	41.1 (0.03)	26.0 (1.23)	.41 (0.03)
Women						
Total Desire	45.1 (0.02)	144.3 (13.77)	.43 (0.02)	32.3 (0.02)	138.1 (9.69)	.30 (0.03)
Dyadic Desire	43.7 (0.03)	69.3 (5.67)	.42 (0.03)	40.9 (0.04)	60.3 (4.29)	.39 (0.04)
Solitary Desire	44.9 (0.01)	37.2 (2.39)	.43 (0.03)	37.7 (0.02)	27.4 (1.71)	.37 (0.03)
Women Dyadic						
Total Desire				32.0 (0.04)	145.7 (11.62)	.29 (0.04)
Dyadic Desire				42.9 (0.04)	61.0 (4.80)	.41 (0.04)
Solitary Desire				41.9 (0.05)	27.7 (2.73)	.41 (0.05)
Men						
Total Desire	22.7 (0.05)	151.1 (24.56)	.19 (0.05)	13.1 (0.03)	147.5 (15.71)	.11 (0.04)
Dyadic Desire	28.5 (0.09)	67.3 (11.38)	.26 (0.09)	22.3 (0.06)	68.0 (7.24)	.18 (0.07)
Solitary Desire	20.5 (0.02)	33.5 (2.47)	.18 (0.07)	28.6 (0.05)	28.5 (1.79)	.27 (0.05)
Men Dyadic						
Total Desire				17.4 (0.04)	143.5 (18.00)	.14 (0.05)
Dyadic Desire				28.1 (0.03)	67.1 (5.08)	.25 (0.04)
Solitary Desire				28.7 (0.06)	29.5 (3.40)	.26 (0.06)

Figure 1

The Top-10 Most Important Predictors for Dyadic Desire in Sample 1

Note. The left graph presents the mean effect size for each variable and the right graph shows the size and direction of the effect for each data point.

Figure 2

The Top-10 Most Important Predictors for Dyadic Desire in Sample 2 with Actor Effects Only

Note. The left graph presents the mean effect size for each variable and the right graph shows the size and direction of the effect for each data point.

Figure 3

The Top-10 Most Important Predictors for Dyadic Desire in Sample 2 with Both Actor and Partner Effects

Note. The left graph presents the mean effect size for each variable and the right graph shows the size and direction of the effect for each data point.

Figure 4

The Top-10 Most Important Predictors for Solitary Desire in Sample 1

Note. The left graph presents the mean effect size for each variable and the right graph shows the size and direction of the effect for each data point.

Figure 5

The Top-10 Most Important Predictors for Solitary Desire in Sample 2 with Actor Effects Only

Note. The left graph presents the mean effect size for each variable and the right graph shows the size and direction of the effect for each data point.

Figure 6

The Top-10 Most Important Predictors for Solitary Desire in Sample 2 with Both Actor and Partner Effects

Note. The left graph presents the mean effect size for each variable and the right graph shows the size and direction of the effect for each data point.

Figure 7

The Results for the Most Important Moderators for Dyadic Desire in Sample 1

Note. The Y axis shows the relative contribution each level of the interaction has on the outcome prediction.

Figure 8

The Results for the Most Important Moderators for Solitary Desire in Sample 1

Note. The Y axis shows the relative contribution each level of the interaction has on the outcome prediction.

Figure 9

The Results for the Most Important Moderators in Sample 2 for Dyadic and Solitary Desire for Actor Effects Only

Note. The Y axis shows the relative contribution each level of the interaction has on the outcome prediction.

Figure 10

The Results for the Most Important Moderators in Sample 2 for Dyadic and Solitary Desire for Actor and Partner Effects

Note. The Y axis shows the relative contribution each level of the interaction has on the outcome prediction.