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Is Infidelity Predictable? Using Explainable Machine Learning to Identify the Most Important Predictors of Infidelity

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ABSTRACT

Infidelity can be a disruptive event in a romantic relationship with a devastating impact on both partners' well-being. Thus, there are benefits to identifying factors that can explain or predict infidelity, but prior research has not utilized methods that would provide the relative importance of each predictor. We used a machine learning algorithm, random forest (a type of interpretable highly non-linear decision tree), to predict in-person and online infidelity across two studies (one individual and one dyadic, N = 1,295). We also used a game theoretic explanation technique, Shapley values, which allowed us to estimate the effect size of each predictor variable on infidelity. The present study showed that infidelity was somewhat predictable overall and interpersonal factors such as relationship satisfaction, love, desire, and relationship length were the most predictive of online and in person infidelity. The results suggest that addressing relationship difficulties early in the relationship may help prevent infidelity.

Infidelity is the most commonly reported cause of divorce in the United States (Amato & Previti, 2004). The fallout from infidelity can have devastating consequences for both members of the couple in relationships, including feelings of discontent, depression, blame, and frustration (Thompson & O'Sullivan, 2016). The prevalence estimates for lifetime infidelity range between 20% and 52% depending on the way infidelity is defined and measured (Mark & Haus, 2019; Mark et al., 2011; Thompson & O'Sullivan, 2016). Definitions of infidelity vary widely across studies but can broadly be defined as engaging in emotional or sexual relations outside of the agreed-upon bounds of the relationship (Mark & Haus, 2019), and may include behaviors such as flirting, having an emotional connection, sexual intercourse, or using pornography (Blow & Hartnett, 2005b). With the emergence of the internet and smartphones, computer-mediated behaviors (e.g., sexting, sending explicit photos, or watching live webcam porn) have also become more commonplace as forms of infidelity (Albright, 2008).

A recent systematic review (Haseli et al., 2019) extended the ecological model (Bronfenbrenner, 1994) to examine predictors of infidelity in relationships and developed the Ecological Couples System Diagram (ECSD; Haseli et al., 2019). The ECSD suggests that both partners' individual variables (e.g., attachment style, socio-demographic variables, sexual attitudes) as well as couple variables (e.g., sexual and relationship satisfaction, relationship length) can predict one partner's infidelity. Partners create a "union system of dyadic exclusivity" (Haseli et al., 2019, p. 1169) which suggests that one partner's characteristics may create a context in which their partner may engage in infidelity. Therefore, infidelity is often a result of an environment that is created by both couple members. In the present study we focused primarily on comparing the individual, partner, and dyadic factors of infidelity because these are the most often studied predictors of infidelity.

Previous Research on Predictors of Infidelity

There are several socio-demographic variables that have been examined in relation to infidelity. The evolutionary theory suggests that men should be more motivated to engage in sexual infidelity to maximize their reproductive success. Indeed, many studies have found that men are more likely to engage in sex outside of a relationship (Labrecque & Whisman, 2017; Petersen & Hyde, 2010) whereas women may be more likely to engage in emotional infidelity (Selterman et al., 2019). However, a greater number of studies have found more similarity than difference between the genders' engagement in infidelity, especially when both sexual and emotional forms of infidelity are considered (Allen et al., 2006; Fincham & May, 2017; Mark et al., 2011; Treas & Giesen, 2000). Other demographic variables that have been previously associated with infidelity include relationship status, education, and religion. Some studies have found that more committed individuals are less likely to engage in infidelity (Amato & Previti, 2004; Fincham & May, 2017) and highly educated individuals are more likely to engage in infidelity (Atkins et al., 2001; Martins et al., 2016; Treas & Giesen, 2000) whereas other studies have found the opposite pattern or no difference for education (Allen et al., 2006; Fincham & May, 2017). Finally, individuals with no religious affiliation have been reported to be more likely to engage in infidelity in some studies (Burdette et al.,

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2007; Fincham & May, 2017; Mattingly et al., 2010) but not in others (Haseli et al., 2019; Mark et al., 2011), especially when other factors are also considered (Mark et al., 2011).

In addition to demographic variables, there are other intraindividual factors that have previously been linked to infidelity. For example, individuals with more permissive sexual attitudes have been shown to be more likely to engage in infidelity (Fincham & May, 2017; Haseli et al., 2019; Martins et al., 2016). Similarly, higher sexual interest in both men and women has been associated with a higher likelihood of engaging in sexual infidelity (Fincham & May, 2017; Treas & Giesen, 2000). Several studies have found that individual differences in attachment predict infidelity. Specifically, more anxious individuals (i.e., individuals who feel unlovable and unworthy and thus seek excessive reassurance and support in relationships) and avoidant individuals (i.e., individuals who do not trust in other's capacity to be there for them and thus focus on independence and self-reliance) are more likely to engage in infidelity compared to more secure individuals (i.e., individuals who feel lovable and trust others; Fincham & May, 2017; Haseli et al., 2019; McDaniel et al., 2017).

At the couple system level, there are factors that are associated with greater likelihood of infidelity. Although not consistent across all studies, most studies have found relationship satisfaction to be a significant predictor of infidelity (Atkins et al., 2001; Fincham & May, 2017; Haseli et al., 2019; Owen et al., 2013). Dissatisfaction with one's sexual relationship, especially related to a decline in frequency of sex as relationship length increases has also been associated with greater likelihood of infidelity for men (Liu, 2000). Furthermore, incompatibility between partners in terms of sexual attitudes has been associated with infidelity, at least for women (Haseli et al., 2019; Mark et al., 2011).

Machine Learning Approach to Predicting Infidelity

While several predictors have been found to be associated with infidelity, the findings are often inconsistent (Blow & Hartnett, 2005a, 2005b). To address these inconsistencies, it is important to compare a number of factors in the same analyses. Previous research has also exclusively utilized traditional linear models, which are ill-equipped to handle a large number of predictors simultaneously, are unable to estimate non-linear associations or complex interactions, and tend to produce unreliable estimates that leave models completely uninterpretable (Breiman, 2001a; Lundberg et al., 2020; Yarkoni & Westfall, 2017). A small number of studies in relationship science to date have used machine learning to overcome issues with linear models (Großmann et al., 2019; Joel et al., 2020, 2017).

Machine learning algorithms are more flexible than traditional statistical models in that they can handle a large number of predictors at once, learn highly non-linear relationships between variables, and estimate complex interactions between predictor variables. As such, they provide a much more flexible and powerful approach to predicting an outcome. Machine learning algorithms are traditionally used to maximize prediction of an outcome by giving the model as many predictor variables as possible. Out of these predictors, the machine learning algorithm learns which variables are important for predicting the outcome. It will use the variables that are relevant for the prediction and assign a low value to variables that are not relevant. In the present study, we used a random forest algorithm (Breiman, 2001b), which is a form of interpretable decision tree that can handle highly non-linear relationships and complex interactions without overfitting to the data and estimate a large number of predictors simultaneously, enabling us to compare the effect sizes across different variables.

Prior studies utilizing the random forest algorithm have not been able to estimate the size or the direction of the effect of each individual predictor variable on the model outcome. However, recent developments in machine learning have provided tools that allow interpretation of the results through *explanations* of machine learning models (Lundberg et al., 2017, 2019). This work is particularly interesting because it enables researchers to combine the use of powerful machine learning algorithms and state-of-the-art tools for model explainability that can provide accurate predictions *and* increase our understanding of which factors are the most important in predicting the outcome. The latter is of particular importance because one of the principal aims of psychology is to develop a deeper understanding of human behavior (Grosz et al., 2020). In the present study, we took advantage of this new development in machine learning by using Shapley values (Lundberg et al., 2017, 2019) to estimate the effect size and direction of the effect of each variable predicting past infidelity.

The Current Study

The main aims of the present study were to determine whether we could predict sexual and online infidelity[1] and estimate which variables contribute the most variance in the outcomes. To maximize prediction and to potentially gain new insights, we included all variables available in the datasets in the models. For variables which are unimportant to the prediction, the model will simply assign no weight. Because the study was exploratory in nature and machine learning is more suitable for exploratory research (Yarkoni & Westfall, 2017), we did not make any *a priori* hypotheses. However, we used k-fold cross-validation, in which the model is trained on one part of the data and tested on another. Therefore, this technique evaluates the model generalizability on unseen test data, effectively providing a confirmatory analysis. We used data from two different studies: one in which data were collected from individuals (Study 1) and one in which data were collected from both members of the couple (Study 2). Because many previous studies have found differences between men and women, we analyzed each dataset together for all participants and separately for men and women. In Study 2 we also estimated the models including both dyad members' variables as predictors to explore whether partner variables were also associated with the self's outcome as predicted by the ECSD model.

[1]The datasets did not include a question on emotional infidelity and therefore we were unable to address it.

Method

Study 1

Participants and Procedure

The data were collected as part of a larger cross-sectional study conducted in 2014. 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), e-mail 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 monogamous romantic relationship. Ethical approval was obtained from the University of Kentucky institutional review board and all participants provided a written informed consent at the start of the baseline survey.

A total of 1,097 participants consented to participate. Participants who had not completed the study, had a large amount of missing data, or were missing the outcome variable were removed from the analyses. 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 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 at least one child (24.5%), 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

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. These included demographic questions on age, race/ethnicity, gender, sexual orientation, relationship status, children, and education. Participants also completed questions around their contraceptive use, sexual behaviors, whether they wanted sex or communication more or less than they were currently engaging in, and mental and physical health. The outcome, infidelity, was measured using a single-item question for in person infidelity ("I had sex (e.g., vaginal sex, anal sex, oral sex) with someone other than my current partner") and online infidelity ("I interacted sexually with someone other than my current partner on the Internet (had chat room sex, web cam sex, etc.)"). Both questions were dichotomized with yes = 1 and no = 0. The following constructs were assessed using previously validated questionnaires:

Sexual desire was assessed using the Sexual Desire Inventory (SDI; Spector et al., 1996). The scale was used as both a single scale (13 items) as well as divided into dyadic (nine items) and solitary desire (four items) and assesses an individual's interest in sexual activity over the past month, with higher scores being indicative of higher sexual desire. Sexual desire was also assessed using the Halbert Index for Sexual Desire (HISD; Yousefi et al., 2014) which measures sexual desire using 25 items, with higher scores being indicative of higher sexual desire[2] Sexual satisfaction was assessed using the General Measure of Sexual Satisfaction Scale (GMSEX; Lawrance & Byers, 1992). 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; Lawrance & Byers, 1992). Both GMREL and GMSEX are scored on a 7-point semantic differential scale and higher scores are indicative of greater satisfaction. Dispositional mindfulness was measured using the Five Facet Mindfulness Questionnaire – short form (FFMQ-SF; Bohlmeijer et al., 2011). The scale comprises a total of 24 items that are divided into five subscales: being non-reactive, observant, acting with awareness, describing feelings, and non-judgmental attitude. The items are scored on a 5-point Likert scale, with higher scores indicating participants' agreement with the statement. Attitudes Toward Sexuality Scale (ATSS; Fisher & Hall, 1988) was used to assess participants' attitudes toward sexuality. The scale comprises 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; Hendrick & Hendrick, 2002) measures one's attitudes toward love and sex comprising four subscales: love is most important (six items), sex demonstrates love (four items), love comes before sex (four items), and sex is declining (three items). The items are measured on a 5-point Likert scale with higher scores indicating higher agreement. Attachment style was assessed using the Experience in Close Relationships Scale – Short form (ECR-S; Wei et al., 2007). The ECR-S consists of two 6-item Likert scales: one for anxiety and one for avoidance. Higher scores indicate higher levels of insecure attachment.

Study 2

Participants and Procedure

We used baseline data from a longitudinal study of couples collected in 2012. The couples 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 monogamous relationship for a minimum of 3 years, 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 e-mail address. Partners were then emailed the same information that the initial potential participant was provided and asked the same eligibility criteria questions. If the partner also met eligibility criteria and agreed to participate, they were both sent individual unique links to the baseline survey. Participants who completed the baseline were provided with a $10 gift card ($20/couple). Ethical approval was obtained from the University of Kentucky institutional review board and all participants provided a written informed consent at the start of the baseline survey.

[2]There were two measures of sexual desire in the dataset and they were both included in the analyses to evaluate which sexual desire measure was more predictive of infidelity. Machine learning models do not suffer from multicollinearity and thus including highly correlated variables as predictors is not an issue..

The sample consisted of 202 mixed-sex couples (404 individuals). The majority of participants (89%) were from the United States, with a minority of the participants from Canada (11%). The mean age of the sample was 32.5 (SD = 8.90) and relationship length of the couples was 9.19 (SD = 6.85) years. Most of the sample identified as heterosexual (93%), with a minority identifying as bisexual (5%), questioning or uncertain (1%), and other (1%). The majority of participants were White (89%) and this was a fairly educated sample, with 96% indicating they had attended at least some college.

Measures

The study used many of the same measures as Study 1 and had a total of 66 variables[3] The following questionnaires were not available in the sample: attachment styles (ECR-S), attitudes toward sexuality (ATSS), Halbert Index of Sexual Desire (HISD), trait mindfulness (FFQM-SF), and perception of love and sex (PLSS). The study had an additional scale measuring romantic love, the Romantic Love Scale (Rubin, 1970). 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 Study 1.

Data Analysis

Data Preparation. All categorical variables were dummy coded (0 and 1) with each option included in the models. Any variables that were essentially the same as the outcome variable were removed from the analyses. Any missing variables were imputed using random forest multiple imputation. Less than 0.1% of the data were missing, and any missing data points were imputed using the *scikit-learn* package *Iterative Imputer* (Pedregosa et al., 2011) with a Bayesian ridge estimator.

Analyses. All data were analyzed at the individual level with the full sample, with men only, and with women only. Additionally, the data from dyads in which both members of the couple had responded to the questionnaire was also analyzed separately for men and women including both actor and partner effects in the model. The results were analyzed using Python 3.7 and the code can be found here: https://github.com/matthewvowels1/Shapley_Forest. Each dataset was analyzed using a balanced random forest classifier (Breiman, 2001b; Chen et al., 2004) for categorical outcomes. A random forest is a type of decision tree that trains on bootstrapped subsamples of the data to avoid overfitting. We chose to use a random forest classifier because random forests have been shown to perform well with their default settings without hyperparameter tuning (Probst et al., 2019). Tuning hyperparameters requires a separate train/test split that would have reduced our sample size. The random forest tree can model highly non-linear relationships in the data, and therefore represents a significantly more flexible model than a logistic regression. In cases where one class occurs much more often than another, many classifiers may learn to predict the majority class well, but not learn important associations necessary to predict the minority class. The balanced random forest variant, for categorical outcomes, is designed to provide better results in scenarios where there may be a class imbalance in the dataset. In the current study, there was imbalance between participants who had engaged in infidelity and those who had not. The balanced random forest can mitigate the problems associated with unequal class "support" by undersampling the majority class in the bootstrapping process, thereby balancing the classes during training.

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 that reduces the effective sample size available for training and testing. Therefore, we use the default "imbalanced-learn" balanced random forest classifier (IMBLEARN) and the default "scikit learn" random forest regressor (Pedregosa et al., 2011) with k-fold cross-validation. The out-of-bag error is a built-in metric frequently used to estimate the performance of random forests (Joel et al., 2020, 2017), but in some circumstances this metric been shown to be biased above the true error (Janitza & Hornung, 2018; Mitchell, 2011). 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). It is essential that the trained model is tested on a separate partition of the dataset, even for less complex linear models, when any data-driven decisions are made (Heyman & Smith Slep, 2001; Yarkoni & Westfall, 2017).

A 10-fold cross-validation scheme was used to train and test the model. This means the total dataset is randomly split into 10 equally sized folds. The model is trained on nine out of 10-folds, tested on the tenth, and the test fold performance is recorded. This is repeated until all 10- folds have been used as a test set. The average performance, as well as the standard error across the 10- folds, provide an estimate of model performance on unseen data. The metrics for test data model performance are the precision, recall, F1-score, and Matthews Correlation Coefficient (MCC). These metrics provide a more complete picture than an accuracy score, particularly for imbalanced data. For instance, if a dataset contained a 90/10 imbalance, an accuracy of 90% could be achieved simply by predicting the majority class for all new datapoints and is therefore meaningless. In contrast, precision is the ratio of true positives to the sum of true positives and false positives; recall is the ratio of true positives to the sum of true positives and false negatives, and the F1-score is the harmonic mean of precision and recall. These metrics therefore provide a more complete picture about a classifier's performance on imbalanced data. Arguably the best summary statistic for imbalanced classification problems is MCC (Boughorbel et al., 2017; Chicco & Jurman, 2020; Matthews, 1975). The MCC provides

[3]The lower number of variables in the dataset is mainly due to the sample being of dyadic mixed-sex couples and therefore many of the variables had fewer categories and thus fewer dummy coded variables (e.g., relationship status, sexual orientation).

a score bounded between [−1, 1] and is directly analogous to Pearson's correlation coefficient. If *MCC = 0* then the classifier is no better than random chance, if *MCC = 1* then the classifier achieves perfect prediction, and if *MCC = −1* the classifier perfectly predicts the opposite of the correct class.

The last model to be trained as part of the k-fold cross-validation process was saved, and explained using the "SHapley Additive exPlanations" package (SHAP) (Lundberg et al., 2017, 2020, 2019). The SHAP package is a unified framework for undertaking model explainability, and derives from the seminal game theoretic work of Lloyd Shapley (Shapley, 1952). The framework conceives of predictors as collaborating agents seeking to maximize a common goal (i.e., the regressor performance). The approach involves systematically evaluating changes in model performance in response to including or restricting the influence from different combinations of predictors. 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 explanations with certain theoretic guarantees (Lundberg et al., 2020). The SHAP *TreeExplainer* function provides estimations of the per-datapoint, per-predictor impact on model output, as well as the average predictor impacts. This function provides estimations of the impact of per-datapoint pairwise interactions on model output. 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-datapoint, 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

Prevalence of Infidelity

Most participants in Study 1 were currently in a relationship but only one member of the couple responded to the survey. They were asked about infidelity in their current or most recent relationship: 32.0% of a total of 891 participants (43.4% of men; 25.7% of women) had engaged in in-person infidelity compared to 26.6% in online infidelity (41.6% of men; 18.5% of women). In Study 2, both members of the couple responded to the surveys and reported on engagement in sexual infidelity in person or online in their current relationship: 17.4% of a total of 404 participants (18.8% of men; 15.9% of women) had engaged in in-person infidelity compared to 14.1% in online infidelity (16.8% of men; 11.4% of women).

Prediction Accuracy

We estimated models for all participants as well as for men and women separately. In Study 2, we also estimated the models with and without partner effects for men and women. We also estimated the models for each outcome. This resulted in a total of 16 models. The results for the overall model performances can be found in Table 1. We report precision, recall, and F1 scores for each class (0 = no infidelity, 1 = infidelity) as well as an overall measure of the model performance using Matthews correlation coefficient (MCC). The MCC coefficient can be interpreted as an overall effect size for the model using established effect size guidelines for Pearson's correlation: .1 = small, .3 = medium, and .5 = large effect (Cohen, 1992).

Overall, the effect size for in-person infidelity for all participants was between .28 and .36 indicating a medium effect size. The effect size for men was between .28 and .32 when only actor effects were included in the models and between .42 when partner effects were also included. The effect size for women was between .25 and .35 when only actor effects were included in the models and .35 when both actor and partner effects were included in the models. Overall, including partner effects in the models only improved the model performance for men not for women. The prediction effect size for online infidelity was medium to large for all participants (.36 to .38). The effect size for men was between .28 and .33 and for women between .18 and .49. When both actor and partner effects were included in the models, the overall effect size decreased from .33 to .24 for men and from .49 to .40 for women suggesting that partner effects did not add any information and may even detract from the model performance.

The Most Important Predictors of Infidelity

In addition to using the models to predict infidelity, we also estimated each predictor variable's contribution to the model performance using Shapley values. We include the top-10 most important predictors for each model in Figures 1–4. Due to space limitations, we only provide results for the models without partner effects given that partner effects did not generally improve the models' predictive ability. However, for interested readers, all results can be found on the OSF project page (https://osf.io/ehzkm/) including the importances for Top-20 variables. The left side of each figure provides the mean effect of each variable on the model outcome for each class. 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. For the outcome variable, points on the right side of the figure show an increase in the likelihood of engaging in infidelity, whereas the left of the middle point show a decreased likelihood of engaging in infidelity. It is important to note that the two samples differed somewhat in the predictor and outcome variables that were available and therefore the results for the most important predictors vary somewhat across the samples. For the sake of brevity, we have not discussed each predictor variable in the top-10 in detail as all the results can be seen in the figures. We have provided examples of interpretation and discussed the most interesting and/or consistent predictors below.

There were several variables that were included in the top-10 most predictive variables of in-person infidelity (Figures 1 and 2) across both samples across most of the analyses (all, men, women): relationship satisfaction, solitary desire, dyadic desire, relationship length, and some sexual activities (had anal sex, oral sex, or vaginal sex). Overall, higher scores on relationship satisfaction predicted a decreased likelihood of having engaged in infidelity and lower satisfaction an increased

Table 1. The overall results for infidelity, infidelity online, and intention toward infidelity across the two studies.

		Sample 1				Sample 2				Sample 3			
Outcome	Class	Pre	Rec	F1	MCC[a]	Pre	Rec	F1	MCC	Pre	Rec	F1	MCC
Infidelity													
All:	0	.81 (.02)	.65 (.02)	.72 (.02)	.28 (.03)	.92 (.01)	.80 (.02)	.85 (.01)	.36 (.06)	.92 (.02)	.71 (.02)	.80 (.02)	.30 (.04)
	1	.48 (.03)	.69 (.02)	.56 (.02)		.40 (.05)	.62 (.06)	.48 (.06)		.32 (.03)	.69 (.06)	.42 (.03)	
Men:	0	.70 (.05)	.66 (.03)	.66 (.03)	.28 (.08)	.91 (.03)	.69 (.03)	.78 (.02)	.32 (.03)	.91 (.03)	.64 (.05)	.74 (.03)	.15 (.10)
	1	.58 (.04)	.63 (.05)	.59 (.03)		.34 (.03)	.73 (.07)	.44 (.04)		.20 (.06)	.58 (.13)	.28 (.07)	
Men dyadic:	0					.92 (.02)	.77 (.03)	.84 (.02)	.42 (.06)	.90 (.03)	.54 (.03)	.67 (.03)	.08 (.09)
	1					.43 (.06)	.75 (.07)	.52 (.05)		.16 (.04)	.57 (.13)	.25 (.06)	
Women:	0	.84 (.02)	.65 (.03)	.73 (.02)	.25 (.04)	.92 (.02)	.79 (.03)	.85 (.03)	.35 (.09)	.92 (.02)	.73 (.02)	.81 (.01)	.33 (.05)
	1	.39 (.03)	.62 (.05)	.46 (.03)		.36 (.07)	.64 (.10)	.79 (.08)		.35 (.04)	.67 (.07)	.45 (.04)	
Women dyadic:	0					.93 (.02)	.78 (.04)	.84 (.02)	.35 (.08)	.93 (.02)	.70 (.04)	.79 (.03)	.23 (.08)
	1					.36 (.06)	.65 (.11)	.44 (.07)		.26 (.06)	.54 (.11)	.34 (.08)	
Infidelity online													
All:	0	.87 (.02)	.70 (.02)	.77 (.01)	.36 (.02)	.94 (.02)	.80 (.02)	.86 (.01)	.38 (.06)				
	1	.46 (.03)	.71 (.02)	.55 (.02)		.36 (.06)	.71 (.08)	.44 (.06)					
Men:	0	.72 (.06)	.64 (.04)	.67 (.04)	.28 (.08)	.94 (.03)	.80 (.03)	.86 (.02)	.33 (.05)				
	1	.56 (.04)	.65 (.06)	.59 (.04)		.36 (.04)	.71 (.09)	.44 (.04)					
Men dyadic:	0					.90 (.03)	.67 (.02)	.77 (.02)	.24 (.05)				
	1					.27 (.04)	.68 (.08)	.37 (.05)					
Women:	0	.88 (.02)	.63 (.02)	.73 (.02)	.18 (.05)	.98 (.01)	.85 (.04)	.90 (.02)	.49 (.07)				
	1	.27 (.03)	.60 (.07)	.36 (.04)		.41 (.07)	.79 (.10)	.51 (.08)					
Women dyadic:	0					.96 (.01)	.87 (.03)	.91 (.02)	.40 (.11)				
	1					.39 (.11)	.62 (.14)	.45 (.11)					
										% Var	MSE	R^2	
Intention toward infidelity													
All										42.0 (.05)	0.82 (.08)	.47 (.05)	
Men										58.0 (.04)	0.79 (.09)	.56 (.04)	
Men dyadic										58.8 (.06)	0.85 (.10)	.54 (.06)	
Women										31.6 (.05)	0.93 (.14)	.26 (.04)	
Women dyadic										40.5 (.05)	0.80 (.10)	.36 (.06)	

Standard error across the ten folds is in brackets. 0 = no infidelity, 1 = infidelity. Pre = precision, Rec = recall, MCC = Matthews correlations coefficient, % Var = percentage of variance explained, MSE = mean squared error.
[a]MCC is the overall effect size of the classification that consider the true and false positives and negatives in each class and provides an overall measure of accuracy. The MCC can be interpreted akin to Pearson's correlation coefficient with effect sizes of small = .1, medium = .3, and large = .5.

Figure 1. The top-10 most important predictors for in-person infidelity in Study 1.

likelihood of engaging in infidelity. However, some highly satisfied individuals were also more likely to have engaged in infidelity, suggesting a more complex relationship between relationship satisfaction and infidelity. Higher solitary and dyadic desire as well as longer relationship length predicted an increase in likelihood of having engaged in infidelity across the samples. Higher sexual satisfaction and romantic love (compared to lower) in Study 2 also predicted a decreased likelihood of having engaged in infidelity. More liberal attitudes toward sexuality in Study 1 also predicted a higher likelihood of having engaged in infidelity.

For online infidelity, having never had anal sex with the current partner decreased the likelihood of also having engaged in infidelity and higher relationship length and sexual desire increased the likelihood of having engaged in online infidelity. Relationship and sexual satisfaction were only in the top-10 predictors in Study 2. Romantic love was also predictive of online infidelity in Study 2. Use of hormonal contraceptives decreased the likelihood of men having engaged in online infidelity in Study 1, whereas it increased the likelihood of both men and women having engaged in online infidelity in Study 2.

Figure 2. The top-10 most important predictors for in-person infidelity in Study 2.

Discussion

Infidelity is relatively common, with up to half of those in relationships having engaged in infidelity (Mark & Haus, 2019; Mark et al., 2011; Thompson & O'Sullivan, 2016) with potentially devastating consequences for relationships causing distress (Thompson & O'Sullivan, 2016) and often divorce (Amato & Previti, 2004). Infidelity is likely to affect not only the couple members but also their children, extended family, and friends. It is important to identify potential risk factors for infidelity to target interventions that could prevent infidelity from occurring in the first place. The purpose of the present study was to identify potential factors associated with infidelity and to quantify and compare different factors to better understand which variables are the most strongly associated with infidelity.

A large body of literature has attempted to identify which factors contribute to infidelity. However, the studies have relied exclusively on linear models, which are often completely uninterpretable due to problems such as incorrect specification of the underlying causal structure, multicollinearity, unattainable parametric assumptions, and inability to examine complex

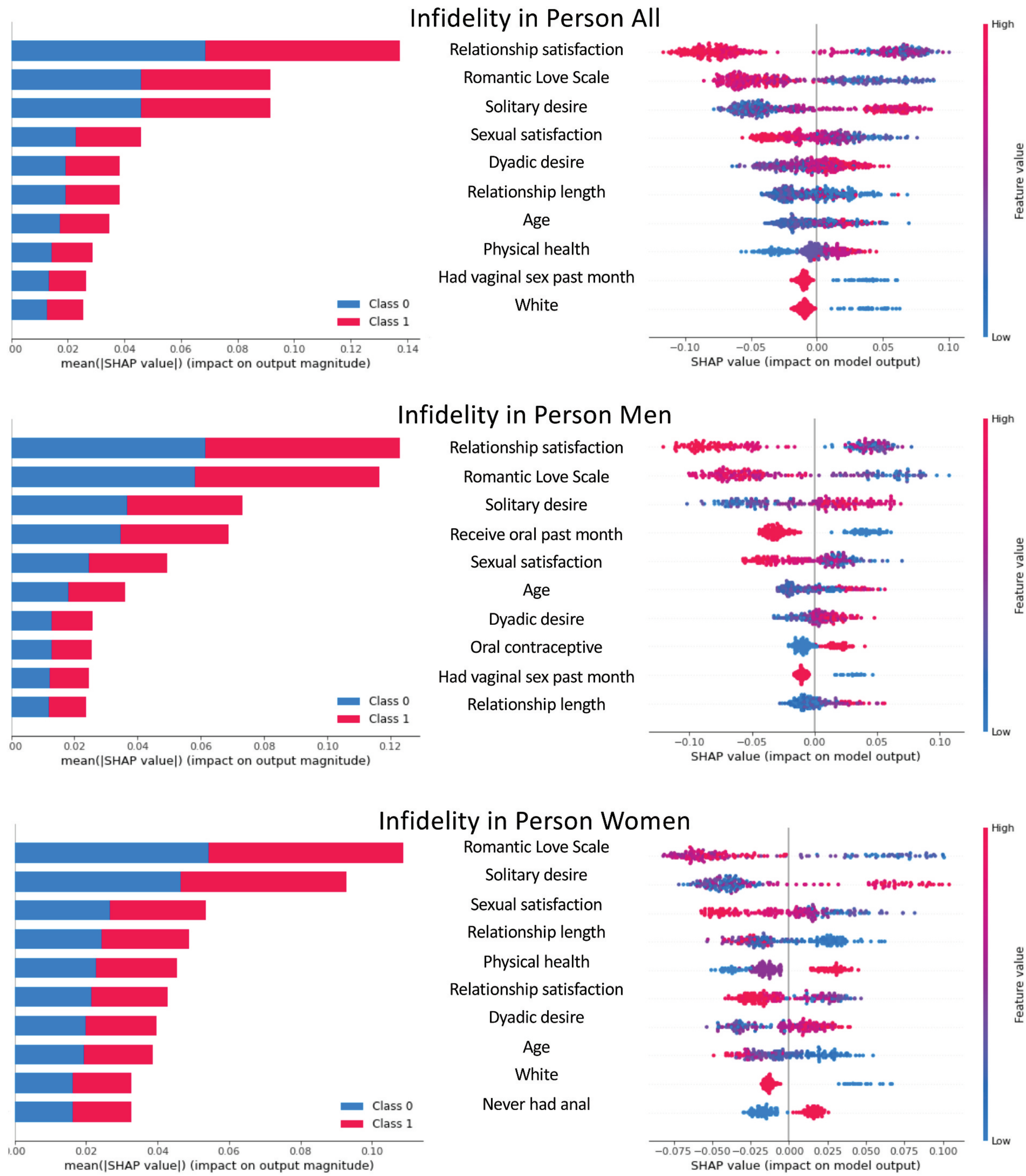

Figure 3. The top-10 most important predictors for online infidelity in Study 1.

associations (Breiman, 2001a; Lundberg et al., 2020; Yarkoni & Westfall, 2017). The present study is the first of its kind to examine predictors of infidelity using interpretable predictive models: random forests (Breiman, 2001b) with Shapley values (Lundberg et al., 2017, 2019). Based on our findings, the short answer to the question posed in the title, "is infidelity predictable?," is somewhat. The effect sizes that consider the true and false positives and negatives of both classes ranged between small (.18) to large effect (.49) across analyses and samples suggesting that even though we were able to predict infidelity generally well above chance level, there are also other factors that we had not accounted for.

The Comparison of Predictors of Infidelity

While we examined the predictive accuracy of our models, our main aim was to compare a range of different factors in their ability to predict infidelity. A recent systematic review found that while demographics and individual characteristics are inconsistently associated with infidelity, relationship variables tend to be more consistent across studies (Haseli et al., 2019). We also found that relationship characteristics (relationship satisfaction, relationship length, dyadic desire, sexual satisfaction, romantic love, and some sexual activities within the relationship) were consistently in the top-10 most important predictors across different samples. These findings suggest that

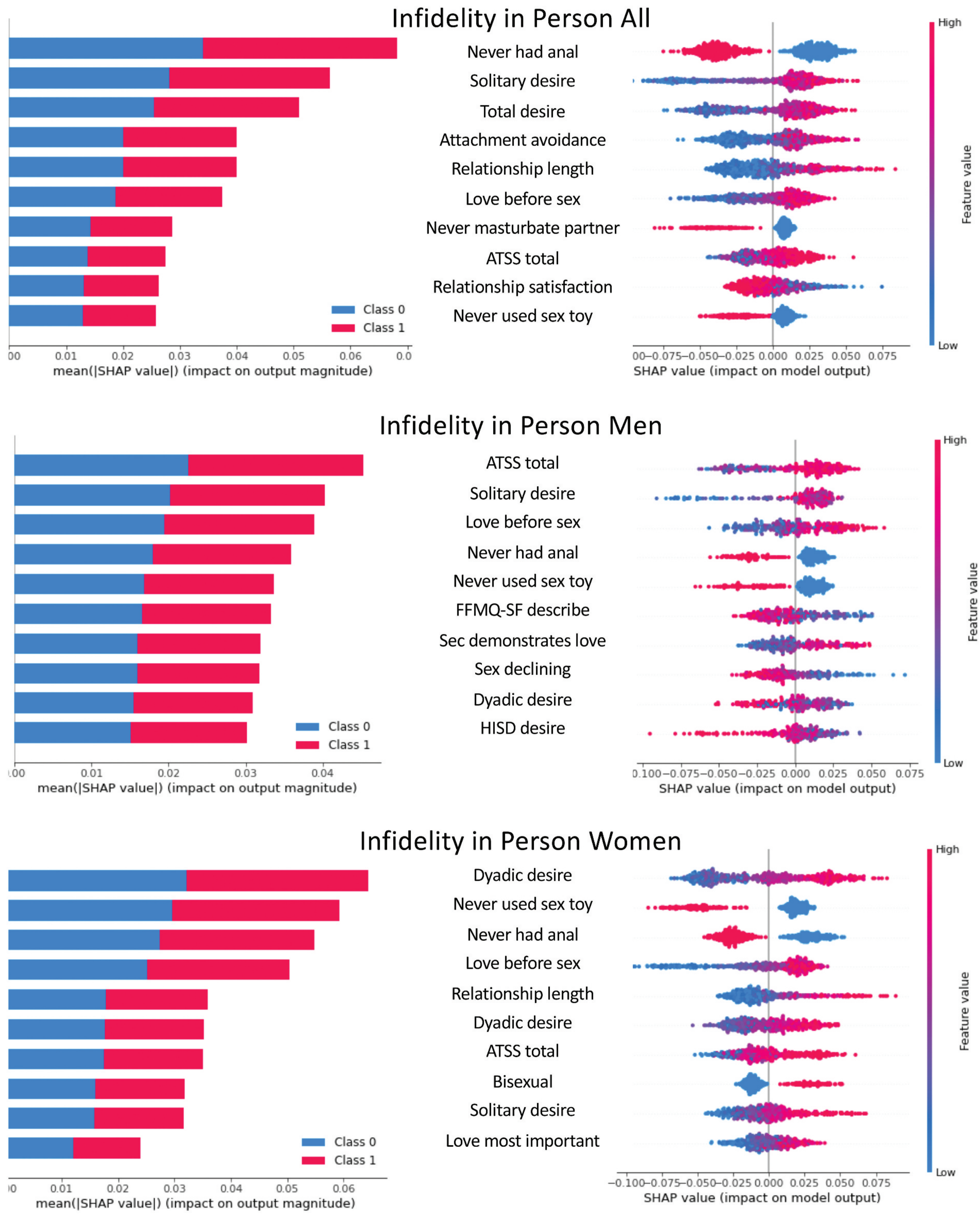

Figure 4. The top-10 most important predictors for online infidelity in Study 2.

addressing relationship issues may buffer against the likelihood of one partner going out of the relationship to seek fulfillment. However, it is also important to note that while individuals who were more satisfied in their relationship were generally less likely to engage in infidelity, a subsample of highly satisfied individuals had engaged in infidelity in the past. This may either reflect the idea that infidelity does also occur in happy relationships (Perel, 2017) or perhaps couples have worked through the infidelity and by the time they responded to the survey were satisfied in their relationship (Olson et al., 2002).

Furthermore, because online infidelity has become more commonplace given the technological advances in recent years (Albright, 2008), we also examined predictors of online infidelity. Interestingly, one of the strongest predictors of a decreased likelihood of having engaged in infidelity online was never having had anal sex in the present relationship. This may reflect more restrictive attitudes toward sexuality overall. Indeed, attitudes toward sexuality were measured in Study 1 and ranked among the Top-10 predictors of online infidelity. However, the relationship was more complex, with the most liberal sexual attitudes predicting an increase in likelihood of having engaged in infidelity whereas more moderate and conservative attitudes predicted a decrease. These results are in line with other studies that have found that more permissive sexual attitudes have been associated with an increased likelihood of having engaged in infidelity (Fincham & May, 2017; Haseli et al., 2019; Martins et al., 2016). Higher relationship length and sexual desire also increased the likelihood of having engaged in online infidelity. However, sexual and relationship satisfaction were only among the top predictors in one of the two samples.

The results of the present study corroborate many of the existing studies, and akin to a recent systematic review (Haseli et al., 2019), show that the most robust predictors of infidelity lie within the relationship: individuals who are more satisfied and in love in their relationship are less likely to have engaged in infidelity. There are also a number of factors that have previously been associated with infidelity that were not among the most important predictors in the present study: education (Atkins et al., 2001; Martins et al., 2016; Treas & Giesen, 2000), relationship status (Amato & Previti, 2004; Fincham & May, 2017), and attachment (Fincham & May, 2017; Haseli et al., 2019; McDaniel et al., 2017). We only examined attachment in Study 1 and higher attachment avoidance did predict an increased likelihood of having engaged in infidelity in the total sample but was not among the top-10 predictors for men or women. Attachment anxiety was not predictive of past infidelity. Furthermore, many previous studies suggest that men are more likely to engage in sexual infidelity than women (Labrecque & Whisman, 2017; Petersen & Hyde, 2010). In the present study, being a man was only an important predictor of past online infidelity in one sample, supporting studies that have found that the gender gap in infidelity is decreasing (Allen et al., 2006; Fincham & May, 2017; Mark et al., 2011; Treas & Giesen, 2000).

There were also some inconsistencies in the findings across the two samples. In Study 1, hormonal contraceptives decreased the likelihood of men having engaged in online infidelity whereas in Study 2 the use of hormonal contraceptives increased the likelihood of both men and women having engaged in online infidelity. The use of hormonal contraceptives does not prevent sexually transmitted infections and therefore increases the likelihood of passing any potential infections from the infidelity partner to the primary partner. This may deter people from engaging in infidelity face-to-face and instead seek alternative partners online. It is not clear why in one sample hormonal contraceptives increased the likelihood of engaging in infidelity and in another decreased it and the role of contraceptives on infidelity warrants further investigation. Furthermore, because each individual predictor only predicted very little variance in the outcome, interpreting each individual variable becomes more difficult. When the signal is stronger (i.e., a variable predicts a larger amount of variance) the prediction also becomes more accurate.

Implications for Theory and Future Research

The present study examined predictors of infidelity from the ecological theory perspective (Bronfenbrenner, 1994). Specifically, we tested the ECSD model from a recent systematic review that suggested that both partners' individual as well as couple's factors predict infidelity. We found little evidence to suggest that partner variables predicted actor's engagement in infidelity. In fact, in some analyses the predictive accuracy of the models decreased as a result of including partner variables in the models, suggesting that adding partner factors in the models may add noise that makes it more difficult for the model to make accurate predictions. Additionally, the present study suggested that relationship-related variables contributed the most to the prediction. However, it is important to caveat these findings in that we were essentially predicting infidelity in the past from the present variables. Therefore, it is possible that couples in which infidelity had occurred had worked through the infidelity and were now happier in their relationship than before.

In addition to relational variables, variables that tapped into people's attitudes were also predictive of both in person and online infidelity. Overall, having less permissive attitudes toward sexuality suggested a decreased likelihood of having engaged in infidelity. Individuals with highly liberal attitudes were the most likely to have engaged in infidelity in the past. Certain sexual behaviors such as the use of sex toys, anal sex, and masturbation with a partner may also have acted as a proxy for attitudes in the present study. Indeed, previous studies have suggested that sexual attitudes and behaviors go hand in hand (Lefkowitz et al., 2014). The results of the present study suggested that individuals who had not engaged in traditionally more permissive sexual behaviors such as using sex toys or having anal sex were less likely to also have engaged in infidelity. Most other individual variables were not consistently among the Top-10 predictors of infidelity, which may explain why the results from previous studies (Haseli et al., 2019; Mark & Haus, 2019) have been inconsistent, especially when examining socio-demographic variables.

Finally, the purpose of the present study was to examine a range of variables in their ability to predict infidelity. Overall, each variable alone predicted little variance in infidelity. Therefore, the results do not suggest that there is one single, or a few, variables that are highly predictive of infidelity. Instead, a large number of variables together resulted in the algorithm's overall ability to predict infidelity with a moderate to large effect size. Relationship variables together explained the largest amount of variance in the predictions. Relationship variables, however, are more likely to vary over time compared to certain individual characteristics (such as socio-demographic variables or attachment style). The prediction accuracy may have increased if the infidelity and relationship quality had been measured closer in time. Therefore, future research is needed to examine recent infidelity to more fully understand how relationship characteristics relate to infidelity. Additionally, because each variable contributed little to the overall prediction accuracy, using machine learning models with a large number of variables instead of focusing on single variables for predicting infidelity may be more fruitful in being able to predict who has or will engage in infidelity. This does not help target-specific factors but may be used to identify individuals or relationships who may be at a higher risk.

Strengths and Limitations

The present study adds to our understanding of the most important predictors for infidelity across two samples. We used a powerful interpretable machine learning technique that allowed us to produce reliable estimates of the effect sizes of each variable both for the mean effect as well as the spread of the individual effects (Lundberg et al., 2017, 2019). Using this method, we were also able to compare a large number of predictors simultaneously and estimate any non-linear associations and complex interactions. We also examined both in-person and online infidelity.

However, the study also had several limitations that should be considered. First, we used a single-item measure of in-person and online infidelity. We were thus unable to account for specific infidelity behaviors and did not examine emotional infidelity. Future research is needed to examine a wider range of infidelity behaviors to better understand whether the same predictors generalize across multiple forms of infidelity or whether these are predicted by different variables. The results from the present study suggest that these may be somewhat different given that the most important predictors of in-person and online infidelity also varied. Second, while we examined infidelity across two large samples with one sample including data from both members of the couple, the studies were all cross-sectional and it is not clear how recently the infidelity occurred. Therefore, some of the factors may have changed from when the infidelity occurred to when the participants completed the survey. This is a difficulty across most other studies on infidelity, but future research should examine infidelity over time or to conduct surveys on individuals who have just engaged in infidelity. Third, over 30% of the participants in Study 1 reported past infidelity. However, the number of participants who had engaged in infidelity in the dyadic sample was much lower. This made it more difficult for the algorithm to accurately predict infidelity which is reflected in lower precision and recall for the infidelity class compared to no infidelity. We used balanced random forests to mitigate this issue, but we still had less data available of people with past infidelity.

Furthermore, each variable contributed very little to the overall classification accuracy. Therefore, interpretation of the results may be less accurate than when individual variables have a clearer signal. Additionally, while random forests are a powerful tool that will take advantage of any correlations and interactions in the data, no matter how non-linear, it cannot be used to estimate causality. However, in the absence of a means to reliably estimate causality when examining factors relating to infidelity (after all we cannot create experiments in which we make people engage in infidelity), we believe that using a predictive model is perhaps the best option. Finally, we chose to use a random forest algorithm because of a moderate sample size. Random forests have been shown to perform well with their default settings without the need for hyperparameter tuning (Probst et al., 2019). Tuning hyperparameters requires a separate training set which would make the sample size in the test data smaller. However, there may be other algorithms that would perform better or similarly with hyperparameter tuning. Therefore, future research in larger samples could use different algorithms to compare the performance of different algorithms.

Conclusion

In conclusion, the present study provides the most robust and reliable evidence of factors associated with past in-person and online infidelity. The results showed that relationship variables were the most robust predictors of infidelity whereas demographics and individual differences variables were not consistently associated with infidelity. These results suggest that intervening in relationships when difficulties first arise may be the best way to prevent future infidelity. Furthermore, because sexual desire was one of the most robust predictors of infidelity, discussing sexual needs and desires and finding ways to meet those needs in relationships may also decrease the risk of infidelity.

Disclosure Statement

No potential conflict of interest was reported by the authors.

Data availability

The data are available upon request from the third author.

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References

Albright, J. M. (2008). Sex in America online: An exploration of sex, marital status, and sexual identity in internet sex seeking and its impacts. *Journal of Sex Research*, *45*(2), 175–186. https://doi.org/10.1080/00224490801987481

Allen, E. S., Atkins, D. C., Baucom, D. H., Snyder, D. K., Gordon, K. C., & Glass, S. P. (2006). Intrapersonal, interpersonal, and contextual factors in engaging in and responding to extramarital involvement. *Clinical Psychology: Science and Practice*, *12*(2), 101–130. https://doi.org/10.1093/clipsy.bpi014

Amato, P. R., & Previti, D. (2004). People's reasons for divorcing: Gender, social class, the life course, and adjustment. *Journal of Family Issues*, *24*(5), 602–626. https://doi.org/10.1177/0192513x03254507

Atkins, D. C., Baucom, D. H., & Jacobson, N. S. (2001). Understanding infidelity: Correlates in a national random sample. *Journal of Family Psychology*, *15*(4), 735–749. https://doi.org/10.1037//0893-3200.15.4.735

Blow, A. J., & Hartnett, K. (2005a). Infidelity in committed relationships I: A methodological review. *Journal of Marital and Family Therapy*, *31* (2), 183–216. https://doi.org/10.1111/j.1752-0606.2005.tb01555.x

Blow, A. J., & Hartnett, K. (2005b). Infidelity in committed relationships II: A substantive review. *Journal of Marital and Family Therapy*, *31*(2), 217–233. https://doi.org/10.1111/j.1752-0606.2005.tb01556.x

Bohlmeijer, E., Klooster, P. M., Fledderus, M., Veehof, M., & Baer, R. (2011). Psychometric properties of the five facet mindfulness questionnaire in depressed adults and development of a short form. *Assessment*, *18*(3), 308–320. https://doi.org/10.1177/1073191111408231

Boughorbel, S., Jarray, F., & El-Anbari, M. (2017). Optimal classifier for imbalanced data using Matthews Correlation Coefficient metric. *PLoS ONE*, *12*(6), e0177678. https://doi.org/10.1371/journal.pone.0177678

Breiman, L. (2001a). Statistical modeling: The two cultures. *Statistical Science*, *16*(3), 199–231. https://doi.org/10.1214/ss/1009213726

Breiman, L. (2001b). Random forests. *Machine Learning*, *45*(1), 5–32. https://doi.org/10.1023/A:1010933404324

Bronfenbrenner, U. (1994). Ecological models of human development. In *The international encyclopedia of education* (2nd ed., pp. 1643–1647). Elsevier.

Burdette, A. M., Ellison, C. G., Sherkat, D. E., & Gore, K. A. (2007). Are there religious variations in marital infidelity? *Journal of Family Issues*, *28*(12), 1553–1581. https://doi.org/10.1177/0192513X07304269

Chen, C., Liaw, A., & Breiman, L. (2004). *Using random forest to learn imbalanced data*. UC Berkeley: Department of Statistics. https://statistics.berkeley.edu/sites/default/files/tech-reports/666.pdf

Chicco, D., & Jurman, G. (2020). The advantages of the Matthews Correlation Coefficient (MCC) over F1 score and accuracy in binary classification evaluation. *BMC Genomics*, *21*(1), 6. https://doi.org/10.1186/s12864-019-6413-7

Cohen, J. (1992). A power primer. *Psychological Bulletin*, *112*(1), 155–159. https://doi.org/10.1037/0033-2909.112.1.155

Fincham, F. D., & May, R. W. (2017). Infidelity in romantic relationships. *Current Opinion in Psychology*, *13*, 70–74. https://doi.org/10.1016/j.copsyc.2016.03.008

Fisher, T. D., & Hall, R. G. (1988). A scale for the comparison of the sexual attitudes of adolescents and their parents. *Journal of Sex Research*, *24* (1), 90–100. https://doi.org/10.1080/00224498809551400

Großmann, I., Hottung, A., & Krohn-Grimberghe, A. (2019). Machine learning meets partner matching: Predicting the future relationship quality based on personality traits. *PLoS ONE*, *14*(3), 1–16. https://doi.org/10.1371/journal.pone.0213569

Grosz, M. P., Rohrer, J. M., & Thoemmes, F. (2020). The Taboo Against Explicit Causal Inference in Nonexperimental Psychology. *Perspectives on Psychological Science*, *15*(5), 1243–1255. https://doi.org/10.1177/1745691620921521

Haseli, A., Shariati, M., Nazari, A. M., Keramat, A., & Emamian, M. H. (2019). Infidelity and its associated factors: A systematic review. *Journal of Sexual Medicine*, *16*(8), 1155–1169. https://doi.org/10.1016/j.jsxm.2019.04.011

Hendrick, S. S., & Hendrick, C. (2002). Linking romantic love with sex: Development of the perceptions of love and sex scale. *Journal of Social and Personal Relationships*, *19*(3), 361–378. https://doi.org/10.1177/0265407502193004

Heyman, R. E., & Smith Slep, A. M. (2001). The hazards of predicting divorce without crossvalidation. *Journal of Marriage and Family*, *63*(2), 473–479. https://doi.org/10.1111/j.1741-3737.2001.00473.x

Janitza, S., & Hornung, R. (2018). On the overestimation of random forest's out-of-bag error. *PLoS ONE*, *13*(8), e0201904. https://doi.org/10.1371/journal.pone.0201904

Joel, S., Eastwick, P. W., Allison, C. J., Arriaga, X. B., Baker, Z. G., Bar-Kalifa, E., Bergeron, S., Birnbaum, G., Brock, R. L., Brumbaugh, C. C., Carmichael, C. L., Chen, S., Clarke, J., Cobb, R. J., Coolsen, M. K., Davis, J., Jong, D. C., De, Debrot, A., DeHaas, E. C., & Wolf, S. (2020). Machine learning uncovers the most robust self-report predictors of relationship quality across 43 longitudinal couples studies. *Proceedings of the National Academy of Sciences of the United States of America*, *117*(32), 19061–19071. https://doi.org/10.1073/pnas.1917036117

Joel, S., Eastwick, P. W., & Finkel, E. J. (2017). Is romantic desire predictable? Machine learning applied to initial romantic attraction. *Psychological Science*, *28*(10), 1478–1489. https://doi.org/10.1177/0956797617714580

Labrecque, L. T., & Whisman, M. A. (2017). Attitudes toward and prevalence of extramarital sex and descriptions of extramarital partners in the 21st century. *Journal of Family Psychology*, *31*(7), 952–957. https://doi.org/10.1037/fam0000280

Lawrance, K., & Byers, E. S. (1992). Development of the interpersonal exchange model of sexual satisfaction in long-term relationships. *The Canadian Journal of Human Sexuality*, *1*(2), 123–128. https://doi.org/10.1111/j.1475-6811.1995.tb00092.x

Lefkowitz, E. S., Shearer, C. L., Gillen, M. M., & Espinosa-Hernandez, G. (2014). How gendered attitudes relate to women's and men's sexual behaviors and beliefs. *Sexuality & Culture*, *18*(4), 833–846. https://doi.org/10.1007/s12119-014-9225-6

Liu, C. (2000). A theory of marital sexual life. *Journal of Marriage and Family*, *62*(2), 363–374. https://doi.org/10.1111/j.1741-3737.2000.00363.x

Lundberg, S. M., Allen, P. G., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. *Neural Information Processing Systems*. https://github.com/slundberg/shap

Lundberg, S. M., Erion, G., Chen, H., DeGrave, A., Prutkin, J. M., Nair, B., Katz, R., Himmelfarb, J., Bansal, N., & Lee, S. I. (2020). From local explanations to global understanding with explainable AI for trees. *Nature Machine Intelligence*, *2*(1), 56–67. https://doi.org/10.1038/s42256-019-0138-9

Lundberg, S. M., Erion, G. G., & Lee, S.-I. (2019). *Consistent individualized feature attribution for tree ensembles*. http://github.com/slundberg/shap

Mark, K. P., & Haus, K. R. (2019). Extradyadic relations. In A. C. Michalos (Ed.), *Encyclopedia of quality of life and well-being research* (pp. 2102–2105). Springer.

Mark, K. P., Janssen, E., & Milhausen, R. R. (2011). Infidelity in heterosexual couples: Demographic, interpersonal, and personality-related predictors of extradyadic sex. *Archives of Sexual Behavior*, *40*(5), 971–982. https://doi.org/10.1007/s10508-011-9771-z

Martins, A., Pereira, M., Andrade, R., Dattilio, F. M., Narciso, I., & Canavarro, M. C. (2016). Infidelity in dating relationships: Gender-specific correlates of face-to-face and online extradyadic involvement. *Archives of Sexual Behavior*, *45*(1), 193–205. https://doi.org/10.1007/s10508-015-0576-3

Matthews, B. W. (1975). Comparison of the predicted and observed secondary structure of T4 phage lysozyme. *Biochimica et Biophysica Acta (BBA) - Protein Structure*, *405*(2), 442–451. https://doi.org/10.1016/0005-2795(75)90109-9

Mattingly, B. A., Wilson, K., Clark, E. M., Bequette, A. W., & Weidler, D. J. (2010). Foggy faithfulness: Relationship quality, religiosity, and the perceptions of dating infidelity scale in an adult sample. *Journal of Family Issues*, *31*(11), 1465–1480. https://doi.org/10.1177/0192513X10362348

McDaniel, B. T., Drouin, M., & Cravens, J. D. (2017). Do you have anything to hide? Infidelity-related behaviors on social media sites and marital satisfaction. *Computers in Human Behavior*, *66*, 88–95. https://doi.org/10.1016/j.chb.2016.09.031

Mitchell, M. W. (2011). Bias of the random forest out-of-bag (OOB) error for certain input parameters. *Open Journal of Statistics*, *1*(3), 205–211. https://doi.org/10.4236/ojs.2011.13024

Olson, M. M., Russell, C. S., Higgins-Kessler, M., & Miller, R. B. (2002). Emotional processes following disclosure of an extramarital affair. *Journal of Marital and Family Therapy*, *28*(4), 423–434. https://doi.org/10.1111/j.1752-0606.2002.tb00367.x

Owen, J., Rhoades, G. K., & Stanley, S. M. (2013). Sliding versus deciding in relationships: Associations with relationship quality, commitment, and infidelity. *Journal of Couple & Relationship Therapy*, *12*(2), 135–149. https://doi.org/10.1080/15332691.2013.779097

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, É. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, *12*, 2825–2830. http://scikit-learn.org

Perel, E. (2017). *The state of affairs: Rethinking infidelity - A book for anyone who has ever loved*. Hachette.

Petersen, J. L., & Hyde, J. S. (2010). A meta-analytic review of research on gender differences in dexuality, 1993–2007. *Psychological Bulletin*, *136* (1), 21–38. https://doi.org/10.1037/a0017504

Probst, P., Wright, M. N., & Boulesteix, A. (2019). Hyperparameters and tuning strategies for random forest. *Wiley Interdisciplinary Reviews. Data Mining and Knowledge Discovery*, *9*(3), e1301. https://doi.org/10.1002/widm.1301

Rubin, Z. (1970). Measurement of romantic love. *Journal of Personality and Social Psychology*, *16*(2), 265–273. https://doi.org/10.1037/h0029841

Selterman, D., Garcia, J. R., & Tsapelas, I. (2019). Motivations for extradyadic infidelity revisited. *Journal of Sex Research*, *56*(3), 273–286. https://doi.org/10.1080/00224499.2017.1393494

Shapley, L. S. (1952). *A value for n-person games*. RAND Corporation.

Spector, I. P. I. P., Carey, M. P. M. P., & Steinberg, L. (1996). The sexual desire inventory: Development, factor structure, and evidence of reliability. *Journal of Sex & Marital Therapy*, *22*(3), 175–190. https://doi.org/10.1080/00926239608414655

Thompson, A. E., & O'Sullivan, L. F. (2016). Drawing the line: The development of a comprehensive assessment of infidelity judgments. *Journal of Sex Research*, *53* (8), 910–926. https://doi.org/10.1080/00224499.2015.1062840

Treas, J., & Giesen, D. (2000). Sexual infidelity among married and cohabiting Americans. *Journal of Marriage and Family*, *62*(1), 48–60. https://doi.org/10.1111/j.1741-3737.2000.00048.x

Wei, M., Russell, D. W., Mallinckrodt, B., & Vogel, D. L. (2007). The Experiences in Close Relationship scale (ECR)-short form: Reliability, validity, and factor structure. *Journal of Personality Assessment*, *88*(2), 187–204. https://doi.org/10.1080/00223890701268041

Yarkoni, T., & Westfall, J. (2017). Choosing prediction over explanation in psychology: Lessons from machine learning. *Perspectives on Psychological Science*, *12*(6), 1100–1122. https://doi.org/10.1177/1745691617693393

Yousefi, N., Farsani, K., Shakiba, A., Hemmati, S., & Nabavi Hesar, J. (2014). Halbert Index of Sexual Desire (HISD) questionnaire validation. *Scientific Journal of Clinical Psychology & Personality*, *2*(9), 107–118.