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# The Predictive Validity of Intimate Partner Violence Warning Signs

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**Abstract**

Intimate partner violence (IPV) is harmful and prevalent, but leaving abusive partners is often challenging due to investments (e.g., children, shared memories). Identifying warning signs of abuse early on is one prevention strategy to help people avoid abusive long-term relationships. Using university and online samples, the present studies identified warning signs and protective factors that predicted overall, physical, psychological, and sexual abuse cross-sectionally (Study 1) and prospectively over 6 months (Study 2). These studies demonstrated that the number of warning signs a person experienced and the frequency with which they experienced those warning signs predicted overall abuse. Seven warning signs emerged as predictors in both studies (e.g., "My partner acted arrogant or entitled"), suggesting that they are particularly important for identifying potentially abusive relationships. This is the first research to identify warning signs that prospectively predict abuse; findings have implications for IPV prevention efforts in academic and public contexts.

**Keywords**

intimate partner violence, domestic violence, warning signs, red flags, predicting abuse

Intimate partner violence (IPV)—physical, psychological, or sexual violence committed by individuals toward their romantic partners—is prevalent and often leads to serious physical and psychological health consequences (Black et al., 2011; Campbell et al., 2002; Capaldi et al., 2012). Unfortunately, there is a dearth of research on indicators that reliably precede and predict the onset of abuse in developing relationships, which could help people avoid violent relationships. In the present studies, we seek to identify prospectively predictive warning signs of abuse that can inform future research and public interventions to prevent IPV.

## Leaving Is Not Easy

"Why did you stay?" is a frequently heard and dreaded question asked of abuse victims, as many people do not understand the difficulty of leaving a violent relationship. Researchers have identified many reasons why people do not leave their abusers, including having no alternative means of economic support, concern for children, and lack of social support (World Health Organization [WHO], 2012). Crucially, survivors are often invested in their relationships by the time violence occurs. Based on interdependence theory (Kelley & Thibaut, 1978), the investment model (Rusbult, 1980) posits that relationship satisfaction, quality of alternatives (e.g., other partners, being single), and investments (e.g., children, shared memories) contribute to people's commitment to their relationships. This model can help explain why people stay in dissatisfying relationships: they may lack alternatives or have too many investments. Taken a step further, the investment model can help us understand why people stay with abusers. Although IPV decreases relationship satisfaction (Rhatigan & Street, 2005; Rusbult & Martz, 1995; Yoon & Lawrence, 2013), many of the barriers described above can be considered investments (e.g., children) or lack of alternatives (e.g., no social support), which can lead to dissatisfied people staying with abusers. Supporting this, Rusbult and Martz (1995) found that abused women at a shelter reported stronger relationship commitment when they had poorer alternatives and greater investments. Furthermore, women were more likely to return to their abusers if they were more committed. Ultimately, these difficulties demonstrate that more efforts are needed to help people avoid investing in what may become a violent relationship. Helping people evade violence before it occurs by identifying warning signs could therefore be more efficient than helping people overcome barriers and investments, so that they can leave after violence has begun.

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## Warning Signs of IPV

Identifying warning signs of violence, or red flags, is a promising avenue for helping people avoid abusive relationships. These thoughts, feelings, and behaviors occur early in relationships and may precede violence (Murphy & Smith, 2010). Jealousy, checking on whereabouts, and using extreme charm are examples of warning signs (Murphy et al., 2012; Short et al., 2000). Survivors and researchers have indicated that information about warning signs may be helpful for keeping people out of future abusive relationships (Hughes & Rasmussen, 2010; Short & McMahon, 2008). Furthermore, the dyadic slippery slope model (Murphy et al., 2012) proposes that seemingly innocuous behaviors, such as warning signs, may be precursors to serious abuse, and research in related fields (i.e., criminal risk assessments) suggests that observations of nonviolent behaviors (e.g., seeking to be the center of attention) can predict future violence and other forms of misconduct (Hausam et al., 2018).

Previously, researchers identified warning signs by interviewing survivors or asking individuals to describe potentially harmful relationship behaviors. Similar warning signs tend to emerge among people from different backgrounds and across different studies (e.g., Murphy et al., 2012; Short et al., 2000). However, despite empirical progress, the current warning signs literature has some key drawbacks. Although it is generally assumed that warning signs covary with experiences of violence, no research to our knowledge has quantitatively tested this association. More importantly, no longitudinal research on IPV warning signs exists: the extent to which red flags actually predict future violence is unknown. Finally, scholars have noted that identifying warning signs is difficult because some behaviors may not be problematic if occurring in isolation or rarely, but that the intensity, frequency, or "constellation" of warning signs may be what is associated with violence (Kearney & O'Brien, 2021; Short et al., 2000). Thus, whether violence is associated with different numbers of warning signs and the frequency with which they appear should be investigated.

## The Current Study

We conducted a series of studies to identify warning signs of IPV: thoughts, feelings, or behaviors that positively predict abuse, but are not themselves abusive. What indicators of future abuse can people observe and identify early on in their relationships before barriers to leaving become difficult to overcome? Given the diversity of ways in which warning signs have previously been identified, we strove for a data-driven and bottom-up approach with the present research. We first conducted two pilot studies (see Supplemental Materials) to differentiate abusive and nonabusive (i.e., potential warning signs) behaviors, as well as estimate when these behaviors first occur. We then used machine learning to detect warning signs that predict IPV cross-sectionally (Study 1) and over time (Study 2).

## Hypotheses

We hypothesized that we would identify warning signs that predicted overall abuse (i.e., an aggregate of all types of abuse), physical abuse, psychological abuse, and sexual abuse (H1–H4). Based on research about warning signs in isolation or "constellation" (Kearney & O'Brien, 2021; Short et al., 2000), we also predicted that the number of different warning signs people experience (H5), and the frequency with which they experience them (H6) would predict overall abuse. In addition, we explored the robustness of the overall abuse model against overfitting via cross-validation (E1) and determined the extent to which warning signs predicted abuse above and beyond earlier experiences of violence (E2).

## Pilot Studies

We conducted two pilot studies to develop the list of abusive behaviors and potential warning signs used in this research (see Supplemental Materials).

# Study 1

The goal of Study 1 was to identify warning signs of overall, physical, psychological, and sexual IPV using random forests analyses in a cross-sectional sample. We also sought to determine whether the number and frequency of warning signs a person experienced predicted overall abuse. Study 1 was pre-registered at https://osf.io/4vb8e; pre-registration deviations, materials, code, and de-identified data can be viewed at https://osf.io/48hwn/.

### Method

*Participants.* One hundred fifty-seven individuals were recruited from Prolific in February 2021. Inclusion criteria included residing within the United States or Canada (see https://osf.io/4vb8e for all criteria). Participants were told the study was about early events in individuals' dating lives, that they would be asked to recall when certain experiences occurred, and that some questions would inquire about abusive behaviors. Participants were compensated £3.35. The final sample was 147 participants because 10 failed to meet inclusion criteria. Table 1 displays demographic information. Sample size was determined by budget.

Clear rules for determining sample size in random forests using regression trees have yet to be established. Our key random forests model included 17 features predicting a continuous outcome variable. Thus, we conducted a power analysis based on the equivalent linear regression model using the WebPower package in R (Zhang et al., 2022). The obtained sample size of 147 participants has 97% power to

**Table 1.** *Demographic Information for Studies 1 and 2*

| Demographics | Study 1 (*N* = 147) | | Study 2, Time 1 (*N* = 355) | |
|---|---|---|---|---|
| | *M* (*SD*) | | *M* (*SD*) | |
| Age in years | 24.48 (6.75) | | 21.98 (3.90) | |
| Partner age in years | 25.03 (6.67) | | 22.55 (4.33) | |
| Relationship length in months | 6.25 (2.83) | | 3.71 (1.40) | |
| | *N* | % | *N* | % |
| Gender | | | | |
| Women | 85 | 57.82 | 264 | 74.37 |
| Men | 57 | 38.78 | 90 | 25.35 |
| Identified otherwise | 5 | 3.40 | 1 | 0.28 |
| Partner gender | | | | |
| Women | 66 | 44.90 | 98 | 27.61 |
| Men | 77 | 52.38 | 256 | 72.11 |
| Identified otherwise | 4 | 2.72 | 1 | 0.28 |
| Ethno-racial background | | | | |
| Asian | 23 | 15.65 | 110 | 30.99 |
| Black | 11 | 7.48 | 4 | 1.13 |
| East Indian | 0 | 0.00 | 20 | 5.63 |
| Hispanic | 5 | 3.40 | 8 | 2.25 |
| Indigenous | 1 | 0.68 | 0 | 0.00 |
| Middle Eastern | 1 | 0.68 | 11 | 3.10 |
| Multiple identities | 23 | 15.65 | 21 | 5.92 |
| White | 83 | 56.46 | 167 | 47.04 |
| Identified otherwise | 0 | 0.00 | 13 | 3.66 |
| Partner ethno-racial background | | | | |
| Asian | 21 | 14.29 | 88 | 24.79 |
| Black | 9 | 6.12 | 9 | 2.54 |
| East Indian | 0 | 0.00 | 21 | 5.92 |
| Hispanic | 4 | 2.72 | 9 | 2.54 |
| Indigenous | 1 | 0.68 | 0 | 0.00 |
| Middle Eastern | 0 | 0.00 | 15 | 4.23 |
| Multiple identities | 36 | 24.49 | 15 | 4.23 |
| White | 76 | 51.70 | 185 | 52.11 |
| Identified otherwise | 0 | 0.00 | 12 | 3.38 |

detect a predictor with a small effect size ($f^2$ = .10) in a linear regression model with 16 other predictors.

*Materials and Procedure.* We presented a list of 200 abusive and non-abusive thoughts, feelings, and behaviors to participants. To develop these items, we reviewed relevant peer-reviewed literature on IPV and warning signs (e.g., Short et al., 2000), warning signs scales (e.g., Murphy et al., 2012), and public informational websites about warning signs (e.g., Rape, Abuse & Incest National Network [RAINN], 2017). When this search was saturated (i.e., we could no longer find new warning signs), we created a list of 309 abusive behaviors, likely warning signs, and neutral behaviors based on the review. Details of this process are provided here https://osf.io/t7pvy. Then, we conducted Pilot studies (see Supplemental Materials) to determine which behaviors should be considered abusive versus non-abusive (Pilot 1) and most likely to emerge in early stages of romantic relationships (Pilot 2). Resulting items included physically, sexually, and psychologically abusive behaviors committed by the partner, as well as potential warning signs. Behaviors are referred to as "potential" warning signs unless they are shown to predict abuse in the random forests analyses.

Participants indicated how frequently each item had occurred since they had started dating their partner (1 = *Never*, 4 = *Sometimes*, 7 = *Frequently*). Participants who practiced BDSM (bondage, discipline/dominance, and submission/sadomasochism) were asked to report on only non-consensual behaviors. Eight items were inappropriate for the Likert-type scale (e.g., "My partner and I moved in together"), so participants responded to these by checking a box (1 = yes, 0 = no). Individual potential warning signs were used as predictors, and aggregate abuse variables were created and used as outcomes in random forests analyses.

We determined that 86.39% of the sample ($n$ = 127) experienced at least one instance of abuse (i.e., responded with anything other than "never" to at least one abuse item), but the mean frequency with which participants experienced abuse was low. All abuse variables had skewness levels above 2, and two had kurtosis levels above 7, indicative of a skewed distribution (West et al., 1995). Table 2 displays descriptive statistics.

*Data Analytic Strategy.* Random forests, a nonparametric machine learning technique (Breiman, 2001), is capable of identifying key variables from a large number of predictors, even with low sample sizes and non-normal outcome distributions. The random forests procedure involves training a model on a "forest" of decision trees made of many different samples of the data and predictors to generate a set of forecasts (i.e., predicted values; Breiman, 2001).

All analyses were conducted in R 4.1.1 (R Core Team, 2021). We conducted four random forests analyses using the randomForest package (Liaw & Wiener, 2018) to establish which individual warning signs predicted aggregate physical, sexual, psychological, and overall abuse variables. We used regression trees because outcome variables were continuous. Each model was constructed from 5,000 trees, each built on a different bootstrapped sample of two thirds of the data set (with replacement). One third of the total number of predictors was randomly sampled at each split. Prior to conducting each random forests analysis, 149 potential warning signs were entered into VSURF (Genuer et al., 2019), a package that eliminates variables that fail to reduce each model's error rate. Notably, VSURF can identify variables at either liberal, moderate, or stringent cutoffs (Genuer et al., 2015, 2019); we retained variables that reached the moderate (i.e., "interpretation") cutoff. Using variable selection is preferable to running random forests with all possible variables, as some predictors may not add to the model's predictive strength, and variable selection ensures those are not included, which simplifies interpretation.

**Table 2.** *Descriptive Statistics for Abuse Variables for Studies 1 and 2*

| Type of Abuse | *N* | *M* | *SD* | *Skewness* | *Kurtosis* |
|---|---|---|---|---|---|
| Overall abuse | | | | | |
| Study 1 | 147 | 1.28 | 0.38 | 2.46 | 6.90 |
| Study 2 | | | | | |
| Time 1 | 354 | 1.38 | 0.47 | 2.64 | 9.12 |
| Time 2 | 355 | 1.36 | 0.47 | 2.86 | 11.36 |
| Physical abuse | | | | | |
| Study 1 | 147 | 1.14 | 0.36 | 5.14 | 36.35 |
| Study 2 | | | | | |
| Time 1 | 354 | 1.16 | 0.37 | 4.02 | 21.07 |
| Time 2 | 355 | 1.15 | 0.37 | 4.61 | 27.72 |
| Psychological abuse | | | | | |
| Study 1 | 147 | 1.37 | 0.48 | 2.19 | 5.26 |
| Study 2 | | | | | |
| Time 1 | 354 | 1.55 | 0.66 | 2.10 | 5.02 |
| Time 2 | 355 | 1.50 | 0.63 | 2.14 | 5.42 |
| Sexual abuse | | | | | |
| Study 1 | 147 | 1.26 | 0.49 | 3.28 | 12.54 |
| Study 2 | | | | | |
| Time 1 | 354 | 1.29 | 0.50 | 2.90 | 10.08 |
| Time 2 | 355 | 1.31 | 0.52 | 2.92 | 10.43 |

*Note.* The scale ranged from 1 = *Never* to 4 = *Sometimes* to 7 = *Frequently.* Sample sizes are different between time points in Study 2 because one participant skipped abuse items at Time 1 but not Time 2.

*Accounting for Non–Normal Dependent Variables.* Random forests are, in principle, robust against non-normality (Berk, 2010). However, given the skewed distributions of the dependent variables (see Table 2), we probed this assumption by creating four baseline models with random forests. Specifically, we used the grand mean of each form of abuse to predict the same form of abuse (e.g., the grand mean of physical abuse predicting physical abuse). Variance explained by the models ranged from −1.38% for psychological abuse to −1.33% for physical abuse. This absence of an effect indicates that the non-normal distributions of the dependent variables were not responsible for any of the variance predicted in the pre-registered models.

## Results and Discussion

*Predicting Overall Abuse.* Analyses revealed that 17 predictors accounted for 60.89% of the variance in overall abuse, $MSE = 0.06$, providing support for the first hypothesis (H1) that we would identify warning signs of overall abuse. We examined the relative importance of each individual predictor as indicated by the %IncMSE (i.e., percentage increase in mean squared error; see Figure 1). The %IncMSE score represents the percentage by which the model's mean squared error increases when the variable's values are randomly shuffled (note that these values cannot be meaningfully compared across models). A higher mean squared error indicates poorer model fit. Thus, if randomly shuffling a variable increases this value, that suggests that the model would be less predictive without the variable. Higher %IncMSE values indicate greater importance (i.e., a larger contribution to the model's overall performance).

As the random forests technique is nonparametric, the contribution of each variable within the model may or may not be linear. However, we examined correlations between each predictor and overall abuse to determine which variables were likely functioning as warning signs (i.e., positive correlates) versus protective factors (i.e., negative correlates). One predictor was a protective factor ("My partner valued my abilities and opinions"), whereas the remaining 16 variables were warning signs.

*Predicting Physical, Psychological, and Sexual Abuse.* We conducted additional random forests models to determine predictors of physical, psychological, and sexual abuse. After VSURF's variable selection process, two variables accounted for 31.75% of the variance in physical abuse, $MSE = 0.09$; 11 variables accounted for 73.06% of the variance in psychological abuse, $MSE = 0.06$; and seven variables accounted for 47.42% of the variance in sexual abuse, $MSE = 0.12$. These findings support Hypotheses 2–4 asserting that we would identify warning signs for each type of abuse. We examined the relative importance of each predictor, as well as each predictor's correlation with the corresponding abuse variable. We identified one protective factor for psychological abuse, one protective factor for sexual abuse, and no protective factors for physical abuse. See Figures S1–S4 in the Supplemental Materials for the predictors of each type of abuse, their importance, and correlation statistics.

*Cross-Validation.* In principle, random forests analyses are robust against overfitting because they test each tree on a subset of data not used to fit that tree. However, one can directly verify this by manually training the model on one sample and testing it on another. This process, called cross-validation, tests the true predictive power of the model by predicting values not used to build the model. Cross-validation therefore provides a more accurate estimate of out-of-sample performance (Yarkoni & Westfall, 2017).

For the present study, we explored the robustness of the model predicting overall abuse (E1) by randomly splitting the data into training ($N = 73$) and testing data ($N = 74$). VSURF identified eight predictors in the training data. We used the training data to build a random forests model that predicted overall abuse using those eight predictors. Next, we fed the predictor variables from the testing data into the algorithm to generate predicted abuse values. Note that the model did not have access to the real abuse scores from the testing data: it estimated the values solely by plugging the predictor variables into the model built with the training data. Predicted abuse values were then compared with the actual reported abuse values in the testing data to determine how well the model was able to predict abuse. Results showed that 40.48% of the variance in the testing data could

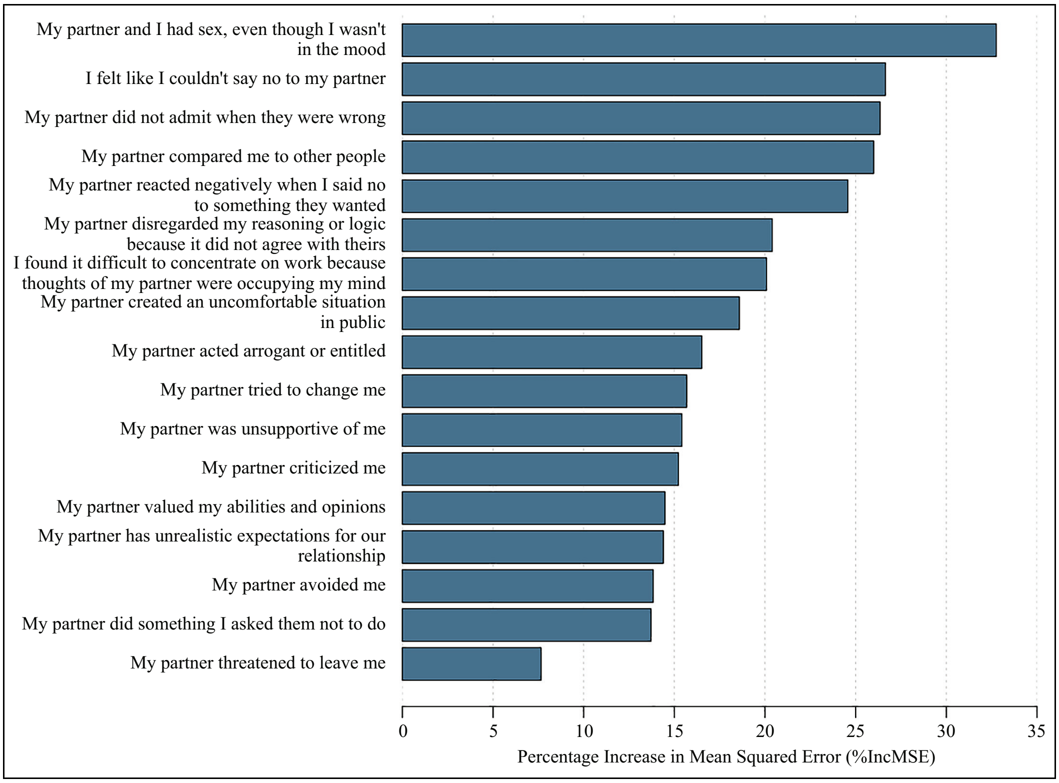


**Figure 1.** *Importance of Predictors of Overall Abuse in Study 1*
*Note.* Variables with higher %IncMSE are more important to the model because randomly shuffling their values causes a higher increase in mean squared error, which is indicative of poorer model fit.

be explained by the model generated with the training data, $MSE = 0.10$. This demonstrates that the model is robust against overfitting, as it can predict a substantial proportion of variance in abuse (40.48%) using untouched data.

*Number and Frequency of Warning Signs.* We hypothesized (H5) that the number of warning signs experienced would predict overall abuse. Using the 16 previously identified warning signs, we created a standardized count variable representing the number of warning signs each participant experienced (95% of participants experienced at least one warning sign). We used this to predict overall abuse in a linear regression, and found a moderately sized effect, $\beta = 0.28$, $t(145) = 12.70$, $p < .001$, 95% CI (0.23, 0.32). We also hypothesized (H6) that the frequency with which people experienced warning signs would predict overall abuse. We created a standardized mean representing the frequency with which people experienced warning signs and used this as a predictor in a linear regression, with overall abuse as the outcome. We found a moderately sized effect, $\beta = 0.32$, $t(145) = 17.84$, $p < .001$, 95% CI (0.28, 0.35). Given the non-normal distributions of the dependent variable, we also conducted log transformations on overall abuse, which did not change the patterns of results.

## Study 2

In Study 1, we cross-sectionally identified warning signs associated with overall, physical, psychological, and sexual abuse, and showed that the number of warning signs a person experienced and the frequency with which they experienced those signs predicted overall abuse. In Study 2, we sought to replicate and extend Study 1 by identifying warning signs that prospectively predicted violence 6 months later. We also examined whether the number of warning signs a person experienced, and the frequency with which they experienced them, would predict overall abuse 6 months later. Study 2 was pre-registered at https://osf.io/6389b; pre-registration deviations, materials, code, and de-identified data can be viewed at https://osf.io/dctzw/. Some pre-registered hypotheses are presented in the Supplemental Materials.

### Method

*Participants.* Recruitment took place between May 2020 and July 2021. Most participants were recruited from the University of Western Ontario's Mass Email Recruitment listserv (95%), although some were recruited from social media (1%) and Prolific (4%). Participants were told the study was about individuals' early dating lives, that some questions would inquire about abuse, and that they would be asked to recall past experiences. Participants met several inclusion criteria, including having been dating their partner for 6 months or less (see https://osf.io/6389b for all criteria). Prolific participants were compensated £8.50 per survey. All other participants were compensated with a $10 USD or $15 CAD gift card. Sample size was determined by budget.

Six hundred ninety-eight individuals submitted the first survey. Of those, 181 participants failed to meet inclusion criteria, and 162 participants experienced a breakup by the second wave and were excluded from the present analyses (see Supplemental Materials). The final sample included 355 participants. See Table 1 for demographic information. A power analysis conducted with WebPower in R (Zhang et al., 2022) suggests that this sample size has 99% power to detect a predictor with a small effect size ($f^2$ = .10) in a linear regression model with 11 other predictors.

## Materials and Procedure

*Time 1.* As in Study 1, participants were asked to indicate how frequently each of 200 abusive and non-abusive items had occurred within their romantic relationship since they started dating their partner (1 = *Never*, 4 = *Sometimes*, 7 = *Frequently*). Potential warning signs were used as predictors in random forests analyses.

*Time 2.* Six months later, participants were presented with 43 abusive behaviors and asked to indicate how frequently each behavior had occurred within the past 6 months. These items were used to calculate means for physical, psychological, sexual, and overall abuse, which were used as outcome variables in random forests analyses.

Although most participants (88.98%, $n$ = 315) experienced at least one instance of abuse (i.e., responded with anything other than "never" to at least one abuse item), the mean frequency with which participants experienced abuse was low at both time points (see Table 2). As described in Study 1, we created baseline models in Study 2 to determine whether the non-normal distributions affected our results, and we found no effects.

## Results and Discussion

*Predicting Overall, Physical, Psychological, and Sexual Abuse.* Random forests analyses were conducted using the same strategy described in Study 1. The model predicting overall abuse at Time 2 (T2) revealed that 12 variables accounted for 54.45% of the variance, $MSE$ = 0.10, supporting H1. The importance of each predictor was assessed via %IncMSE (see Figure 2). Further random forests analyses were conducted predicting physical, psychological, and sexual abuse at T2, respectively. Two predictors accounted for 22.86% of the variance in physical abuse, $MSE$ = 0.11; eight predictors accounted for 55.15% of the variance in psychological abuse, $MSE$ = 0.18; and 14 predictors accounted for 45.54% of the variance in sexual abuse, $MSE$ = 0.15; these findings provide support for the second, third, and fourth hypotheses. We examined correlations between each predictor and its respective outcome variable and no protective factors (i.e., positive correlations) were found. See Figures S5–S8 in the Supplemental Materials for the predictors of each type of abuse, their importance, and correlation statistics. Seven warning signs emerged in Study 2, which also appeared in Study 1; these are displayed in Table 3.

*Cross-Validation.* We used cross-validation to better estimate of out-of-sample performance for the model predicting overall abuse (E1). Data were randomly split into training ($N$ = 177) and testing ($N$ = 178) sets. VSURF identified eight predictors in the training set that were then used in the random forests analysis. We then ran this model on the test data to generate predicted scores for overall abuse, and we compared scores with the true overall abuse values in the test set. Results revealed that 45.42% of the variance in the testing data was explained by the model created with the training data, $MSE$ = 0.11. We did not use Study 2 data as the test sample for the Study 1 model because we wanted to determine whether different warning signs would emerge in a longitudinal rather than cross-sectional context.

*Hierarchical Model.* We next explored the extent to which the identified warning signs could predict abuse at T2 above and beyond the predictive power of abuse at Time 1 (T1; E2). To do this, we compared the results of a random forests analysis that included important abuse items from T1 as predictors to a model with both important abuse items and warning signs, and examined whether the second model accounted for more variance than the first. This method is analogous to the design of a hierarchical regression (see Joel et al., 2020 for a similar example). Specifically, we conducted a VSURF analysis using the 43 abusive behaviors at T1 as predictors and overall abuse at T2 as the outcome variable. VSURF identified four predictors (i.e., My partner . . . "treated me like I was stupid," "tried to manipulate or control me," "made me feel like I was crazy," and "did things that harmed my mental health") which were then entered into a random forests analysis predicting overall abuse at T2; results showed that these variables accounted for 52.70% of the variance in overall abuse, $MSE$ = 0.11. All predictors positively correlated with overall abuse at T2. We ran a second random forests analysis using these four variables and the 12 previously identified warning signs of abuse at T1 as predictors of overall abuse at T2. Analyses revealed that these 16 variables accounted for 58.72% of the variance in overall abuse at T2, $MSE$ = 0.09, which is 6.02% more variance accounted for compared with the abuse variables alone.

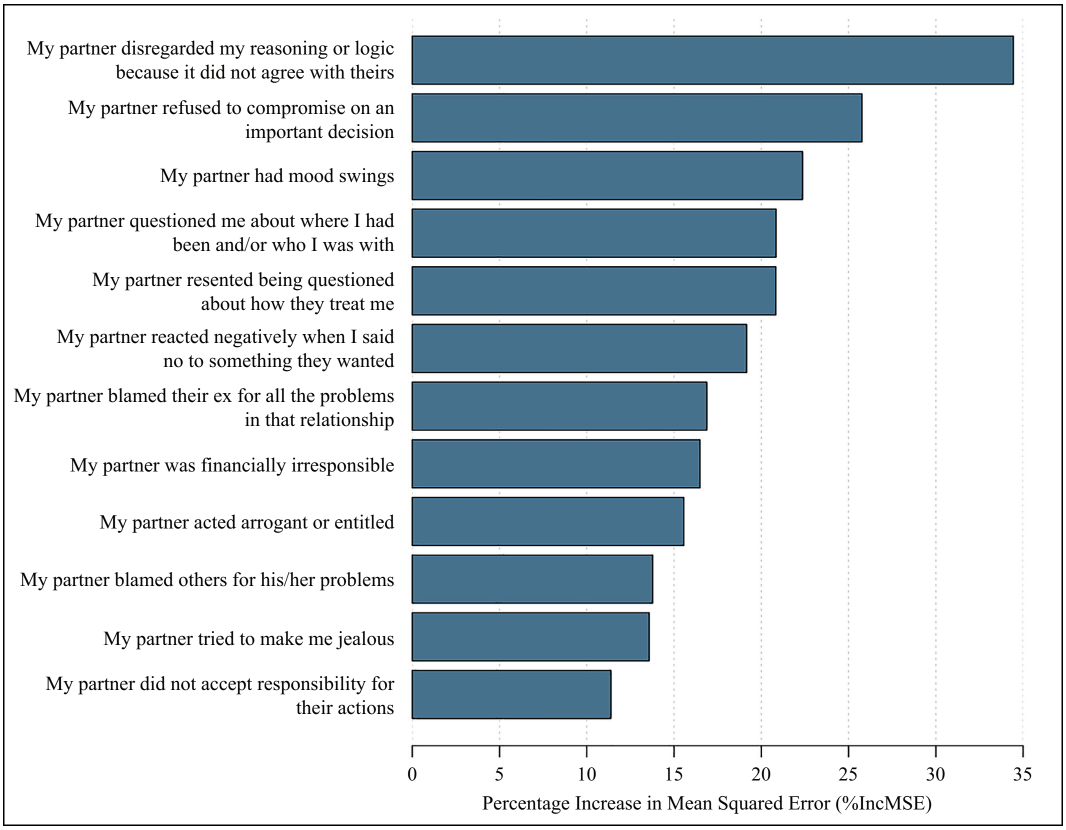


**Figure 2.** *Importance of Predictors of Overall Abuse in Study 2*
*Note.* Variables with higher %IncMSE are more important to the model because randomly shuffling their values causes a higher increase in mean squared error, which is indicative of poorer model fit.

**Table 3.** *Warning Signs That Predicted Abuse in Both Studies*

| Warning Signs That Predicted Abuse in Both Studies |
|---|
| My partner acted arrogant or entitled |
| My partner and I disagreed about something sexual |
| My partner and I had sex, even though I was not in the mood |
| My partner created an uncomfortable situation in public |
| My partner disregarded my reasoning or logic because it did not agree with theirs |
| My partner reacted negatively when I said no to something they wanted |
| My partner resented being questioned about how they treat me |

*Note.* Warning signs are not presented in any particular order.

These findings suggest that abusive behaviors are the strongest predictors of future abuse, but, to a limited extent, warning signs can indeed predict abuse above and beyond prior experiences of violence.

*Number and Frequency of Warning Signs.* We conducted a linear regression with a standardized count of the number of the 12 previously identified warning signs a person experienced at T1 (91% of participants experienced at least one warning sign) predicting overall abuse at T2, and found a moderately sized effect, $\beta = 0.28$, $t(353) = 14.00$, $p < .001$, 95% CI (0.24, 0.32). Then, we conducted another linear regression model with the standardized mean frequency with which a person experienced warning signs at T1 predicting overall abuse at T2; results revealed another moderately sized effect, $\beta = 0.35$, $t(352) = 20.59$, $p < .001$, 95% CI (0.32, 0.38). Patterns of results did not change if overall abuse was log transformed. Thus, Hypotheses 5 and 6 were supported. In addition, although not pre-registered, we conducted these analyses controlling for overall abuse at T1. Both predictors remained significant, indicating that the number and frequency of warning signs a person experiences are associated with increases in abuse over time.

## General Discussion

These methodologically innovative studies are the first to identify warning signs that, although not abusive themselves, cross-sectionally and prospectively predict abuse.

Study 1 identified warning signs and protective factors accounting for 60.89%, 31.75%, 73.06%, and 47.42% of the variance in overall, physical, psychological, and sexual abuse, respectively. Similarly, Study 2 identified warning signs that prospectively predicted overall, physical, psychological, and sexual abuse occurring 6 months later, explaining 54.45%, 22.86%, 55.15%, and 45.54% of the variance, respectively. Seven warning signs emerged in both studies that are likely especially important for predicting abuse. Finally, both studies indicated that the number of warning signs a person experiences, and the frequency with which they experience them, predict future violence.

Importantly, these red flags accounted for meaningful portions of variance in abuse. For comparison, an analytically similar study using 43 dyadic longitudinal data sets from 29 laboratories found that actor-reported relationship variables (e.g., relationship length, trust) accounted for 45% of the variance in relationship satisfaction and actor-reported individual variables (e.g., age, personality) accounted for 19% of the variance (Joel et al., 2020). Thus, the warning signs in the present research are roughly as good at predicting violence as variables like relationship length and trust are at predicting relationship satisfaction, and are better at predicting violence than variables like age and personality are at predicting relationship satisfaction.

The warning signs identified here can provide support for theories and models of IPV. Our findings show that relatively innocuous behaviors (i.e., warning signs) can predict future violent behaviors, which aligns with the dyadic slippery slope model (Murphy et al., 2012). Furthermore, certain warning signs, such as "My partner tried to change me," hint at the presence of one partner attempting to control the other; this finding aligns with power and feminist theories of violence suggesting that power and gender dynamics underlie violence (Dardis et al., 2015). "My partner acted arrogant or entitled" also emerged as a predictor, consistent with personality theories of violence arguing that perpetrators typically have certain personality traits (Dardis et al., 2015). Demonstrating that items associated with different theories are predictive of abuse provides support for the integration of IPV theories ("theory knitting"), as this aligns with the notion that no single theory has yet been shown to fully explain all instances of IPV (Bell & Naugle, 2008; Dardis et al., 2015). Gaining a deeper understanding of the intersections between warning signs and different IPV theories would further illuminate the value of predictors of abuse.

## Limitations and Future Directions

This research has several limitations. First, both studies took place during the COVID-19 pandemic, which may have affected the types and amount of warning signs and abuse experienced. Second, although difficult to determine, some participants may have inaccurately responded to the abuse items, possibly to protect their partners or because of selective memory issues. Third, both samples are not representative of the general population and are limited by their low proportions of men, people of color, and gender diverse individuals. Future research should explore whether unique warning signs exist for those from marginalized backgrounds, especially because people from these groups are at an elevated risk of violence (Capaldi et al., 2012). Fourth, Study 1 was cross-sectional, and similar levels of abuse were happening at both time points in Study 2. Thus, the warning signs identified here are limited in their prospective predictive validity because they were conflated with abuse. Despite this unanticipated effect, our findings are still informative because they identify non-abusive behaviors that on average precede abuse (see Pilot 2 in the Supplementary Materials), are associated with abuse (Study 1), and predict abuse 6 months later (Study 2). Finally, abuse frequency in both studies was relatively low, suggesting that these warning signs may be more indicative of situational couple violence (SCV), which is less severe, frequent, and controlling, opposed to coercive controlling violence (CCV), which is more frequent, severe, one-sided, and typically perpetrated by men (Johnson, 1995, 2010; Kelly & Johnson, 2008). Researchers should make extra efforts to study CCV, such as by recruiting from high-risk populations, and determine the extent to which warning signs of CCV and SCV differ.

## Violence Prevention Efforts

Considering the difficulties of leaving abusers (e.g., high investment; Rusbult & Martz, 1995), researchers and intervention developers can build upon the present findings to help (potential) survivors avoid violent relationships. Given that both warning signs and abuse can start appearing within the first few months of relationships (see Pilot 2), interventions should be directed toward people who are single or newly dating to make responding to concerning behaviors as easy as possible. Interventions should help motivate and equip people to look for and address warning signs in their own relationships (Fisher & Fisher, 2002), and also recognize that this can be challenging because people often wear "rose-tinted glasses." Therefore, prevention efforts should also include information for informal (e.g., friends, family members) and formal (e.g., teachers, medical professionals) supports, so that third parties can look for warning signs in others' relationships and provide support or direct people to resources as needed. Ultimately, by combining knowledge of warning signs with the ability and incentive to respond to them, individuals and those around them will have the best possible chance of preventing relationship violence.

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## Supplemental Material

Supplemental material for this article is available online.

## References

Bell, K. M., & Naugle, A. E. (2008). Intimate partner violence theoretical considerations: Moving towards a contextual framework. *Clinical Psychology Review*, *28*(7), 1096–1107. https://doi.org/10.1016/j.cpr.2008.03.003

Berk, R. (2010). An introduction to statistical learning from a regression perspective. In A. Piquero, & D. Weisburd (Eds.), *Handbook of quantitative criminology* (pp. 725–740). Springer. https://doi.org/10.1007/978-0-387-77650-7_34

Black, M. C., Basile, K. C., Breiding, M. J., Smith, S. G., Walters, M. L., Merrick, M. T., Chen, J., & Stevens, M. R. (2011). *The National Intimate Partner and sexual violence survey (NISVS): 2010 summary report*. National Center for Injury Prevention and Control, Centers for Disease Control and Prevention. https://www.cdc.gov/violenceprevention/pdf/nisvs_report2010-a.pdf

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

Campbell, J., Jones, A. S., Dienemann, J., Kub, J., Schollenberger, J., O'Campo, P., Gielen, A. C., & Wynne, C. (2002). Intimate partner violence and physical health consequences. *Archives of Internal Medicine*, *162*(10), 1157–1163. https://doi.org/10.1001/archinte.162.10.1157

Capaldi, D. M., Knoble, N. B., Shortt, J. W., & Kim, H. K. (2012). A systematic review of risk factors for intimate partner violence. *Partner Abuse*, *3*, 231–280. https://doi.org/10.1891/1946-6560.3.2.231

Dardis, C. M., Dixon, K. J., Edwards, K. M., & Turchik, J. A. (2015). An examination of the factors related to dating violence perpetration among young men and women and associated theoretical explanations: A review of the literature. *Trauma, Violence, & Abuse*, *16*, 136–152. https://doi.org/10.1177/1524838013517559

Fisher, J. D., & Fisher, W. A. (2002). The information-motivation-behavioral skills model. In R. J. DiClemente, R. Crosby, & M. C. Kegler (Eds.), *Emerging theories in health promotion practice and research: Strategies for improving public health* (pp. 40–70). John Wiley & Sons.

Genuer, R., Poggi, J., & Tuleau-Malot, C. (2019). *VSURF: Variable selection using random forests* (Version 1.1.0) [Computer software]. https://cran.r-project.org/web/packages/VSURF/index.html

Genuer, R., Poggi, J. M., & Tuleau-Malot, C. (2015). VSURF: An R package for variable selection using random forests. *The R Journal*, *7*(2), 19–33. https://doi.org/10.32614/RJ-2015-018

Hausam, J., Lehmann, R. J., & Dahle, K. P. (2018). Predicting offenders' institutional misconduct and recidivism: The utility of behavioral ratings by prison officers. *Frontiers in Psychiatry*, *9*, Article e00679. https://doi.org/10.3389/fpsyt.2018.00679

Hughes, M. J., & Rasmussen, L. A. (2010). The utility of motivational interviewing in domestic violence shelters: A qualitative exploration. *Journal of Aggression, Maltreatment & Trauma*, *19*, 300–322. https://doi.org/10.1080/10926771003705213

Joel, S., Eastwick, P. W., Allison, C. J., Arriaga, X. B., Baker, Z. G., Bar-Kalifa, E., Bergeron, S., Birnbaum, G. E., Brock, R. L., Brumbaugh, C. C., Carmichael, C. L., Chen, S., Clarke, J., Cobb, R. J., Coolsen, M. K., Davis, J., de Jong, D. C., 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

Johnson, M. P. (1995). Patriarchal terrorism and common couple violence: Two forms of violence against women. *Journal of Marriage and the Family*, *57*, 283–294. https://doi.org/10.2307/353683

Johnson, M. P. (2010). *A typology of domestic violence: Intimate terrorism, violent resistance, and situational couple violence*. Northeastern University Press. https://doi.org/10.1111/j.1741-3737.2009.00634.x

Kearney, M. S., & O'Brien, K. M. (2021). Is it love or is it control? Assessing warning signs of dating violence. *Journal of Interpersonal Violence*, *36*(11–12), 5446–5470. https://doi.org/10.1177/0886260518805105

Kelley, H. H., & Thibaut, J. W. (1978). *Interpersonal relations: A theory of interdependence*. John Wiley & Sons. https://doi.org/10.1111/j.1744-1617.2008.00215.x

Kelly, J. B., & Johnson, M. P. (2008). Differentiation among types of intimate partner violence: Research update and implications for interventions. *Family Court Review*, *46*, 476–499.

Liaw, A., & Wiener, M. (2018). *randomForest: Breiman and Cutler's random forests for classification and regression* (Version 4.6.14) [Computer software]. https://cran.r-project.org/web/packages/randomForest/index.html

Murphy, K. A., & Smith, D. I. (2010). Adolescent girls' responses to warning signs of abuse in romantic relationships: Implications for youth-targeted relationship violence prevention. *Journal of Interpersonal Violence*, *25*, 626–647. https://doi.org/10.1177/0886260509334392

Murphy, K. A., Smith, D. I., & Xenos, S. (2012). TREAD: A promising change-target for partner abuse prevention with adolescents. *Journal of Family Violence*, *27*, 345–356.

Rape, Abuse & Incest National Network. (2017, February 6). *Early warning signs of dating violence*. https://www.rainn.org/news/early-warning-signs-dating-violence

R Core Team. (2021). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. https://www.R-project.org/

Rhatigan, D. L., & Street, A. E. (2005). The impact of intimate partner violence on decisions to leave dating relationships: A test of the investment model. *Journal of Interpersonal Violence*, *20*, 1580–1597. https://doi.org/10.1177/0886260505280344

Rusbult, C. E. (1980). Commitment and satisfaction in romantic associations: A test of the investment model. *Journal of Experimental Social Psychology*, *16*, 172–186. https://doi.org/10.1016/0022-1031(80)90007-4

Rusbult, C. E., & Martz, J. M. (1995). Remaining in an abusive relationship: An investment model analysis of nonvoluntary dependence. *Personality and Social Psychology Bulletin*, *21*, 558–571. https://doi.org/10.1177/0146167295216002

Short, L. M., & McMahon, P. M. (2008). Early warning signs of intimate partner violence. In C. M. Renzetti, & J. L. Edleson (Eds.), *Encyclopedia of interpersonal violence* (pp. 211–212). SAGE.

Short, L. M., McMahon, P. M., Chervin, D. D., Shelley, G. A., Lezin, N., Sloop, K. S., & Dawkins, N. (2000). Survivors' identification of protective factors and early warning signs for intimate partner violence. *Violence Against Women*, *6*, 272–285. https://doi.org/10.1177/10778010022181840

West, S. G., Finch, J. F., & Curran, P. J. (1995). Structural equation models with nonnormal variables: Problems and remedies. In R. H. Hoyle (Ed.), *Structural equation modeling: Concepts, issues, and applications* (pp. 56–75). SAGE.

World Health Organization. (2012). Intimate partner violence. In *Understanding and addressing violence against women (Sexual and reproductive health)*. https://www.who.int/reproductive-health/topics/violence/vaw_series/en/

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

Yoon, J. E., & Lawrence, E. (2013). Psychological victimization as a risk factor for the developmental course of marriage. *Journal of Family Psychology*, *27*, 53–64. https://doi.org/10.1037/a0031137

Zhang, Z., Mai, Y., & Yang, M. (2022). *WebPower: Basic and advanced statistical power analysis* (Version 0.8.6) [Computer software]. https://CRAN.R-project.org/package=WebPower

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