Machine Learning for Community-Based Intervention Studies: Predicting Post-Program Levels of and Changes in Relationship Quality Following Couple Relationship Education Participation

by

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Abstract

With the understanding that applying machine learning methods to study predictors of Couple Relationship Education (CRE) program outcomes could be particularly helpful for identifying critical factors for CRE program designs, the current study used a racially and economically diverse sample of CRE participants to investigate the most important predictors of post-program levels of and changes in relationship quality over the time of one year following CRE program start. Using 79 possible predictors that included participant characteristics, relationship history, relationship skills and practices, individual functioning, and class contextual factors, random forest models identified that up to 33% of the variance in CRE program participants' post-program levels of relationship quality at one year following program-start, and using 158 possible predictors, 17% of the variance in their changes in relationship quality one year after program-start could be predicted by several, key relational processes variables, individual functioning variables, and family environment variables, regardless of individual characteristics and other contextual variables. Models provided information on the most salient 20-26 factors and align well with a recent framework used for guiding key topics for Couple Relationship Education (CRE). The top five predictors for post-program levels of relationship quality were self-reported satisfaction with dyadic coping in the relationship, partner's dyadic coping, family harmony, partner's conflict management, and knowledge of partner. For changes in relationship quality following CRE participation, the top five predictors were self-reported satisfaction with dyadic coping in the relationship, partner's dyadic coping, acceptance of partner, partner's negative health control messages, and family environment chaos. Self-reported individual mental health was another important predictor, uniquely accounting for additional variance in changes in relationship quality but not post-program levels of relationship quality.

This study offers critical information for skill-based CRE program designs. The current study demonstrated the feasibility of applying machine learning methods to community-based CRE studies and further validated the content emphasis on a broad spectrum of relational processes in skill-based CRE programs. Research and practical implications were discussed.

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One of the first and the best advice that I've gotten about grad school was: "To get your PhD, is not about how smart you are, is not about how novel your research is, sometimes is not even about how hardworking you are, it is about if you could persevere"; and I remember thinking to myself: "Good, because that is the one thing I know I could do". It is true. I don't give up. I don't give up even when things get hard, very very hard. It is a core part of who I am as a person that once I set my mind on something, I will find a way to achieve it no matter what it takes. So, in a way, I guess this is what I meant to do. I usually struggle to give myself credits or to acknowledge my work, but I would like to say "thank you" to myself this time.

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CRE	Couple Relationship Education
CART	Classification and Regression Trees
SSE	Sum of Standardized Error
LOOCV	Leave-One-Out Cross-Validation
MSE	Mean Squared Error
RMSE	Residual Mean Squared Error
RCT	Randomized Control Trial
RQ	Research Question
QMI	Quality Marriage Index
CSI	Couple Satisfaction Index
CFI	Comparative Fit Index
TLI	Tucker-Lewis Index
MI	Multiple Imputation
MCAR	Missing Completely at Random
MCRS	Mindfulness in Couple Relationship Scale
DCI	Dyadic Coping Index
VSA	Vulnerability-Stress-Adaptation Model

Chapter 1: Introduction

Google Scholar generates over 1,000,000 results for the search term "romantic relationship quality" and over 200,000 results for the search of "romantic relationship quality predictors." Spanning decades, social science fields including family science, psychology, sociology, and public health have all been interested in the questions related to romantic relationship quality, as well as its association with individual well-being. Family science is a theory-oriented and theory-rich field; many established family and relationship theories provide pathways and elements that can be and have been empirically tested to help uncover the factors and processes associated with relationship quality. So much so that the accumulated information now may make it more challenging than ever to determine relevance and potency of a long and growing list of factors that may influence relational health and influence change.

Classic theories such as attachment theory (Hazan & Shaver 1994), interdependence theory (Kelley et al., 1983), family system theory (Broderick, 1993), and family stress and resilience theories (Boss et al., 2016) all provide theoretical foundations for understanding factors that are closely tied to romantic relationship quality from individual, relational, familial, and contextual perspectives. Using theoretical lenses, numerous factors associated with romantic relationship quality have been identified in empirical research. These include characteristics of individuals and relationships such as age (Bühler et al., 2021) and relationship length (Bühler et al., 2021), as well as more malleable characteristics and behaviors, such as attachment styles (Butzer & Campbell, 2008; Olderbak & Figueredo, 2009), personality (Malouff et al., 2010), communication skills (Olderbak & Figueredo, 2009), and emotion regulation (Levenson & Gottman, 1985). These elements stand out as comparatively robust predictors in meta-analytical studies. While multi-factor regression models and meta-analytic studies offer useful information and offer opportunities to distill the growing list of predictors of romantic relationship quality, the recent introduction of machine learning methods in family science is an important and logical next step in relationship science. These advanced methods offer unprecedented rigor and capacity for managing large predictive models that can move us towards understanding even more about predictors' comparative relevance and potency in explaining expected relationship quality.

In relationship science, machine learning methods have primarily been used in basic science predictive models (e.g., Joel et al., 2020). While these efforts have offered important information on the most robust predictors of romantic relationship quality, which are perceived relational or interpersonal process variables such as commitment, partner support, and conflicts (e.g., Brown et al., 2022; Joel et al., 2020), no studies have used a community sample receiving relational intervention programs, despite the important implications that these findings have on intervention programs. Applying machine learning methods to intervention studies could be particularly helpful for informing program designs and implementation. With an economically and racially diverse sample, the current study aims to address this research gap and to investigate the most predominant predictors for individuals' changes in relationship quality after participating in relational intervention programs.

Chapter 2: Literature Review and Methodological Background

Studying Predictors of Relationship Quality

When looking at the collective efforts made in basic science research and applied science research, relationship quality and the predictors of it seem to be well-explored. Process variables associated with relationship quality (e.g., perceived partner support, relationship skills), individual dimensions of health (e.g., mental health symptoms, physical health), and the unchangeable, fixed variables associated with relationship quality (e.g., relationship history, family life history, relationship length) have all been studied as predictors of relationship quality. However, many studies often do not offer enough consideration of the multitude of individual, relational, and contextual factors together as predictors of relationship quality.

Typically in social science studies, the use of control variables is a popular way to address the potential confounding effects that more static, fixed variables may have, to better distinguish the relationship between the dependent and independent variables of interest. Demographic variables such as age and gender are often included as covariates or control variables in analyses (Bernerth & Aguinis, 2016). Although there is nothing inherently inappropriate with such practice, for the question of relationship quality, someone's interpersonal process variables and individual identities could both be important predictors of their relationship quality, or changes in relationship quality in the case of intervention. Critical information could be lost in the practice of using demographic variables as covariates, rather than concurrent predictors. While moderation studies emphasize the value of considering social location variables such as one's race, gender, and socioeconomic status, and exploring a more nuanced relationship between the dependent and independent variables (i.e., differences in change trajectories), these types of analyses do not test the comparative predictive power of these types of variables alongside malleable variables in prediction models focused on relationship quality or changes in relationship quality. More advanced modeling techniques can explore how much variance changeable individual trait and process variables (e.g., relational processes, individual mental health) versus the fixed social address variables (e.g., age, gender, adverse childhood experiences) predict. The linear regression models that have been widely used for decades have received critique for problems of overfitting and difficulty of replication related to the over-performance of the regression models in a specific sample (Hindman, 2015). Machine learning models, on the other hand, are particularly useful when it comes to prediction, especially replicable predictions due to their capacity to train and test models in "unseen" data. Machine learning models are capable of handling a large number of predictors while avoiding issues of overfitting (Grimmer et al, 2021), which makes them ideal models for family scientists to answer research questions with an inductive approach and to better manage and interpret cumulative knowledge (Joel et al., 2020).

The Context of Couple Relationship Education

The use of and research on Couple Relationship Education, or CRE, has grown significantly in the past two decades. In recent year, CRE gained popularity as a primary prevention tool in the U.S. and around the globe, targeting couples' relationship functioning (Markman et al., 2021). Expectantly, the aforementioned critical predictors of relationship quality are cornerstones of CRE programs. As recent reviews summarized, most research-based CRE programs focus on three areas of relationship processes: 1) enhancing communication and emotional regulation skills, 2) fostering positive interactions and connections, and 3) prioritizing the relationship and focusing on commitment (Markman et al., 2021; Stanley et al., 2020). Meta-analytical studies investigating CRE's effectiveness consistently find a small to medium effect size for relationship quality, the primary targeted and most tested program outcome in CRE (Briggs et al., 2020; Hawkins et al., 2008). There is also ample and robust evidence showing that CRE programs are effective for the average program participants in improving not only their relational outcomes such as relationship satisfaction and quality, but also individual outcomes such as individual mental and physical health, and family outcomes such as family harmony, co-parenting quality, and child outcomes (e.g., Adler-Baeder et al., 2022; Barton et al., 2021; Hawkins, Hill, et al., 2022; Spuhler, et al., 2025).

Other CRE studies focused on the mechanisms behind program participants' changes and potential moderators. A considerable number of studies report that changes in relational processes, such as communication, positive interactions, and commitment are directly related to changes in relationship quality post CRE participation (Adler-Baeder et al., 2022; Rauer et al., 2014). In studies regarding changes in relationship quality, one study found that up to 73% of the variance in improvements in participants' relationship quality at immediate post-program could be predicted using improvements in positive interactions, commitments, and decreases in negative interactions from baseline to immediate post-program (Rauer et al., 2014). Another study found similar results where baseline levels of perception of relationship instability and relationship quality accounted for up to 49% of the post-program levels of relationship quality (McGill et al., 2016). It is critical to note, however, that most of the variance predicted in these studies were accounted for by the baseline levels of relationship quality. Also, evidence on the amount of variance predicted in relationship quality after one or two years following CRE program participation seemed to be relatively scarce as most program evaluation studies are more interested in program effects that are usually demonstrated by the participants' changes in targeted program outcomes.

Moreover, many studies support the view that there are differences in the amount of gains that participants could have while participating in CRE programs; specifically, participants who are at higher risks tend to benefit the same or more from the programs compared to the average participants (Hawkins et al., 2019; Markman et al., 2021; Stanley et al., 2020). Some examples include that lower-income participants were found to benefit more from CRE studies compared to their higher-income counterparts (e.g., Adler-Baeder et al., 2010; Rauer et al., 2014), racial/ethnic minority participants were found to benefit the same or more from CRE programs (e.g., Stanley et al., 2014), and relationally distressed couples were found to have gained more from programs than those who were not as distressed (e.g., Bradford et al., 2017). Although, one recent study did counter the findings for distressed couples and found that only individuals who were happier at program-start benefited from the program (Urganci et al., 2024).

Additionally, what program results are considered "program effects" is also a point of discussion in CRE studies. For example, if couples entering programs had high relationship quality at baseline and maintained their high levels of relationship quality over time, a statistical interpretation would be that there were "no improvements" for these couples, known as the ceiling effect. Whereas couples entering programs who started at a lower level of relationship functioning could demonstrate more improvements in their functioning but their post-program levels could still be lower than those who started high in functioning and maintained. Because of this, it is valuable to consider predicting both post-program levels (i.e., where the participants ended after the programs), and the amount of change that happened during and after program participation, in order to paint a comprehensive picture of CRE program results. As such, machine learning methods could provide opportunities to further answer the question "for whom

CRE works", and the amount of changes to be expected when the comparative predictive ability of individual, relational, and contextual variables are tested together, adopting an ecological lens.

Predicting Relationship Quality: Machine Learning Studies

To date, four machine learning studies used relationship satisfaction or relationship quality as the dependent variable, using different approaches and with different study aims. Each of the studies contributed to our understanding of concurrent predictors of relationship quality or satisfaction and predictors of normative change (Ascigil et al., 2023; Brown et al., 2022; Großmann et al., 2019; Joel et al., 2020). Among these four studies, the Joel et al. 2020 study had the strength of a sample size of over 10,000 couples from 43 different longitudinal datasets, as well as a comprehensive list of predictors (range = 12 – 189 predictors) across these 43 datasets. This ground-breaking study revealed that self-reported relationship-specific variables were able to predict up to 45% of the variance in concurrent couples' relationship satisfaction. The top five most important variables were individuals' perceived levels of partner commitment, appreciation for partner and relationship, sexual relationship satisfaction, perceived levels of partner satisfaction, and frequency of conflicts. This study also considered individual-centered predictors, such as one's own education level, mental health symptoms, substance use, and stress. These individual-centered variables were able to uniquely predict up to 21% of the variance in relationship satisfaction. The most robust individual-centered predictors were satisfaction with life, mental health symptoms, and anxious or avoidant attachment style. In addition, both self-reported relational- and individual-centered variables were able to predict 18% and 12% of relationship quality at a later time point respectively. However, neither the relational- or individual-centered variables were found to be reliable for predicting normative changes in relationship satisfaction over time compared to predicting relationship satisfaction concurrently, as that no analyses predicted more than 5% of the variance in changes in relationship quality (Joel et al., 2020).

Different from the Joel et al., 2020 study, Brown and coauthors (2021) used a different approach for predictor variable selection. With the overarching aim to better understand predictors for African American couples' relationship satisfaction, Brown et al. adopted a theory-informed approach to predictor selection. They evaluated general and socioculturally relevant predictors of African American individuals' relationship satisfaction at individual, relational, familial, and social/contextual levels (*N* = 306 individuals who were coupled). Results showed that the combined power of African American individuals' individual, relational, social, and contextual factors could predict 44% of the variance in African American individuals' relationship satisfaction. Notably, several sociocultural factors including criminal behavior, neighborhood violence, and community factors played important roles in predicting African American individuals' relationship satisfaction. This approach informed the understanding of determinants of relationship satisfaction from a more systematic perspective, and may have specific implications for intervention efforts for African American couples and families. For example, program providers should consider appropriate program development or adaptation to incorporate the critical socialcultural contexts into the programs provided when serving African American families.

With the specific context of the Covid-19 pandemic, Ascigil and coauthors (2023) chose to group their predictors into demographic variables, pandemic-related variables, well-being-related variables, stressor-related variables, and relational variables, and analyzed these groups of predictors in separate models. Each of the models predicted some amount of variance (range = 1.21% - 70.86%) in relationship satisfaction during the pandemic, with 27 relationship process variables (e.g., quality time, appreciation for partner, shared laughter, perceived partner support) uniquely explaining up to an overwhelming 71% of the variance in relationship satisfaction.

Finally, instead of employing a wider range of predictors, Großmann and coauthors (2019) focused specifically on personality traits as predictors of changes in relationship satisfaction over time using a relatively small sample of 192 individuals in romantic relationships. This study found that relationship-related personality traits (e.g., sexuality, charm, and bond) were the more robust predictors of relationship satisfaction than general personality traits (e.g., neuroticism, intelligence, and ambition). A comprehensive list of personality traits could predict up to 37% of the variance in relationship quality four years after personality was assessed.

These four studies each contributed significantly to the cumulative understanding of the determinants of relationship quality. Specifically, relationship process variables and experiences in romantic relationships such as partner warmth, commitment, appreciation, and quality time emerged to be the more important predictors for romantic relationship quality across several machine learning studies (Ascigil et al., 2023; Brown et al., 2022; Joel et al. ,2020). Individual centered variables like mental health symptoms or contextual variables like neighborhood disadvantages played comparatively less important yet still significant roles for predicting relationship quality. These studies did also note that demographic and contextual variables as predictors of relationship quality warrant future investigations, partially because none of the studies used a racially and economically diverse sample. Further, little is known about the most reliable predictors of normative changes in relationship quality. Future studies with diverse samples may, 1) confirm that relational process variables are the most important predictors for relationship quality for different groups of the population, 2) uncover that certain individual and contextual variables are also important predictors of relationship quality when tested together with the relational process variables, and 3) add to the understanding of predicting normative changes in relationship quality over time. The current study seeks to explore predictors of later relationship quality; however, it will uniquely consider changes after intervention rather than normative changes. This is an uncharted area of research where machine learning, relationship science, and relational intervention intersect.

Utility of Machine Learning in Intervention Studies

As noted, machine learning methods have been applied to several recent basic science studies investigating predictors of relationship quality, and two studies have explored predictors of normative change in relationship quality. However, no known studies focused on CRE intervention programs have utilized machine learning methods, even though influencing change in relationship quality is considered the most important outcome variables in CRE. Changes in relationship quality in general also warrant more investigation based on the Joel et al., 2020 study results where self-reported individual and relational variables at one timepoint could not reliably predict changes in relationship quality (no more than 5% of the variance were accounted for in changes in relationship quality over time).

Although it has not been widely applied in intervention studies, machine learning methods could be immensely helpful to researchers and practitioners to identify the most important variables related to post-program levels and changes in relationship quality, and in turn inform practice and implementation efforts. When it comes to intervention, it is also important to recognize that a program could be effective for the average participants, but not equally effective for every participant (Pearson et al., 2018). In other words, individual traits, which a program cannot affect, may be a stronger predictor of relationship quality over time compared to the targeted relational processes. This would be important information for practitioners to have when recruiting for intervention participation. If program outcomes could be successfully predicted based on a more complex formula of factors, researchers could subsequently identify which individuals are more or less likely to respond positively to the program, thus enhancing the knowledge base of policymakers as well as program staff.

What is Machine Learning and Why Use It in Family Science?

Hypotheses testing has long been a foundational part of scientific methods in family science. Usually driven by theoretical frameworks, hypotheses testing or statistical testing seeks to explain associations between a set of variables through a deductive approach. Contrary to hypotheses testing, new developments in statistical methods such as machine learning models allow a data-driven, person-centered, and inductive approach, which address several problems with traditional statistical testing. In family science, traditional statistical testing may rely on simple or complex theories when it comes to variable selection; however, these approaches face difficulties when testing complex frameworks since it is challenging to accommodate a large number of predictive variables in the same model. As such, these traditional models often face issues with overfitting and are not best suited for comparing a list of predictor variables against one another (Lewis, 2000). Further, there are usually intricate and complex relationships among the variables that exist in the data – one variable (e.g., relationship length) may be considerably intertwined with another variable (e.g., relationship skills) and such relationships affect the relative importance of each of the variables (Lewis, 2000). However, certain machine learning algorithms are nonparametric, meaning that the models are sensitive to nonlinear relationships among the variables, and they are well suited to process a large number of variables.

Machine learning can be broadly explained as a field of study that trains computers to have the ability to learn and analyze data using provided information so that they could eventually learn and investigate future, unknown data on their own (Alzubi et al., 2018; Samuel, 1959). Further, machine learning can be divided into supervised learning and unsupervised learning. Supervised learning models deal with labeled data and the outcome is known. The goal of supervised learning is to make an accurate prediction, through classification for categorical results or through regression for continuous results. Unsupervised learning models seek to detect underlying patterns in the data without any predetermined labels. Examples of unsupervised learning algorithms are cluster analysis and mixture modeling analysis. For the current study, regression-based algorithm (namely random forest) was used to predict CRE program participants' post-program levels of relationship quality and changes in relationship quality from baseline to one year after baseline.

Algorithms Selection

Random Forest. The current study used a popular regression-based machine learning algorithm, random forest, to explore the study aims. The random forest algorithm is essentially an ensemble model of the regression trees models, which is commonly practiced in the CART (classification and regression trees) framework (Breiman et al., 1984, 2001). To grow a regression tree, the model begins by splitting the entire data set in half by looking for the predictor that splits the data so that the overall Sum of Standardized Error (*SSE*) is the lowest; the model keeps splitting the data in a similar fashion until each terminal node (leaves of the tree) only has very few observations. But this approach often faces the issue of overfitting, resulting in the tree having good performance in the training data (in-sample-performance), but weak performance in the testing data (out-of-sample-performance). Typically in regression trees, to address the issue of overfitting, a pruning process is introduced to decrease the variance at the cost of adding bias so that the smaller tree may perform better with the testing data. One of the ways to improve the single decision tree is through bagging, or bootstrap aggregation. To improve the out-of-sample performance of the models, bootstrapped samples are used to grow individual trees and an average of all the predictions generated by all trees is taken. Although considered an improvement from single trees, bagged trees approach does have the challenge of having highly correlated trees. Because the dominant variable (the one that reduces the *SSE* the most) always shows up in each of the bootstrapped samples and their trees leading the trees to look similar to one another. Random Forest (Breiman, 2001), however, addresses all aforementioned concerns by decorrelating the bagged trees. Random Forest achieves that by not allowing all variables to be considered after each split (at each node), and the common recommendation is to randomly select and allow a number of variables that is the rounded square root of the number of predictors for each tree (i.e., five variables are allowed at each node if there are 25 predictors total; Rigatti, 2017). This approach balances the power of the bagging approach by increasing the variability of the model and it makes the average of the trees much more reliable than the bagged trees. Overfitting is generally not a concern for random forests because each tree in the forest is not replicated, therefore the model is not affected by the number of trees.

Cross-Validation

Cross-validation is an important aspect of machine learning methods as it tests the models' performance on "unseen" data. There is a list of cross-validation approaches that are commonly seen in practice including the validation set approach (splitting data into training and testing sets), leave-one-out cross-validation approach (LOOCV; leaving only one observation out in the testing data and repeating the process *n* times), *k*-fold cross-validation approach (using a parameter "k" to determine the number of training and testing subsets), and the Monte Carlo approach (repeating random splits of training and testing). Each of these cross-validation approaches has their advantages and disadvantages. The validation set approach splits the data into training set and testing test to hold out a dataset from the original dataset, and that data would be used to evaluate the model. This process involves fitting the model on the training data, and utilizing the mean squared error (*MSE*) of the fitted model to evaluate the performance of the testing dataset. Commonly recommended approaches include using 2/3 of the data for training and 1/3 of the data for testing, and such splitting approach is considered close to optimal (Dobbin & Simon, 2011). Although this approach is widely used and easy to implement, it has the disadvantage that only one set of the data is being used to evaluate the model performance and the error rate is highly dependent on observation size. The LOOCV approach does not suit large samples well because it only holds one observation out in each training set and takes a large computational power. Finally, the Monte Carlo approach has the disadvantage that while it randomly selects observations into training and testing data and repeats the process, some observations may be selected multiple times whereas other observations may not get selected at all.

As such, the current study opted to use the *k*-fold cross-validation approach, an approach that balances computational power and error rate. The *k*-fold method randomly splits training data into *k* equal subsets, and *k* is usually set at 5 or 10. Out of the *k* subsets of training data, *k*-1 are used to train the models. In the case of the current study, a 10-fold validation was used, which means that the data were split into 10 equal sets, 9 of which were used for training and the remaining 1 subset were used for testing. This process was repeated 10 times, one for each subset, so that each subset was tested. The *MSE* in *k*-fold validation was computed by averaging the *MSE* for each of the test subsets.

Current Study

The CRE program considered in the current study is the ELEVATE: Taking Your Relationship to the Next Level (Futris & Adler-Baeder, 2013) curriculum. This program was empirically tested in a randomized control trial (RCT), and it showed program effects for enhancing program participants' relationship quality, relationship skills, family environment, mental health symptoms, as well as sleep quality over one year, when compared to control-group participants (Adler-Baeder et al., 2022). Having an empirically tested, evidence-based intervention program as the operational foundation of the current study, this study also benefited from having a racially and economically diverse sample. As Joel et al. pointed out, the reason demographic variables did not stand out to be reliable predictors of relationship quality in their study might be that their study samples were not diverse enough in race, education, or income level to reflect the potential predictive power of the demographic variables (2020). The current study sample presents variabilities in various social identities.

Although machine learning as a methodological approach is typically considered atheoretical in nature, the approach for conducting machine learning studies can be theoretically informed, especially for family science studies. The current study considers determinants of relationship quality at various theoretical and analytical levels, specifically adopting an ecological model lens. Thus, individual (e.g., race, individual mental health), relational (e.g., relationship skills, sexual satisfaction), familial (e.g., family harmony), and contextual (e.g., adverse childhood experience, experience with racism; class environment) levels of variables were all considered together. The approach in this study may be particularly beneficial to intervention designs, as it may inform whether it is meaningful to include content in intervention programs regarding non-actionable processes such as the influence that family of origin has on romantic relationships (Stanley et al., 2020). With the overarching goal to inform best practices in CRE, using machine learning methods and leveraging dyadic data, a series of analytical models were tested in the current study aiming to answer the following questions:

Research Question (RQ) 1a – How much variance can self-reported, or partner-reported, or combined self- and partner-reported individual, relational, familial, and contextual variables together predict in CRE program participants' post-program levels of relationship quality one year after program start?

RQ 1b – What are the top self-reported, or partner-reported, or combined self- and partner-reported variables that have the most predictive power for CRE program participants' post-program levels of relationship quality one year after program start?

RQ 2a: – How much variance can self-reported, or partner-reported, or combined self- and partner-reported individual, relational, familial, and contextual variables together predict in changes in relationship quality (individual slope of changes as the outcome) for CRE program participants from program start to one year after program start?

RQ 2b – What are the top self-reported, or partner-reported, or combined self- and partner-reported variables generated by recursive partitioning (i.e., feature selection) that are the most predictive of changes in relationship quality for CRE program participants from program start to one year after program start?

Chapter 3: Methods

Study Procedure and Participants

Participants of the current study were a part of a larger RCT study testing and comparing the efficacy of a weekly and a monthly delivery plan of the research-based ELEVATE (Futris & Adler-Baeder, 2013) skilled-based couple relationship education program. The recent efficacy study validated the program as evidence-based and showed that participants receiving the ELEVATE program improved their relationship quality, relationship skills, individual mental health, individual sleep quality, and family harmony over one year when compared to participants in the no-program control group (Adler-Baeder et al., 2022). Positive program impact is also evident for participants who identify as sexual and gender minorities (Wei et al., under review). Program participants were recruited through word of mouth, flyers, online advertisements, and various community engagement activities. Eligible participants must be 19 years old and are in a romantic relationship. The 12-hour, 6-module program was implemented by the central research team at the university and by six different family resource centers across the state. Participants were incentivized $40 for each survey that they completed at baseline (T1), three months (T2), six months (T3), and one year (T4) after baseline.

The analytical sample for the current study were 1,219 couples who received the ELEVATE programming from 2020 to 2023 and provided data at any timepoint. The average age of the participants was 37 years old (*SD* = 10.82, range = 19 - 88) and the average length of relationships was 6.91 years (*SD* = 6.99, range = 0.08 - 60) at baseline. Most of the participants identified as men (45.3%) or women (54.3%), and 0.4% identified as non-binary, genderqueer, or transgender. About half of the participants reported being African American or Black (52%), 40% reported being Caucasian or White, 3.5% reported being Asian or Asian American, 2%

reported being biracial or multiracial, and 2.5% reported being Native-American, Native-Hawaiian, or Pacific Islander, and another race. About 90% of the participants identified as heterosexual or straight, 2.1% identified as gay or lesbian, 4.5% identified as bisexual or pansexual, 0.4% identified as queer, 0.3% were questioning or unsure, and 1.7 did not disclose their sexual orientation. For educational attainment, 5% of the participants had less than high school education, 36.7% had high school diploma or GED, 18.6% had 2-year degrees (vocational/technical certification or associate's degree), 21.7% had bachelor's degrees, and 17.9% had advanced degrees. Sixty-one percent of the participants reported being employed full-time. For individual income, 32.7% reported an annual income of under $19,999 before taxes, 27% reported an income of $20,000 - $39,999, 28% reported $40,000 - $74,999, and 12.4% reported an income over $75,000 a year.

Measures

Predictor Variable Selection

One of the current study's aims is to investigate the combined predictability of individual, relational, familial, and contextual factors of CRE program participants' levels of relationship quality one year after program start and the amount of changes in their relationship quality across the time of one year. Thus, all available data that fall under the umbrella of these four predictor categories were entered into the models. Variables regarding program experiences were also included in the model, including participants' ratings of facilitators' cultural competency and CRE classroom environment. A total number of 79 variables were entered into the models for the self-reported variable and partner-reported variables models, and 158 variables were entered in the combined model. See Table 1a to Table 1i for the full list of predictor variables separated into individual categories. Examples of the individual level predictors include demographic predictors such as gender, race, age, sexual orientation, and individual income. Individual functioning variables were also included, such as individual mental health, substance use, sleep quality, and self-efficacy. Relational predictors also included both demographic and functioning variables. Examples of relational demographic variables are relationship length and relationship type, and examples of relational functioning variables are relationship skills, relationship instability, and dyadic coping. Baseline relationship quality was not included in the models. Some of the familial variables that were included in the models were family harmony, parental status, number of children, and levels of chaos/calmness in the household. Finally, contextual variables such as adverse childhood experiences, financial difficulties, and experiences with racism were also included.

Outcome Variable

The outcome variable of the current study is CRE participants' relationship quality. Their relationship quality was measured by a combined sum score of the Quality Marriage Index (QMI; three items; Norton, 1983), Couple Satisfaction Index (CSI; four items; Funk & Rogge, 2007), and the Confidence and Dedication Scale (three items; Stanley & Markman, 1992). These three measures are well-established measures that assess the same concept, current relationship quality, and demonstrate high correlations among these measures in the current sample (r = .72 - .86). A three-factor Confirmatory Factor Analysis was conducted with the study sample to evaluate if these three measures could be scored together, and the model showed good fit with the data (CFI = .99, TLI = .98, RMSEA = .07, SRMR = .03) with factor loadings ranging from .65 to .93. Cronbach's alpha of each of the individual measures and the combined measure shows good reliability with the current sample (α = .90 - .97). This composite sum score approach combining established relationship quality measures into one measure has been used in other published studies, including the recent efficacy study of the ELEVATE program (e.g., Adler-Baeder et al., 2022).

Analytical Plan

Treatment of Missing Data

The current study data had two types of missingness. The first one was primarily due to attrition and skipped surveys. Out of all participants who received programming, 85.9% completed baseline survey; for those who had a baseline survey, 87.7% completed surveys at T2, 81.9% completed surveys at T3, and 77.6% completed surveys at T4. The non-response rate at item-level ranged from 0.4%-8.8% at T1, 1.5%-8.9% at T2, 1.8%-8.5% at T3, and 1.0%-9.4% at T4. This missingness can be considered unplanned missingness. The second type of missingness in the data was planned missingness. Planned missingness design (Graham et al., 2006) is an effective way to admit more survey items without overburdening participants with long survey questionnaires. The current study used a multiform questionnaire design where some constructs and items on the survey were shown in full to all participants, whereas only about 30% to 50% of the items of some of the constructs were randomly displayed to the participants. The missingness that the planned missingness design creates is missing completely at random (MCAR) due to the complete randomization of items displayed to any given participant on the measures that were designed to have planned missingness. Although the missingness rates are high at the item level when using this approach, this type of planned missingness does not add bias to the analyses (Little et al., 2013). Out of the 29 constructs (i.e., full established measures) that were included in the analyses, there are 304 total items that participants could potentially see, and 170 out of these items were administered to all participants. Each participant was also randomly administered 40% of the 134 items that had planned missingness. As a result, the planned missingness design introduced about 18% MCAR data to the full dataset.

Multiple imputation (MI) is one of the recommended methods for handling planned missingness data (Little et al., 2013), and it is also capable of handling both planned and unplanned missingness (Caron-Diotte et al., 2023; Rioux et al., 2020). Specifically, MI was performed in the "mice" package in RStudio (van Buuren & Groothuis-Oudshoorn, 2011; R Core Team, 2024). The "mice" package uses the Multivariate Imputation by Chained Equations method, which is a method that is equipped to process a large amount of missing data (up to 90% as noted by Madley-Dowd et al., 2019 as long as data are missing at random). This method relies on existing raw data from all respondents to replace missing values in multiple datasets, and the "mice" package uses the classification and regression trees algorithm to achieve that. Various covariates are included in the MI. Examples are gender, race, age, education level, individual and household income, members in the household, relationship type, relationship length, and other various individual and relational demographic information. MI was conducted at the item level and 20 imputed datasets were generated. For the ease of use in analyses, the 20 imputed datasets were averaged at the item level and pooled into a single dataset.

Random Forest Models

The primary analyses were conducted in R Studio (RStudio Team, 2024). To address the dependency in dyadic data, the data were first restructured to be dyadic, and couples were randomly assigned as partner1 or partner2 using their unique couple ID. Then, one of the partner's data were selected to be analyzed as self-reports and their partner's data were used as partner-reports. Although most of the dyads in the data were considered distinguishable by gender, there were about 6% of same-gender couples in the data. Thus, this partner1 and partner2 assignment approach was used as a more inclusive approach to include all participating couples in the analyses. For each RQ, a default random forest model only using self-reported predictors was conducted, followed by feature selection model and another random forest model using only confirmed features. Then, a set of models (default random forest model, feature selection model, and random forest model with confirmed features) with only partner-reported predictors were conducted, followed by a set of models using combined self- and partner-reported predictors. The “caret” package (Kuhn, 2008), “randomForest” package (Liaw &Wiener, 2002), and “Boruta” package (Kursa & Rudnicki, 2010) were used in these analyses. To address RQ 1 that investigates CRE participants’ post-program levels of relationship quality from program-start to one year after program-start, participants’ post-program levels of relationship quality was used as the outcome variables; and to address RQ 2 that investigates predictors of changes in CRE participants’ relationship quality from program-start to one year after program-start, individual regression slopes for each participant generated from regression analyses and stored as coefficients were be used as the outcome variables.

Model Confirmation and Interpretation

To confirm the random forest model findings and to help with model interpretation, linear regression models and regularized regression models (i.e. elastic net) were also conducted following the primary analyses. These models used confirmed features generated from the random forest feature selection models to serve as the benchmark models for model performance, and to help with directional results interpretation. 10-fold cross-validations were also applied to elastic net model parameter tuning and model estimates. Information regarding choosing elastic net for supporting analyses and how elastic net performs feature selection can be found in supplemental materials (S1).

Chapter 4: Results

Random Forest Model and Feature Selection

Self-Reported Predictors of Relationship Quality at One Year Following Program-Start

When testing RQ1 exploring CRE program participants' post-program levels of relationship quality one year after baseline, we found that when using a total of 79 self-reported predictors (18 demographic predictors, 24 relationship processes predictors, 7 physical health related predictors, 9 mental health related variables, 3 traumatic experience related predictors, 2 family environment related predictors, 8 financial condition predictors, and 8 CRE classroom environment related predictors) to predict individuals' post program levels of relationship quality at one year after CRE program-start, 30.17% of the variance in relationship quality was predicted (RMSE = 9.20).

Recursive feature selection was conducted following the model using all predictors using the Boruta method, a method that identifies all relevant predictor variables that contribute to the random forest model. Twenty variables were identified at feature selection. The random forest model was conducted again with only the confirmed features, and the model had slightly better performance than the model using all variables ($R^2 = .33$, RMSE = 9.05). Out of the 20 confirmed features, there were 17 relationship skills or relationship processes variables (e.g., dyadic coping, conflict management skills, and intimate knowledge of partner), two family environment variables (i.e., family harmony and chaos/calmness in home), and one physical health related variable (e.g., partner's health control messages). Notably, predictors in other categories (e.g., demographics predictors, mental health related predictors, CRE classroom environment) were not represented in the top 20 confirmed features. See Figure 1 for variable importance plot and variable importance score for the selected features.

Partner-Reported Predictors of Relationship Quality One Year Following Program-Start

Only 1.2% of the variance in individuals' post-program levels of relationship quality was predicted using their partner's variables (RMSE = 11.25). Fourteen variables were selected in the feature selection process to be the most important partner-reported factors for individuals' levels of relationship quality one year post CRE participation. Nine variables were relational processes (e.g., dyadic coping and conflict management skills), one variable was individual mental health (i.e., satisfaction with life), and one variable was financial condition (i.e., financial distress/well-being). A random forest model was conducted again using only the selected features. Model performance was slightly better compared to the model using all predictors, but the overall variance predicted was still low (R^2=.017, RMSE = 11.20). See Figure 2 for variable importance plot and variable importance score for the selected features.

Combined Self- and Partner-Reported Predictors of Relationship Quality at One Year Following Program-Start

A random forest model testing individuals' post-program levels of relationship quality at one year following CRE program-start with self- and partner-reported predictors (N=158) was also conducted. The model performed worse than the self-reported predictors only model (R^2=.29, RMSE = 9.23). Feature selection suggested that the top variables contributing to relationship quality at one year following program-start were all self-reported variables (N=19), and these top variables all overlapped with the variables identified in the self-reported variables only model. When conducting the random forest model using the confirmed features identified by the combined model, the model performed similarly to the model using only confirmed self-reported features (R^2=.33, RMSE = 9.00).

Self-Reported Predictors of Changes in Relationship Quality over One Year

To test RQ2 that explored CRE program participants' changes in relationship quality over the time from baseline to one year after baseline, individuals' slopes (time coefficients) in their relationship satisfaction over the four timepoints (baseline, three months after baseline, six months after baseline, and one year after baseline) were first extracted from a linear growth model to use as the outcome variable in the random forest models. Then, a random forest model was conducted and the results showed that when 79 self-reported predictors were used in the model, all the variables together predicted up to 15.09% of the variance in changes in individuals' relationship quality over one year (RMSE = 0.81).

Twenty-six variables were confirmed in feature selection as the contributing predictors for predicting changes in individuals' relationship quality from CRE program-start to one year after program start. When conducting the random forest model with the confirmed features, the model improved slightly (R^2=0.16, RMSE = 0.80). Out of the 26 variables, 19 of them were also predictors of participants' post-program levels of relationship quality. The unique predictors for participants' changes in relationship satisfaction were individuals' sexual satisfaction, mental health symptoms, and self-care behaviors. Consistent with predictors of post-program levels of relationship quality, most (20 out of 26) predictors were relationship processes (e.g., dyadic coping, commitment, and intimate knowledge of partner), alongside with two family environment variables (i.e., family harmony and chaos/calmness in the household), as well as individual mental health related variables (e.g., psychological distress and internalizing symptoms). However, individual mental health symptoms (e.g., psychological distress and internalizing symptoms) emerged to be unique predictors of changes in RQ but not post-program levels of RQ. The confirmed features and variable importance scores can be found in Figure 3.

Partner-Reported Predictors of Changes in Relationship Quality over One Year

Similar to the results from the random forest model testing individual's partner-reported one-year post-program levels of relationship quality using partner-reported predictors, the model testing individuals' changes in relationship quality over one year using partner-reported predictors also only predicted a very small portion of the variance in individuials' changes in relationship quality (R^2=0.011, RMSE = 0.89).

The random forest model with confirmed features (N=24) performed about the same compared to the model using all partner-reported predictors (R^2=0.012, RMSE = 0.88). In comparison to the post-program level model, partner-reported predictors predicting individuals' changes model yielded more contributing features (24 compared to 14). These predictors were consistent with other models with the majority (20) being relationship process variables (e.g., dyadic coping, positive connections between partners), and others being family environment variables (i.e., family harmony and chaos/calmness in the family), and mental health variables (i.e., satisfaction with life and internalizing symptoms).

Combined Self- and Partner-Reported Predictors of Changes in Relationship Quality over One Year

Following the self-reported only and the partner-reported only models, a random forest model using combined self- and partner-reported predictors exploring changes in individuals' relationship quality over the time of one year was conducted. The model with both self-reported and partner-reported predictors (N=158) yielded slightly better model results than the self-reported predictors only model (R^2=0.17, RMSE = 0.78). Similar to the post-program model, the confirmed feature identified by this model (N=21) were also only self-reported variables and they were highly consistent with the features suggested by the self-reported only model. The random forest model with confirmed features had highly similar performance compared to the default model with all predictors (R^2=0.17, RMSE = 0.78).

Model Confirmation and Interpretation

Post-Program Models

After running a series of random forest models, linear multiple regression models and regularized regression models (i.e., elastic net models) were conducted to confirm the random forest model results and to assist model interpretation. First, a linear regression model using confirmed features (N=20) indicated by the random forest model using individuals' self-reported variables predicting their own post-program levels of relationship quality was conducted. The model performance was comparable to but slightly worse than the random forest model (R^2=0.30, RMSE = 9.20). However, only 6 variables were significant in the linear regression model. The variables identified by both models were family harmony, dyadic coping, caring for partner, couples' positive social connections, and perception of relational instability. The results indicated that higher baseline levels of self-reported relationship skills and family harmony, as well as lower perceived relational instability were associated with higher levels of relationship quality at one year after CRE program-start. Then, a linear regression model with confirmed partner-reported features generated by the random forest model predicting individuals' post-program levels of relationship quality (N=14) was conducted. This model had worse performance than the random forest model (R^2= .007, RMSE = 11.05), and only one out of the 14 features were statistically significant in the regression model, which was acceptance of partner as who they are. Model performance of the linear regression model using combined self- and partner-reported predictors was worse than the random forest model (R^2= .28, RMSE = 9.25), and only seven out of 19 variables were significant. See Appendix Section 2 Supplemental

Table 1 for the three linear regression model results for post-program levels of relationship quality at one year.

Following these three linear regression models, three elastic net models were conducted with similar procedures. Elastic net models shrink predictors' coefficients to be zero if they do not contribute to the model. Based on the results, all 24 confirmed features suggested by the self-reported predictors only random forest model were important to individuals' post program levels of relationship quality, and model performance was similar to the random forest model (R^2=.31, RMSE = 9.18). For the partner-reported factors predicting individuals' post program levels of relationship quality elastic net model, consistent with other models using partner-reported predictors, this model also had poor model performance (R^2=.008, RMSE = 10.97), but all 14 of the confirmed features remained significant in this model. The elastic net model with confirmed features selected by the combined self- and partner- reported predictors performed worse than the random forest model (R^2=.29, RMSE = 9.20), with 11 out of 19 variables remained to be significant. Coefficient estimates from these models can be found in Appendix Section 2 Supplemental Table 2. See Table 2 for the model performance comparison between random forest models, linear regression models, and elastic net models for post-program levels of relationship quality.

Changes Models

A similar set of linear regression and elastic net models were conducted using confirmed features emerged from the random forest models using self-, or partner-reported, or combined self- and partner-reported variables predicting changes in individuals' relationship quality over the time from CRE program-start to one year after CRE program-start (See Appendix Section 2 Supplemental Table 3). First, a linear regression model was conducted using the individuals' self-reported confirmed features predicting changes in their own relationship quality. Although model performance was similar to the random forest model (R^2=0.16, RMSE=0.81), only four out of 26 confirmed features were significant in the linear regression model. Following the self-reported predictor models, a linear regression model using partner-reported confirmed features selected by the random forest model was conducted. The linear regression model using 24 confirmed features had poor model performance (R^2=0.01, RMSE = 0.88) and there were only three significant variables (i.e., couples' positive social connections, accepting partner as who they are, and satisfaction with life). The linear regression model with combined self- and partner-reported confirmed features had similar model performance to the random forest model and the elastic model with only self-reported confirmed features (R^2=0.16, RMSE=0.80).

The elastic net model using only self-reported confirmed features predicting changes in individuals' relationship quality over one year also performed similarly compared to the random forest or the linear regression model (R^2=0.16, RMSE=0.80), and all confirmed features emerged from the random forest model had non-zero coefficients in the model. Based on the coefficient estimates of the linear regression and elastic net model, lower relationship skills or functioning (e.g., sexual satisfaction, intimate knowledge about partner, caring for partner) was associated with more improvements in relationship quality over one year, and conversely, higher levels of perception of relational instability and higher levels of mental health symptoms were inversely associated with more improvements in relationship quality over one year. Then, an elastic model using partner-reported confirmed features selected by the random forest models was conducted. The elastic net model confirmed that all 24 features contributed to the model but the model performance remained poor (R^2=0.01, RMSE = 0.87). Finally, the elastic net model with combined self- and partner-reported confirmed features had comparable performance to the corresponding random forest model and slightly better performance than the self-reported only elastic net model (R^2=0.17, RMSE = 0.78), all variables were significant in this model. Consistent across the random forest, linear regression, and elastic net models, partner-reported predictors were not reliable for predicting individuals' changes in relationship quality over time and they did not add to the variance predicted solely by the self-reported predictors. See Table 3 for the model performance comparison between random forest models, linear regression models, and elastic net models for changes in relationship quality.

Chapter 5: Discussion

Using a large, community-based, economically and racially diverse sample, the current study applied machine learning methods to explore a critical question for CRE research: what are the most important predictors of primary program outcomes? While this question has been explored in previous research, earlier models have been constrained to including just a few variables and a handful of controls. The current study used a large, comprehensive collection of possible predictors reported by both the participant and their partner, adding additional confidence in the salience of the variables that "rose to the top." The random forest model results showed that among all the baseline individual, relational, and familial characteristics and functioning, 20-26 variables can be viewed as the most influential for post-program levels of relationship quality and changes in participants' relationship quality after participating in a CRE program over one year. Among all the predictors, specific elements of relationship processes that align well with the critical topics for the CRE framework used to develop the ELEVATE program (Futris, et al., 2014) emerged as the most consistent and robust predictors of individuals' relationship quality, followed by family environment (i.e., family harmony, family chaos) and individual mental health. If program providers have program participants' information on the top predictor variables (N=20-26 relational functioning, individual mental health, and family functioning variables) and emphasize these factors in their program, they could be reasonably confident that they could influence the relationship quality of a significant portion of the participants over a one-year period. Somewhat surprisingly, it appeared that factors related to an individual's partner (e.g., their family history, relationship skills, individual characteristics and functioning) that are distinct from the individual matter little in influencing the individual's reported outcomes in couple functioning. Rather it is the person's own factors (i.e., behaviors, skills, and well-being) that best predict their perceptions of couple functioning. These results demonstrated the feasibility of applying machine learning methods to community-based intervention studies and offered support for the skill-based CRE program designs. Specifically, these results highlighted many of the skills that are typically taught in CRE programs as the most important predictors for participants' post-program levels and changes in relationship quality over time, regardless of their individual characteristics and other contextual variables, validating some of the current efforts and highlighting relative saliency among CRE topics. Results can inform practitioners on both what is most salient among CRE topics and what may be less influential in enhancing couple quality. Further discussions centering research and practical implications are detailed throughout the following section.

The Relational Processes that Emerge as the Most Salient Predictors for Relationship Quality Following CRE Participation

Out of the 79 self-reported predictors, 20 predictor variables were the most salient predictors for predicting participants' post-program levels of relationship quality at one year, whereas all other variables did not contribute to the models. Out of the 20 top variables predicting participants' post-program levels of relationship quality, 17 of were relationship processes variables that can be framed by six of the seven key relationship skills emphasized in the ELEVATE curriculum: Choose, Know, Manage, Care, Connect, and Share. Similarly, out of the 26 top variables predicting changes in participants' relationship quality, 20 were variables related to relationship processes, and these variables can be further framed by the six of the seven relationship skills emphasized as critical to healthy relationships: Choose, Know, Manage, Care, Self-Care, and Share. These results suggested the overwhelming power that certain relational processes have for predicting changes in relationship quality over the course of intervention and provided encouragement for CRE program providers who offer skill-based programs.

Broadly, relational processes variables being predictive of relationship quality and changes in relationship quality is well-established in traditional relationship science studies, intervention studies, and even machine learning studies. For decades, relationship processes such as communication (Kanter et al., 2022), conflict management (Gottman et al., 1998), and dyadic coping (Falconier et al., 2015) were repeatedly found to be robust predictors of relationship quality over time. In CRE studies, baseline levels of and/or changes in couples' relationship processes such as positive or negative interactions, use of relationship skills, and communication and self-regulation were found to have direct associations with program participants' later relationship quality at different timepoints following CRE participation anywhere from immediate post-program to as long as four years after program participation (Adler-Baeder et al., 2022; Halford & Wilson, 2009; Rauer et al., 2014). In recent machine learning studies using non-intervention samples, when tested alongside an extensive list of predictors, several key relationship process predictors consistently emerged as the most robust predictors, accounting for more variance in relationship quality compared to individual demographic, individual well-being, and contextual predictors. Some of the variables that emerged in these machine learning studies were highly similar to the top variables in the current study, such as perceived partner warmth and quality time (Ascigil et al., 2021; Brown et al., 2022; Joel et al., 2020).

Dyadic Coping and Conflict Management

The top predictors identified by the random forest models for both post-program levels of and changes in relationship quality were highly consistent with the predictors suggested by existing literature. Individuals' self-reported overall satisfaction with their own and their partner's dyadic coping, as well as their perception of their partner's dyadic coping behaviors were the two most important predictors, outperforming all other relational processes variables. Dyadic coping is a construct related to couples' abilities and behaviors to cope with stress in the context of a romantic relationship. Similar to other dyadic theories, dyadic coping theory has self-oriented and partner-oriented elements, as well as interactive and interdependent elements (Bodenmann, 2005). The full Dyadic Coping Inventory (DCI; Bodenmann, 2008) includes elements of stress communication, delegated coping, supportive coping, negative coping, common dyadic coping, and evaluation of dyadic coping by oneself and by partner. In practical terms, this includes practices such as taking partner's stress seriously, communicating one's own stress with partner, and providing support when partner is stressed. The current study used a shortened and adapted version of the DCI and selected two supportive coping and two negative coping items each by oneself and by partner, as well as the evaluation of dyadic coping. A meta-analytical study found a large correlational effect size between total dyadic coping and relationship quality (r = 0.45) and each of the elements of dyadic coping also had medium to large associations to relationship quality (r = 0.11- 0.53), demonstrating the importance of this single construct (Falconier et al., 2015).

Similarly, conflict management was one of the topic predictors in both models. These items also reflect positive and respectful ways of coping and managing stress and conflict. Conflict management has long been emphasized in research-based CRE programs (Markman et al., 2022) and has been considered as one of the primary targeted outcomes in many CRE studies (Blanchard et al., 2009). The heavy content emphasis on conflict management in CRE was rooted in the seminal work that emerged in the marriage and family therapy field, indicating that how couples handle conflicts was directly associated with relationship satisfaction and dissolution (Gottman et al., 1998). Healthy communication during conflict is undoubtably a crucial pillar for couples' relationship quality. Furthermore, coping skills and conflict management are skills and can be learned. Through participation in CRE, the improvements that happen in these areas is directly linked to improvements in relationship quality (Markmen et al., 2022). The current study's findings offered even more confidence in such content emphasis. Interestingly though, the more predictive variable for individuals' relationship quality was not their own conflict management skills, but rather their perceptions of their partner's conflict management skills. This finding speaks to the dyadic nature of conflict management and sheds light on the importance of employing dyadic measures when studying couple relationships.

Also noteworthy, multiple stress related variables were included as study predictors such as individuals' financial condition, psychological distress, and experiences with racism; noticeably, none of these variables were robust predictors for post-program levels of relationship quality or changes in relationship quality, further validating the importance of higher skills in dyadic coping and conflict management. This finding can be framed by vulnerability-stress-adaptation model (VSA; Karney & Bradbury, 1995; McNulty et al., 2021), that expects the impact of stressful events or experiences on relationship quality depends on the couples' enduring qualities, adaptive processes, and behavioral changes. Thus, the current study's findings further shed light on the importance of equipping couples with stress and conflict management skills individually and in the context of romantic relationships. Participants in CRE programs will benefit from discussion and practice in stress and conflict management, particularly on recognizing one's own and partner's signs of stress, understanding one's own and partner's effective ways of coping, and maintaining healthy communication when managing stress and conflict. Moreover, this is not meant to ignore the sociohistorical evidence of structural oppression and discrimination that leads to stress and conflict from inherently biased systems and inequities in experiences of discrimination. Anti-racist efforts at the policy levels to address inequities should go hand-in-hand with recommendations to enhance individuals' capacities for managing stressors from multiple sources.

Caring and Acceptance

Another category of relational processes was measures of caring, acceptance, non-judgement, and patience towards partner. Significant work emphasizes the value of positivity and other-focused kindness and acceptance in healthy relationships (e.g., Gottman et al., 1998). Viewing the relationship or partner through a positive lens can be viewed as a learned skill. Similarly, accepting one's partner for who they are (a change in attitude and belief), using non-judgement and patience are approaches that emerged as top predictors of relational outcomes. Items used to measure these concepts included "I accept the positive and negative characteristics of my partner" , "Even when it makes me uncomfortable, I allow my partner to express their feelings", "I tune into my partner when they are talking to me without regard for time" (items from Mindfulness in Couple Relationships Scale; McGill et al., 2020), and "Tell your partner things you appreciate about them and how much you care for them" (item from Couple Relationship Skills Inventory; Adler-Baeder et al., 2022). To understand why these skills and approaches are so important for relationship quality, we draw attention to the "perpetual problems" in long term relationships documented by Gottman (1999). Gottman defined these problems as issues that couples have been dealing with and arguing about for a long time, and they usually cannot be resolved. Not surprisingly, when handled inappropriately, these unresolvable issues have negative effects on long-term relationship quality. It is clear that the opposite of continued conflicts revolving around these perpetual issues is accepting all parts of their partner and moving on from trying to find a resolution for the unresolvable. Practically speaking, helping couples identify "perpetual problems" and understanding the importance of practicing unconditional acceptance, patience, and non-judgement of one's partner is an area important to highlight in CRE programs. Relatedly, the use of caring and kind behaviors in every day interactions builds up positivity in the "emotional banks" of couples and is shown to be one of the strongest predictors of high relationship quality (Gottman, 2023). Couples who use caring, kind, accepting behaviors routinely in their relationships, operationalized by expressing affection and appreciation, using kind words, and being open with emotions, just naturally manage their conflicts better when they arise (e.g., Huston & Vangelisti, 1991). These processes are also conceptually similar to one of the top predictors identified in Brown et al., 2022 machine learning study, partner warmth, which further emphasized the saliency of positivity and caring behaviors in couple relationships.

Intentionality and Investment in the Couple Relationship

Several of the top variables convey intentionality and investment in the couple relationship. These measures of attentiveness, active participation and purposeful efforts to spend quality time together are framed by the ELEVATE concepts of "Choose" and "Share." These concepts are rooted in the commitment to work on the relationship, and to foster the idea of unity as a couple. Commitment as a construct is often operationalized as an indicator of relationship quality since the pattern of relationship processes variables predicting commitment is highly similar to the pattern of variables predicting relationship quality (Joel et al., 2020). Commitment, however, is distinct conceptually, and is one's willingness (i.e., attitudes) and efforts (i.e., behaviors) to continually work on the relationship. Moreover, the concept of "Share" also taps into the behavioral aspects of engaging in the commitment, which is operationalized by how often the couples make time for each other, engage in leisure activities together, and exchange thoughts and ideas. Similarly, quality time was found to be one of the most salient predictors of relationship quality in another machine learning study (Ascigil et al., 2023). Taken together, we recommend CRE programs to focus on emphasizing to participants the "doing" of commitment, which is to emphasize the behavioral investment that one puts into the relationship when committed and focused on building and maintaining the couple identity and strength.

Intimate Knowledge and Understanding

Measures of awareness and knowledge about one's partner were also among the top predictors. Both self-reported one's own knowledge of partner, and their perception of their partner's knowledge of them were both top predictors of one's own relationship quality. This measure captures several aspects of the knowledge the partners have about each other. To have intimate knowledge of one's partner is not only to know their everyday stressors and wins, but also their goals and dreams, as well as their preferences, dislikes, and story of their lives. The process of getting to "Know" the partner is usually a common part of mate selection and relationship development, but as a skill in an ongoing relationship, having intimate knowledge and understanding about the partner is about consistently updating knowledge and being open to changes and growths (Adler-Baeder et al., 2022). This relational process is also closely connected to dyadic coping and intentionality and investment in the relationship because the f having and maintaining intimate knowledge involves being open to share one's emotions, thoughts, and stress and being willing to continuously putting in the efforts to stay attuned and update the intimate knowledge.

Social Connections

One of the top predictors that uniquely predicted post-program levels of relationship quality but not changes in relationship quality was the positive social connections that the couples have outside of the couple unit, including family, friends, and other social resources. Social connection has been named a public health priority in recent years because of its direct and robust association with individuals' health and well-being (e.g., Holt-Lunstad et al., 2024). Not surprisingly, the positive effect of social connections also extends to couples. In the current study, social connections were captured from two aspects. The first aspect of social connections is about having family and friends who care about the couple and can help the couple when needed. This type of social support is directly linked to couples' relationship satisfaction and was found to buffer the negative impact that financial distress could have on romantic relationship quality (Barton et al., 2014). The second aspect of social connections is about being able to be helpful to a community and to those in need as a couple. To this end, recent evidence pointed out that having a sense of purpose in life and actively engaging in life predicted relationship maintenance over time (Pfund & Hill, 2022). As such, encouraging couples to foster positive, bidirectionally supportive, social connections with family, friends, and community and helping couples understand the important implications to their own romantic relationships should continue to be an area of emphasis for some CRE programs.

Self-Care

A top predictor only for post-program changes in relationship quality over one year was self-care. There were two distinct sub-categories to self-care in the current study, one was psychological, and another one was physiological. The psychological aspect of self-care measures how well someone takes care of themselves emotionally and mentally. This is related conceptually to measures of self-regulation and self-efficacy, which were also top predictors.

The physiological aspect of self-care, on the other hand, measures how well someone takes care of themselves when it comes to engaging in health-promoting eating, sleeping, and exercising behaviors. With this understanding of the construct of self-care in the current study, we drew evidence from various studies to explain why baseline self-care behaviors could predict changes in relationship quality over time. First, being self-compassionate and being able to regulate challenging emotions were found to be directly related to more positive relational behaviors in couple relationships (Neff & Beretvas, 2013). Higher levels of baseline self-care could indicate a sense of self-efficacy that promotes potential improvements in relationship quality in the context of intervention, or in other words, when someone is more attuned to themselves and their individual emotional and physical well-being, they might be more prone to be attentive and take care of other areas in their lives. Further, self-care was recently found to have an indirect association with family relationship quality through couples' conflict management and the quality of communication (Vasquez et al., 2025), though more empirical research on self-care behaviors and romantic relationship quality is warranted. Finally, a recent study also found that CRE participants' self-care behaviors are closely connected with individual mental and physical well-being outcomes, specifically with stress and sleep outcomes (Wei et al., 2024), further suggesting that self-care could potentially be linked to relationship functioning through various processes and pathways.

Perceptions of Relationship Instability

Another variable that consistently emerged in the top 10 variables across models was perceptions of relationship instability. Our findings added to the existing evidence that couples who were more distressed at baseline could potentially gain more than those who were less or not distressed because the room for improvement is larger (e.g., Bradford et al., 2017; Quirk et al., 2014). Based on the results from the linear regression and the elastic net models, we found that higher levels of perceived relational instability were inversely associated with more improvements in relationship quality over one year. However, the relationship between relational instability, relationship quality, and commitment is certainly a nuanced one evidenced by mixed results across studies of distress and relational outcomes following CRE. For example, one recent study showed that compared to moderately and higher distressed individuals, only happy or stable individuals improved in their relationship quality following CRE participation. The authors suspected that over half of their sample might be more likely to benefit from more personalized and intense intervention such as couple therapy rather than relationship education (Urganci et al., 2024).

Additionally, other evidence indicates that risk factors moderate CRE program effects differently depending on the severity or elevation of the risk factors as well as how easily modifiable these risk factors were (Halford & Bodenmann, 2013; Williamson et al., 2015). Although much intricacy revolves around the topic of if and how much distressed couples can benefit from CRE, the current study's results aligned with most studies suggesting distressed couples tend to benefit more from CRE programs. Collectively, the evidence aligns with current best practices in CRE, which is to implement screening procedures (Stanley et al., 2020). Given the mixed results on the amount of gains that couples at higher risk can have from participating in CRE along with lower risk couples, offering additional resources such as case management and therapy referrals to couples at higher risk might be particularly helpful at the time when they seek CRE.

Family Harmony/Family Chaos

Another distinct group of variables that consistently emerged as top predictors were the family environment variables. Individuals' current family environment was captured by two measures, one of which assesses the happiness and contentment in the household, and the other assesses if the atmosphere in a household is chaotic or calm. These predictors were related to both post-program levels of relationship quality and changes in relationship quality over one year. The assumptions from family systems theory (FST; Johnson & Ray, 2016) that recognize a family's subsystems and the whole system interact and influence one another offers a logical explanation for this relationship. In the case of the current study, higher family relationship functioning at baseline implied that, the subsystem that the couples belonged too were also somewhat stable. Further, having a higher baseline levels of family functioning also suggested that the stressors in the immediate family environment might be limited, which could foster room and opportunities for the subsystem, the couples, to grow and improve. Practically speaking, this finding might be once again tied back to dyadic coping and conflict management, where we recommend CRE programs to consider the boarder context that the couples are in, and the levels of stressors (e.g., coparenting stress in the family) that they might experience. While we found that more relationally unstable couples appeared to benefit in their relationship quality post-program and experience more changes, it is also true that those with more harmony and less chaos in the family reported higher relationship quality and more changes after the program. If we paid attention to the linear regression and elastic net model results, we could see more robust associations between relationship instability and relationship quality than family environment.

The Outperformance of Relational Processes Variables over All Other Variables

One benefit random forest models offer is that they are able to accurately distill the most important predictors from a long list of variables based on the variables' relative potency.

Practically speaking, this could mean that not being identified as the most important variables does not imply that certain variables are not important (e.g., individual demographic, contextual experiences), it only means that certain variables were not as important as other variables. Based on our findings, the unchangeable variables (e.g., individual characteristics such as race or gender, family life history such as adverse childhood experiences) were less important than the changeable variables (e.g., relationship skills). In our case, we found support that skill-based relational processes such as dyadic coping, conflict management, and viewing relationship with a positive lens were undoubtedly the most potent predictors for post-program levels of and changes in relationship quality following CRE participation. This finding, in many ways, should be encouraging news to CRE program providers because it implies that universal skill-based CRE intervention, when targeting the relationship processes framed as stress/conflict management, intentionality, intimate knowledge, caring, quality time, and social connections, should work for most if not all program participants regardless of their individual demographics and social contexts. One interpretation of this finding could be tied to the mechanisms of changes in CRE, as illustrated in the most recent best practices in CRE (Stanley et al., 2020). As suggested by the best practices, although static factors (e.g., financial conditions, family history) are important and relevant to CRE programs, especially in relation to understanding program participants' needs, the potentially malleable or modifiable factors (e.g., beliefs about the partner or relationship) should be the focus of CRE programs as they are more closely linked to mechanisms of changes in CRE.

We also note that the current study provides more robust evidence of relational process over individual characteristics in influencing outcomes. One limitation in previous machine learning studies regarding predictors of relationship quality was the lack of racially and economically diverse samples (Ascigil et al., 2023; Joel et al., 2020). Although relational processes were found to be the most important predictors in these studies, the authors cautioned that the reason demographic or contextual variables were not found to be more important might be due to the homogeneity of the samples. The current study, however, with over half of the participants reporting being racial or ethnic minorities, over 40% of the participants being high-school education equivalent or less, and one third of them having an individual annual income of under $19,999, the findings provided additional evidence that relational processes variables might be, in fact, more important predictors than individual demographic variables for relationship quality and predicting programmatic changes. Stated another way, if we had found that the top predictors of post-program levels of relationship quality and changes in relationship quality were unchangeable characteristics, we would be hard-pressed to argue for the value of short-term interventions focused on relational processes for the broad population of participants.

Still, studies focusing on specific subpopulations is warranted since they offer further understanding for the potency of relational processes variables in comparison with other variables. In one machine learning study that used an African American sample, family life history (i.e., relationship difficulty with primary caregiver) and sociocultural factors (e.g., interactions with law enforcement, neighborhood adverse experiences) were also identified as some of the most important predictors of individuals' relationship quality alongside with relationship processes variables (Brown et al., 2022). These findings suggested that the most important predictors of relationship quality for different populations may in fact differ. Relationship processes variables are likely to continue to be top variables, as well as particular sociocultural variables. For example, outness may be a particularly important predictor to queer individuals' relationship quality (Ballester et al., 2021). When applying these findings to CRE programs, it adds to the ongoing discussion in CRE research on offering specific, tailored programs to different subpopulations rather than the non-tailored, universal programs because there may be unique processes related to romantic relationship functioning for different populations. Nonetheless, results from the current study along with evidence presented in previous machine learning studies, all identified specific relational processes variables to be the most predictive factors for individuals' relationship quality, confirming the current efforts in skilled-based CRE programs to address these elements.

How Does it Differ? Understanding the Predictors for Post-program Levels of Relationship Quality and Changes in Relationship Quality

One distinctive difference between the current study and the previous machine learning studies investigating the most robust predictors of relationship quality was that the current study focused on changes following an intervention, whereas the only previous ML study to explore change, focused on normative changes. According to the Joel et al., 2020 study, self-reported predictors were not well-equipped to predict normative changes in relationship quality one or two years after baseline as no more than 5% of the variance was accounted for in any of their analyses. The current study, however, found that, combining self and partner reports, predictors were able to predict up to 17% of the changes in individuals' relationship quality over one year after they started CRE. Further, the Joel et al., 2020 and the Brown et al., 2022 study did find that self-reported predictors could be used to predict relationship quality at a later timepoint (up to 18% and 48% of the variance predicted respectively compared to 33% of the variance predicted in the current study). Collectively, these findings suggested that there may be distinctive differences between the predictive mechanisms between predicting levels of relationship quality at a certain timepoint versus predicting changes in relationship quality and it is clearly more challenging to predict changes. Changes over time may have less variability than scores at a specific timepoint and also include increases, decreases, or maintaining the same over time.

Comparatively, when looking at the top predictors across the post-program models (N=20) and the change models (N=26), the majority of the predictors overlapped. Eighteen out of top 20 variables in the post-program models were also top predictors in the change models. A note-worthy pattern, however, was that individual mental health symptoms (i.e., internalizing depressive symptoms and distress) were only found to be important predictors for changes in relationship quality, but not for post-program levels of relationship quality. It could be that mental health might have shifted with relationship quality from baseline to one year after baseline, so that the baseline level of mental health functioning was no longer highly associated with later levels of relationship quality. Previous work indicates complex and bidirectional relationships between romantic relationship quality and individual mental health, as well as the processes of changes of both outcomes in CRE programs. Studies find that the pathway between romantic relationships and individual health is bidirectional (Braithwaite & Holt-Lunstad, 2016) – mental health influences individuals' decisions on entering romantic relationships and their experiences in romantic relationships, and romantic relationship functioning influences individuals' mental health. The stronger directional effects though, were more consistently found from romantic relationships to individual mental health than vice versa. Specifically, when individuals' relationship quality improved, their mental health also improved, but not necessarily vice versa (Braithwaite & Holt-Lunstad, 2016). This pathway was replicated in CRE research as well. One recent study found that changes in mental health following CRE participation were associated with later changes in relationship quality, but the associations between earlier changes in relationship quality to later changes in mental health had a stronger directional link (Cooper et al., 2021). Situating the current study's findings in these previous studies, we note that those with greater mental health symptomology appeared to benefit more in their relational functioning after CRE participation. It may be that these enhanced relationships also benefitted their mental health; however, this link was not explored in the current study. This finding further highlighted that mental health likely plays an important role in the mechanisms of changes in CRE programs, and further research of individual mental health both as a program outcome and a moderator for program effects are warranted.

The Limited Predictive Power of Partner-Reported Predictors

Utilizing dyadic data, the current study investigated the predictive power of self-reported variables, partner-reported variables, as well as combined self- and partner-reported variables. Across all models, partner-reported variables never predicted more than 2% of the variance in individuals' post-program levels of or changes in relationship quality one year following CRE program participation. Further, the models using combined self- and partner-reported variables only selected self-reported variables during feature selection as the most important predictors, indicating that having partner-reported variables did not add any predictive powers to the models.

Although this finding might be somewhat surprising from a theoretical perspective, we believe there were several plausible explanations behind the limited predictive power of the partner-reported predictors. Theoretically speaking, one's beliefs/perceptions and behaviors within a dyad are interdependent in nature and have an impact on ones' own and their partner's functioning (e.g., interdependence theory; Kelley & Thibaut, 1978). These self-and-partner links are more often investigated in the context of concurrent associations or concurrent changes for both partners than predictive over time. Empirically, the Joel et al, 2020 study used similar methods as the current study in which they also used self- and partner-reported predictors to predict individuals' outcomes. In the Joel et al., 2020 study, relationship quality was investigated concurrently (baseline predictors predicting baseline relationship quality), at a later time point (baseline levels predictors predicting relationship quality at a later timepoint), and in terms of normative changes over time (baseline predictors predicting individual slopes of relationship quality). At each of the timepoint, self-reported predictors predicted two to four times more of the variance in relationship quality than the partner-reported predictors. Similarly in our study, combining self- and partner-reported predictors predicted essentially equal variance compared to using self-reported predictors and self-reported factors were the top predictors in both models. In the Joel and colleagues' study, when using baseline predictors predicting baseline relationship quality, self-reported predictors predicted 45% of variance in relationship quality, while partner-reported variables predicting 15% of the variance. When predicting relationship quality at a later timepoint, self-reported variables predicted 18% of the variance in individuals' relationship quality, and partner-reported variables predicted 13% of the variance in individuals' relationship quality. Finally, neither self-reported or partner-reported variables predicted more than 5% of the variance in normative changes in individuals' relationship quality, with partner-reported variables predicting only 1% of the variance in normative changes in relationship quality.

These results, combined with the current study's finding, provided some critical information for us when interpreting partner-reported variables' predictive power. Joel and coauthors suspected the underperformance of the partner-reported items were due to actor-reported items fully mediating the relationship between partner-reported predictors and individuals' relationship quality. That is, although partner-reported predictors might be important, they might have an indirect relationship with relationship quality through interpersonal interactions; in other words, the effects of the partner-reported predictors were fully absorbed by the effects of actor-reported predictors (2020). Another way to think about this is, via similar interpersonal interactions. Self-reported relational processes may be highly correlated with partner-reported relational processes so much so that partner-reports of their behaviors do not add unique information. In practice, this could mean that CRE programs could emphasize alignment of skills in couple dynamics. It also is important to focus on the individual's own perceptions and behaviors. That is, shifts in one's own perceptions of the relationship (e.g., the relationship is not in trouble) or behaviors (e.g., implementing more conflict management skills) appear to more critical to the improvements in their own outcomes than the shifts in their partner's perceptions or behaviors. In fact, this pathway was identified in a recent CRE study where individuals' intra-personal gains in relational knowledge were associated with their own better health functioning later, but this link was not found dyadically (Wei et al., 2024). In sum, the limited predictive power of partner-report predictors does not imply that partner-reports were not important, rather, it suggests that self-perceptions of relational processes are potentially more impactful for an individual's relational outcomes.

Model Confirmation and Interpretation

In the current study, to confirm random forest model results and assist model interpretation, linear multiple regression models and regularized regression models (i.e., elastic net) models were conducted using the selected features by random forest models to evaluate 1) model performances, and 2) directional associations between selected features and study outcomes. The use of benchmark models for model confirmation and comparison is a common practice in machine learning studies (e.g., Brown et al., 2022; Pearson et al., 2019). Across 18 models (6 models for each method) using selected top features, linear regression models never performed better than random forest models or elastic net models based on R^2, RMSE, and numbers of variables that were significant in the model. In the random forest models, 14 to 26 variables were selected by the feature selections, but only a small portion of these variables were significant in the linear regression models (range = 1-7). Discrepancies between linear regression models and the random forest models and the underperformance of the linear regression models have been found in past machine learning studies (e.g., Brown et al., 2022; Pearson et al., 2019). One possible explanation for such discrepancies may be that linear regression models assume linearity between the predictor variables and the outcome, as well as among the predictor variables, and they are more prone to overfitting (Lewis, 2000). The random forest models, on the other hand, do not assume linear relationships between the predictors and the outcome, and are sensitive to nonlinear relationships among predictor variables. Further, instead of fitting all predictor variables simultaneously in a model, it uses bootstrapping and decision trees to process a subset of predictor variables at a time, which gives all variables equal consideration and considers out-of-sample performance (Breiman, 2001; Grimmer et al, 2021).

Elastic net models performed the same compared to the random forest models in four of the models, slightly better in one of the models, and slightly worse in one of the models. The selected features remained significant in all but one of the models. This comparison suggested that elastic net was a practical method for handling a large number of nonlinear predictors, and it outperforms linear unregularized regression models by using regularization on regression estimates to address overfitting. As explained in detail in the Appendix Section 1, similar to random forest, elastic net models are also able to handle issues with predictor collinearity and model overfitting through regularization, and it also performs feature selection by shrinking the coefficient estimates (Zou & Hastie, 2005). Also performed in machine learning framework, elastic net and random forest are both popular regression-based machine learning methods but differ meaningfully in the ways they select features. Random forest uses a tree-based approach and searches for the variables that minimizes the MSE to make accurate predictions. Elastic net, on the other hand, performs feature selection by shrinking the coefficient estimates. This study chose random forest as the primary method and linear regression and elastic net as the model confirmation methods because all previous machine learning studies on predictors of relationship quality chose to use random forest models and we could make relevant comparisons with the same method. When it comes to identifying the comparative potency of a list of predictors, random forest models and elastic net are both reliable methods and both considerably outperform linear regression models. A recent intervention machine study found that the most important predictors for their study outcome identified by random forest models and elastic net models overlapped greatly, and their model performances were highly similar (Pearson et al., 2019). For the purpose of feature selection and identifying the most potent predictors for any given study outcome, one method is not inherently better than the other and researchers should carefully evaluate and select the method based on considerations like research questions, study samples, and data structures.

Strengths, Limitations. and Future Directions

The current study advances CRE research and had many strengths, such as having a large, community-based, diverse sample, utilizing machine learning method for the first time in CRE research, adopting an ecological framework for predictor selection, implementing benchmark models to ensure accuracy of the analyses, as well as offering discussions for research and practical implications. Nonetheless, the study findings are viewed under the light of several limitations.

First, although the current study considered a comprehensive list of 79 individually-reported and 79 partner-reported predictors representing individual, relational, familial, and contextual factors, it still may have lacked some critical predictors of relationship quality, particularly those that may be especially relevant for subgroups in the sample. We also did not include some measures of individual traits, such as personality type and attachment style, that have been linked to relationship quality (e.g., Butzer & Campbell, 2008; Großmann et al., 2019). We do recognize, however, it is not likely a single dataset could have all the possible variables that are relevant to relationship quality due to the potential for respondent survey fatigue. One approach to this issue is to use large, secondary datasets that include a wide range of variables. Alternately, a different approach, used in the Joel and colleagues' study (2020), combines existing romantic relationship focused datasets, conducts random forest analyses on each of the datasets, and then investigates the results collectively using meta-analyses. As we continue to move forward to open science, future studies may join these scientific efforts to move the field of relationship science to be more accessible, reproducible, and broadly disseminated.

Further, although we included individuals who identify as sexual and gender minorities (SGM) and/or those who are in same-gender relationships in the analyses, they accounted for a small portion of the sample (6%) and we are not able to assert that our results are generalizable to the SGM participants in CRE. Similarly, these results may not be generalizable to specific subpopulations that may have unique and potent predictors of their relationship functioning that were not considered in the current study. For example, individuals going through significant life stage transitions (e.g., entering parenthood, returning from military services) may exhibit different top predictors of relationship quality during those stages (Knobloch & Theiss, 2011; Trillingsgaard et al., 2014). In the future, scholars who are interested in predictors of a specific subpopulation could consider employing machine learning methods to explore the particular predictors of relationship quality for that subpopulation. The Brown et al., 2022 study is an example of this approach. The authors investigated predictors exclusively for monoracial African American individuals' relationship quality and included factors specific to this subpopulation (e.g., skin tone, lifetime racial discrimination). Studies focusing on specific subpopulations may provide additional information for CRE program providers when considering offering generalized, non-tailored versus targeted, tailored CRE programs.

Moreover, participants in the current study all received the same evidence-based CRE program, ELEVATE (Futris et al., 2014). It may be meaningful for future studies to replicate the current study with samples receiving different and various CRE programs to provide additional information for the variance predicted in changes in relationship quality following CRE program participation. Such information may help program providers identify effect sizes across various CRE programs and choose the best program for the population served. Notably, this study is not an assessment of program effects, but rather, builds on the random control efficacy study of ELEVATE that established its impact on relationship quality by exploring the most potent predictors of post-program levels and changes in relationship quality. Both within and beyond CRE studies, additional machine learning intervention studies could also facilitate an eventual goal of developing algorithms that could predict participants' responses to various intervention programs. Practically, this could involve entering a participant's information in the screening stage, and the predictive algorithm could generate predictions on which program or collection of programs/resources would promote the most improvements in the targeted outcome areas. The usage of such predictive algorithms is being studied in various intervention settings (e.g., Chekroud et al., 2016).

Conclusion

By implementing machine learning methods in CRE research for the first time, the current study provided additional evidence to confirm the validity of the current content emphasis of CRE programs on relationship processes related to relationship skills, perceptions, and attitudes. More specifically, key couple skills for coping and conflict management, maintaining intimate knowledge, intentionality, caring and acceptance, social connections, and efforts to build couple identity and connection, as well as family harmony and self-care and mental wellness matter most in predicting later relational well-being, compared to individual or relational demographics, or contextual factors. This study demonstrated the feasibility of applying machine learning methods to community-based CRE programs and further advanced the understanding of the question “what works in CRE” and provides more assurances of the broad applicability of the critical content in CRE for diverse populations. As a first step towards using machine learning in CRE programs, this study also served as a foundation for future studies to further explore even larger collections of predictors of relationship quality post-program, as well as specific predictors for different subpopulations. These efforts hold the promise for potentially identifying the best intervention plans for individuals and couples seeking helping resources.

Table 1a. Study Predictors – Individual Demographic Predictors (N = 8)

Measure	Citation	Number of Items	Sample Item(s)	Range of Response	Cronbach's Alpha
Gender Identity	N/A	1	I identify as (select all that apply):	1=Woman 2=Man 3=Non-Binary, Genderqueer, Transgender, or other	N/A
Race	N/A	1	Which of the following best describes your race?	1=Asian or Asian-American 2=Black or African-American 3=Multiracial or Biracial 4=Native-American or Alaskan Native 5=Native-Hawaiian or Pacific Islander 6=White or Caucasian	N/A
Age	N/A	1	What is your age in years?	Numeric	N/A
Education	N/A	1	What is the highest degree, diploma, or certification you have earned?	1=No degree or diploma earned 2=High School General Education Development or GED and/or High school diploma 3=Vocational/technical certification, Associate's degree, or other 2 year degrees 4=Bachelor's degree 5=Master's degree/Advanced degree	N/A
Employment Status	N/A	1	What is your current employment status?	1=Not currently employed 2=Part time employment (1-34 hours a week); Employed, but number of hours change from week to week; Temporary,	N/A

				occasional, or seasonal employment 3=Full time employed	
Individual Income	N/A	1	What is YOUR TOTAL PERSONAL INCOME (considering only yourself--not your partner or other household members) in the current year (before taxes)?	1=Under $19,999 2=$20,000 - $39,999 3=$40,000-$74,999 4=$75,000-$99,999 5=Over $100,000	N/A
Household Income	N/A	1	What is your TOTAL HOUSEHOLD INCOME (from you, your partner, and any other wage-earning adult in your household) in the current year (before taxes)?	1=Under $19,999 2=$20,000 - $39,999 3=$40,000-$74,999 4=$75,000-$99,999 5=Over $100,000	N/A
Sexual and Gender Minority Statues	N/A	1	Recoded by authors based on answers to the Gender Identity and Sexual Orientation questions, included those who identified as non-Binary, genderqueer, transgender, bisexual or pansexual, lesbian, gay, and queer.	0=No 1=Yes	N/A

Table 1b. Study Predictors – Couple or Family Demographic Predictors (N = 10)

Measure	Citation	Number of Items	Sample Item(s)	Range of Response	Cronbach's Alpha
Marital History	N/A	1	Have you ever been divorced?	0=No 1=Yes	N/A
Marital History	N/A	1	Have you ever been remarried?	0=No 1=Yes	N/A
Marital History	N/A	1	Have you ever been widowed?	0=No 1=Yes	N/A
Partner Gender	N/A	1	Which description fits your current couple/romantic relationship?	1=Same-gender 2=Different-gender 3=Other	N/A
Relationship Type	N/A	1	How would you describe your current couple/romantic relationship?	1=Committed (not engaged/married) 2=Engaged to be married 3=Married 4=Separated 5=Casually Dating	N/A
Cohabitation Status	N/A	1	Do you live with your partner?	0=No 1=Yes	N/A
Relationship Length	N/A	1	How long have you been together with your current partner?	Numerical, Year and Month	N/A
Parental Status	N/A	1	Are you a parent?	0=No 1=Yes	N/A
Household Size	N/A	1	How many members are in your current household?	Numerical	N/A
Number of Children	N/A	1	How many children do you have? These may be biological children, stepchildren, adopted children, foster children, or any other children that you consider part of your family	Numerical	N/A

Table 1c. Study Predictors – Relationship Processes/Functioning Predictors (N = 24)

Measure	Citation	Measure Description	Number of Items	Sample Item(s)	Range of Response	Cronbach's Alpha
Relationship Skills (Self-care)	Adler-Baeder, F., Futris, T. G., McGill, J., Richardson, E. W., & Dede Yildirim, E. (2022). Validating the Couple Relationship Skills Inventory. Family Relations, 71(1), 279–306.	Self-care behaviors	8	I ask for help from others when needed; I exercise at least 3 or more times a week	1=Very Strongly to 7=Very Strongly Agree	0.77
Relationship Skills (Choose)	Adler-Baeder, F., Futris, T. G., McGill, J., Richardson, E. W., & Dede Yildirim, E. (2022). Validating the Couple Relationship Skills Inventory. Family Relations, 71(1), 279–306.	Intentionalit y	4	I want this relationship to stay strong no matter what rough times we encounter; I always make an effort to focus on my partner's strengths.	1=Very Strongly to 7=Very Strongly Agree	0.81
Relationship Skills (Know, Self-Report)	Adler-Baeder, F., Futris, T. G., McGill, J., Richardson, E. W., & Dede Yildirim, E. (2022). Validating the Couple Relationship Skills Inventory. Family Relations, 71(1), 279–306.	Understandi ng and intimate knowledge of partner	4	I know my partner's current life stresses; I know some of my partner's major aspirations and hopes in life.	1=Very Strongly to 7=Very Strongly Agree	0.88
Relationship Skills (Know, Perception of Partner)	Adler-Baeder, F., Futris, T. G., McGill, J., Richardson, E. W., & Dede Yildirim, E. (2022). Validating the Couple Relationship Skills Inventory. Family Relations, 71(1), 279–306.	Perception of partner's understandi ng and intimate knowledge of the individual	4	My partner knows my current life stresses; My partner knows my own hopes and aspirations	1=Very Strongly to 7=Very Strongly Agree	0.93

Relationship Skills (Share)	Adler-Baeder, F., Futris, T. G., McGill, J., Richardson, E. W., & Dede Yildirim, E. (2022). Validating the Couple Relationship Skills Inventory. Family Relations, 71(1), 279–306.	Efforts to build couple identity and connection	3	Had a stimulating exchange of ideas; Engage in and/or talk about outside interests together.	1=Never to 7=More often than once a day	0.81
Relationship Skills (Care, Self-Report)	Adler-Baeder, F., Futris, T. G., McGill, J., Richardson, E. W., & Dede Yildirim, E. (2022). Validating the Couple Relationship Skills Inventory. Family Relations, 71(1), 279–306.	Caring behaviors	4	Say "I love you" to your partner; Tell your partner things you appreciate about them and how much you care for them	1=Never to 7=More often than once a day	0.83
Relationship Skills (Care, Partner-Report)	Adler-Baeder, F., Futris, T. G., McGill, J., Richardson, E. W., & Dede Yildirim, E. (2022). Validating the Couple Relationship Skills Inventory. Family Relations, 71(1), 279–306.	Partner's caring behaviors	4	Say "I love you" to you; Tell you things they appreciate about you and how much they care for you	1=Never to 7=More often than once a day	0.86
Relationship Skills (Conflict Management, Self-Report)	Adler-Baeder, F., Futris, T. G., McGill, J., Richardson, E. W., & Dede Yildirim, E. (2022). Validating the Couple Relationship Skills Inventory. Family Relations, 71(1), 279–306.	Conflict management skills	5	I am able to see my partner's point of view and really understand it, even if I don't agree; I can easily forgive my partner	1=Very Strongly to 7=Very Strongly Agree	0.70
Relationship Skills (Conflict Management	Adler-Baeder, F., Futris, T. G., McGill, J., Richardson, E. W., & Dede Yildirim, E. (2022). Validating the Couple Relationship Skills	Partner's conflict management skills	5	My partner is able to see my point of view and really understand it, even if they don't agree; My partner can easily forgive me	1=Very Strongly to 7=Very Strongly Agree	0.82

, Partner-Report)	Inventory. Family Relations, 71(1), 279–306.					
Relationship Skills (Connection)	Adler-Baeder, F., Futris, T. G., McGill, J., Richardson, E. W., & Dede Yildirim, E. (2022). Validating the Couple Relationship Skills Inventory. Family Relations, 71(1), 279–306.	Couple's positive social connections	4	Many of our friends are friends of both of us; We know people who care about us and our relationship	1=Very Strongly to 7=Very Strongly Agree	0.74
Relationship Instability	Items adapted from Booth, A., Johnson, D., & Edwards, J. (1983). Measuring Marital Instability. Journal of Marriage and Family, 45(2), 387-394.	Relationship instability	4	Have YOU ever thought about your marriage/relationship might be in trouble?; Has YOUR PARTNER ever thought about your marriage/relationship might be in trouble?	1=Never 2=Yes, in the past, but not recently 3=Yes, recently	0.85
Mindfulness in Couple Relationships Scale (Non-Judging Subscale)	McGill, J., Adler-Baeder, F., & Burke, L. (2022). The mindfulness in couple relationships scale: Development and validation. *Mindfulness*, *13*(9), 2299-2314.	Non-judging	4	I observe my experiences with my partner without judging; Even when it makes me uncomfortable, I allow my partner to express their feelings	1=Very Strongly to 7=Very Strongly Agree	0.84
Mindfulness in Couple Relationships Scale (Patience Subscale)	McGill, J., Adler-Baeder, F., & Burke, L. (2022). The mindfulness in couple relationships scale: Development and validation. *Mindfulness*, *13*(9), 2299-2314.	Patience	4	I carefully listen to my partner when they are speaking without regard for time; I rush through activities with my partner without really paying attention to them (reverse coded)	1=Very Strongly to 7=Very Strongly Agree	0.74
Mindfulness in Couple Relationship	McGill, J., Adler-Baeder, F., & Burke, L. (2022). The mindfulness in couple	Openness to growth in relationship	3	My interactions with my partner are opportunities to learn new things about them; Each moment with my partner is	1=Very Strongly to	0.75

s Scale (Beginner's Mind Subscale)	relationships scale: Development and validation. *Mindfulness*, *13*(9), 2299-2314.			an opportunity for new or unique experiences.	7=Very Strongly Agree	
Mindfulness in Couple Relationships Scale (Trust to Self Subscale)	McGill, J., Adler-Baeder, F., & Burke, L. (2022). The mindfulness in couple relationships scale: Development and validation. *Mindfulness*, *13*(9), 2299-2314.	Trust in Self-efficacy	3	I am capable of being present in my relationship; I am able to purposefully participate in my relationship.	1=Very Strongly to 7=Very Strongly Agree	0.80
Mindfulness in Couple Relationships Scale (Non-Striving Subscale)	McGill, J., Adler-Baeder, F., & Burke, L. (2022). The mindfulness in couple relationships scale: Development and validation. *Mindfulness*, *13*(9), 2299-2314.	Non-striving to change partner	3	I can "just be" with my partner; I do not try to change my partner	1=Very Strongly to 7=Very Strongly Agree	0.60
Mindfulness in Couple Relationships Scale (Acceptance Subscale)	McGill, J., Adler-Baeder, F., & Burke, L. (2022). The mindfulness in couple relationships scale: Development and validation. *Mindfulness*, *13*(9), 2299-2314.	Acceptance of partner	3	During arguments I accept my partner has a different point of view than I do; I accept my partner for who my partner is today	1=Very Strongly to 7=Very Strongly Agree	0.73
Mindfulness in Couple Relationships Scale (Letting Go Subscale)	McGill, J., Adler-Baeder, F., & Burke, L. (2022). The mindfulness in couple relationships scale: Development and validation. *Mindfulness*, *13*(9), 2299-2314.	Ability to let go of negativity	4	I easily let go of negative emotions towards my partner; After conflict I recognize when it is time to let go of negative feelings	1=Very Strongly to 7=Very Strongly Agree	0.73

Mindfulness in Couple Relationships Scale (Noticing Subscale)	McGill, J., Adler-Baeder, F., & Burke, L. (2022). The mindfulness in couple relationships scale: Development and validation. *Mindfulness*, *13*(9), 2299-2314.	Attentiveness to partner and relationship	4	I notice when my partner makes efforts in our relationship; I notice when my partner seems upset	1=Very Strongly to 7=Very Strongly Agree	0.72
Shortened Dyadic Coping Inventory (Partner's Dyadic Coping)	Bodenmann, G. (2008). Dyadisches Coping Inventar: Testmanual. [Dyadic coping inventory]. Bern: Huber.	Partner's Dyadic Coping	4	My partner listens to me and gives me the opportunity to communicate what really bothers me; My partner helps me analyze the situation so that I could better face the problem.	1=Very rarely to 5=Very often	0.87
Shortened Dyadic Coping Inventory (Self's Dyadic Coping)	Bodenmann, G. (2008). Dyadisches Coping Inventar: Testmanual. [Dyadic coping inventory]. Bern: Huber.	Dyadic Coping	4	I show empathy and understanding to my partner; I try to analyze the situation together with my partner in an objective manner and help them to understand and change the problem (reverse coded)	1=Very rarely to 5=Very often	0.66
Shortened Dyadic Coping Inventory (Overall Dyadic Coping)	Bodenmann, G. (2008). Dyadisches Coping Inventar: Testmanual. [Dyadic coping inventory]. Bern: Huber.	Satisfaction with dyadic coping	2	I am satisfied with the support I receive from my partner and the way we deal with stress together; I am satisfied with the support I give to my partner and the way we deal with stress together	1=Strongly disagree to 5=Strongly agree	0.77
Sexual Satisfaction	Rosen, C., Brown, J., Heiman, S., Leiblum, C., Meston, R., Shabsigh, D., Ferguson, R., & D'Agostino, R. (2000). The	Sexual satisfaction	3	With the amount of emotional closeness during sexual activity between you and your partner?; With your sexual relationship with your partner?	1=Very Dissatisfied to 5=Very Satisfied	0.96

	Female Sexual Function Index (FSFI): a multidimensional self-report instrument for the assessment of female sexual function. Journal of Sex &Marital Therapy, 26, 191-208.					
Romantic Self-efficacy	Riggio, H. R., Weiser, D., Valenzuela, A., Lui, P., Montes, R., & Heuer, J. (2011). Initial validation of a measure of self-efficacy in romantic relationships. Personality and Individual Differences, 51, 601-606.	Romantic Self-efficacy	6	Romantic relationships are very difficult for me to deal with; I have difficulty focusing on important issues in my romantic relationship	1=Very Strongly Disagree to 7=Very Strongly Agree	0.95

Table 1d. Study Predictors – Physical Health Related Predictors (N = 7)

Measure	Citation	Measure Description	Number of Items	Sample Item(s)	Range of Response	Cronbach's Alpha
Sleep Quality	Buysse, D. J., Reynolds III, C. F., Monk, T. H., Berman, S. R., & Kupfer, D. J. (1989). The Pittsburgh Sleep Quality Index: a new instrument for psychiatric practice and research. Psychiatry research, 28(2), 193-213.	Sleep dysfunction	19	How long (in minutes) has it taken you to fall asleep each night? (enter NUMBERS ONLY); How would you rate your sleep quality overall?	0 (no sleep dysfunction) to 21 (high sleep dysfunction)	0.79
Physical Problems	Shortened version from Cohen & Hoberman (1983). Positive events and social supports as buffers of life change stress. Journal of Applied Social Psychology, 13, 99-125. Available online at http://www.midss.org/content/cohen-hoberman-inventory-physical-symptoms-chips.	Physical health problems	7	Please mark how much each of the following physical problems have bothered or distressed you during the past two weeks including today: Sleep problems (can't fall asleep, wake up in middle of night or early in morning) Dizziness Diarrhea Migraine headache Pains in heart or chest Stuffy head or nose Muscle tension or soreness Nosebleed	0=Not at all to 4=Extremely	0.75
Substance Use	Adapted from the Substance Use Subscale from Jackson (2006). Relationships between perceived close social support and health practices within community samples of American	Substance use	4	In your average daily routine, how often do you… Use recreational drugs Use tobacco products (cigarettes, dip, vape, etc.)	1=Never to 6=Always	0.51

	women and men. The Journal of Psychology, 140, 229-246. doi: 10.3200/JRLP.140.3.229-246			Use prescription drugs (not as prescribed) Drink alcohol excessively		
Health-Related Social Control (Shortened; Negative tactics)	Shortened version from Butterfield, R.M., & Lewis, M.A. (2002). Health-related social influence: A social ecological perspective on tactic use. Journal of Social and Personal Relationships, 19, 505-526.	Negative health control of partner	6	How often in the last 6 months have you used these tactics to influence your partner to engage in healthy activities? e.g., Guilt (made your partner feel bad for being unhealthy); Expressed negative emotions (displayed anger, frustration, or resentment towards partner for not engaging in healthy activities)	1=Never to 5=Frequently	0.91
Health-Related Social Control (Shortened; Positive tactics)	Shortened version from Butterfield, R.M., & Lewis, M.A. (2002). Health-related social influence: A social ecological perspective on tactic use. Journal of Social and Personal Relationships, 19, 505-526.	Positive health control of partner	6	How often in the last 6 months have you used these tactics to influence your partner to engage in healthy activities? e.g., Asked (asked partner to do something to improve their health); Expressed positive emotions (displayed happiness, pleasure, kindness to partner when engaging in healthy activities)	1=Never to 5=Frequently	0.95
Eating Behavior	Shortened version from Tylka, T. L. & Van Diest, A. M. K. (2013). The Intuitive Eating Scale-2: Item refinement and psychometric evaluation with college women and men. Journal of Counseling Psychology, 60, 137-153.	Intuitive eating	2	I use food to help me soothe my negative emotions; I find myself eating when I am stressed out, even when I'm not physically hungry	1=Strongly Disagree to 5=Strongly Agree	0.65
Eating Behavior	Shortened version from Tylka, T. L. & Van Diest,	Intuitive eating	2	I mostly eat foods that make my body perform efficiently (well); I mostly eat	1=Strongly Disagree to	0.69

	A. M. K. (2013). The Intuitive Eating Scale-2: Item refinement and psychometric evaluation with college women and men. Journal of Counseling Psychology, 60, 137-153.			foods that give my body energy and stamina	5=Strongly Agree	

Table 1e. Study Predictors – Mental Health/Psychological Functioning Related Predictors (N = 9)

Measure	Citation	Measure Description	Number of Items	Sample Item(s)	Range of Response	Cronbach's Alpha
Psychological Distress	Kessler, R. & Mroczek, D. (1994). Final versions of our non-specific psychological distress scale [memo dated 10/3/94]. Ann Arbor, MI: Survey Research Center of the Institute for Social Research, University of Michigan.	Mental health symptoms – psychological distress	10	Please select how often you have felt each of the following in the past 30 days… e.g., Did you feel tired out for no good reason?; Did you feel hopeless?	1=None of the time to 5=All of the time	0.91
Satisfaction with Life	Diener, E., Emmons, R. A., Larsen, R. J., & Griffin, S. (1985). The Satisfaction with Life Scale. Journal of Personality Assessment, 49, 71-75.	Satisfaction with Life	5	In most ways my life is close to my ideal; So far I have gotten the important things I want in life	1=Strongly Disagree to 7=Strongly Agree	0.93
Mental Health Symptoms - Masculine Depression Internalizing Subscale	Shortened version of Magovcevic, M. & Addis, M.E. (2008). The Masculine Depression Scale: Development and Psychometric Evaluation. Psychology of Men & Masculinity, 9, 117-132. doi: 10.1037/1524-9220.9.3.117	Internalizing depressive symptoms	10	I don't feel as powerful; I've felt trapped	0=None/little of the time to 3=All of the time	0.90
Mental Health Symptoms	Shortened version of Magovcevic, M. & Addis, M.E. (2008). The Masculine Depression Scale: Development and	Externalizing depressive symptoms	10	I have been drinking a lot; I've yelled at people or things	0=None/little of the time to 3=All of the time	0.79

	Psychometric Evaluation. Psychology of Men & Masculinity, 9, 117-132. doi: 10.1037/1524-9220.9.3.117					
Mindfulness (Observe feelings and experience subscale)	Baer, R. A., Smith, G.T., Hopkins, J., Krietemeyer, J., & Toney, L. (2006). Using self-report assessment methods to explore facets of mindfulness. Assessment, 13, 27-45.	Observe and notice feelings and experiences	4	I pay attention to physical experiences, such as the wind in my hair or sun on my face; Generally, I pay attention to sounds, such as clocks ticking, birds chirping, or cars passing	1=Never or Very Rarely True to 5=Very Often or Always True	0.92
Mindfulness (Describe feelings and experience subscale)	Baer, R. A., Smith, G.T., Hopkins, J., Krietemeyer, J., & Toney, L. (2006). Using self-report assessment methods to explore facets of mindfulness. Assessment, 13, 27-45.	Ability to describe feelings and experiences	5	I'm good at finding words to describe my feelings; I can easily put my beliefs, opinions, and expectations into words	1=Never or Very Rarely True to 5=Very Often or Always True	0.86
Mindfulness (Nonreactivity to Inner Experience subscale)	Baer, R. A., Smith, G.T., Hopkins, J., Krietemeyer, J., & Toney, L. (2006). Using self-report assessment methods to explore facets of mindfulness. Assessment, 13, 27-45.	Ability to be impartial to inner experience	5	I'm good at finding words to describe my feelings; I can easily put my beliefs, opinions, and expectations into words	1=Never or Very Rarely True to 5=Very Often or Always True	0.89
Mindfulness (Acting with awareness/automatic pilot/concentration subscale)	Baer, R. A., Smith, G.T., Hopkins, J., Krietemeyer, J., & Toney, L. (2006). Using self-report assessment methods to explore facets of mindfulness. Assessment, 13, 27-45.	Ability of be present and to act with attentiveness	5	I find it difficult to stay focused on what's happening in the present moment (reverse coded); I find myself doing things without paying attention (reverse coded)	1=Never or Very Rarely True to 5=Very Often or Always True	0.91

Mindfulness (Nonjudging of experience subscale)	Baer, R. A., Smith, G.T., Hopkins, J., Krietemeyer, J., & Toney, L. (2006). Using self-report assessment methods to explore facets of mindfulness. Assessment, 13, 27-45.	Non-judging of internal experience	5	I tell myself I shouldn't be feeling the way I'm feeling (reverse coded); I disapprove of myself when I have illogical ideas (reverse coded)	1=Never or Very Rarely True to 5=Very Often or Always True	0.92

Table 1f. Study Predictors – Traumatic Experience Related Predictors (N = 3)

Measure	Citation	Measure Description	Number of Items	Sample Item(s)	Range of Response	Cronbach's Alpha
Childhood Experiences	Wade, Jr., R., Cronholm, P. F., Fein, J. A., Forke, C. M., Davis, M. B., Harkins-Schwarz, M., Pachter, L. M., Bair-Merritt, M. H. (2016). Household and community-level Adverse Childhood Experiences and adult health outcomes in a diverse urban population. Child Abuse & Neglect, 52, 135-145.	Adverse childhood experiences	16	How often, if ever, did a parent, stepparent or another adult in your household swear at you, insult you, put you down, or humiliate you? OR act in a way that made you afraid that you might be physically hurt?; Did you live with anyone who was depressed or mentally ill or who was suicidal?	0= Never to 2= More than once OR 0= No 1= Yes OR 0= Never true to 4= Very often true OR 0= Never to 3 = Many Times	N/A
Experience with Racism	Murry, V. M., Brown, P. A., Brody, G. H., Cutrona, C. E., & Simons, R. L. (2001). Racial Discrimination as a Moderator of the Links among Stress, Maternal Psychological Functioning, and Family Relationships. Journal of Marriage and Family, 63(4), 915–926.	Experience with Racism	13	How often has someone said something derogatory or insulting to you just because of your race/ethnicity?; How often have you been treated unfairly because of your race/ethnicity?	1=Never to 4=Several times	0.75
Trafficking Victim Identification Tool	Trafficking Victim Identification Tool (TVIT; 2014). Vera Institute of Justice. New York, New York.	Sex-trafficking victim checklist	4	Have you ever engaged in a sex act for things of value either because A) you were pressured or forced to do this, or B) it was essential for your survival?	0=No 1=Yes	N/A

	https://www.vera.org/downloads/publications/human-trafficking-identification-tool-and-user-guidelines.pdf			(for example money, housing, food, gifts, or favors)		

Table 1g. Study Predictors – Family environment/Familial Functioning Related Predictors (N = 2)

Measure	Citation	Measure Description	Number of Items	Sample Item(s)	Range of Response	Cronbach's Alpha
Family Environment	Banker, B. S. & Gaertner, S. L. (1998). Achieving stepfamily harmony: An intergroup-relations approach. Journal of Family Psychology, 12, 310-325.	Family harmony	3	Generally there is a feeling of contentment and happiness in my house; Overall, there are more happy feelings, than unhappy feelings in my home	1=Very Strongly Disagree to 7=Very Strongly Agree	0.77
Family Chaos	Matheny, A. P., Wachs, T. D., Ludwig, J. L., & Phillips, K. (1995). Bringing order out of chaos: Psychometric properties of the Confusion, Hubbub, and Order Scale. Journal of Applied Developmental Psychology, 16, 429-444.	Chaos in the household	15	It's a real zoo in our home; I often get drawn into other people's arguments at home	1=Not at all to 4=Very much	0.89

Table 1h. Study Predictors – Financial Condition Predictors (N = 8)

Measure	Citation	Measure Description	Number of Items	Sample Item(s)	Range of Response	Cronbach's Alpha
Financial Health (Housing Related)	N/A	Difficulty to pay rent/mortgage	1	Has there ever been a time in the past two years when you were not able to pay your monthly rent/mortgage?	1=Yes this has happened frequently in the past to 3=This has never happened	N/A
Financial Health (Housing Related)	N/A	Housing insecurity	1	In the past 12 months, did you get evicted for not paying rent/mortgage?	1=Yes 0=No	N/A
Financial Health (Housing Related)	N/A	Housing insecurity	1	In the past 12 months, did you move in with people because of financial problems?	1=Yes 0=No	N/A
Financial Health (Basic Needs)	N/A	Basic needs	1	On an average month, how much money do you have to meet yourself and family's basic needs (housing, utilities, food)?	1=Not enough to 3=More than enough	N/A
Financial Health (Daily Needs)	N/A	Difficulty paying bill	1	On an average month, how difficult is it to pay your bills?	1=Very difficult to 3=Not at all difficult	N/A
Overall Financial Condition	N/A	Financial stability	1	Which of the following best describes your household's financial condition?	1=Very comfortable and secure to 5=In over my head	N/A

Food Insecurity	Adapted from the USDA Food Insecurity Index	Food Insecurity	2	I/we couldn’t afford to eat healthy meals; I had a problem with providing food for me/my family	1=Never true to 3=Often true	0.57
Financial Stress	Prawitz, A. D., Garman, E. T., Sorhaindo, B., O’Neill, B., Kim, J., & Drentea, P. (2006). The incharge financial distress/financial well-being scale: Establishing validity and reliability. *Fin Counsel Plan*, *17*, 34-50.	Financial distress	8	What do you feel is the level of your financial stress today?; How frequently do you find yourself just getting by financially and living paycheck to paycheck?	Response option varies but all on 1-10 point Likert scales	0.94

Table 1i. Study Predictors – Couple Relationship Education Classroom Environment Related Predictors (N = 8)

Measure	Citation	Measure Description	Number of Items	Sample Item(s)	Range of Response	Cronbach's Alpha
Family Life Educator Class Environment Scale (Facilitation quality subscale)	Adler-Baeder, F., Futris, T.G., Higginbotham, B., Cooper, E., Gregson, K., Bailey, Z., Turner, J. Developing the class environment scale for couples in community education. Manuscript under development.	Program facilitation quality	5	The facilitators explained the course material clearly; The facilitators effectively encouraged class participation	1=Strongly Disagree to 5=Strongly Agree	0.96
Family Life Educator Class Environment Scale (Group engagement subscale)	Adler-Baeder, F., Futris, T.G., Higginbotham, B., Cooper, E., Gregson, K., Bailey, Z., Turner, J. Developing the class environment scale for couples in community education. Manuscript under development.	Group engagement	5	Class members seemed interested in what was being taught; Class members seemed interested in the activities	1=Strongly Disagree to 5=Strongly Agree	0.94
Family Life Educator Class Environment Scale (Facilitator-participant relationship subscale)	Adler-Baeder, F., Futris, T.G., Higginbotham, B., Cooper, E., Gregson, K., Bailey, Z., Turner, J. Developing the class environment scale for couples in community education. Manuscript under development.	Facilitator-participant relationship quality	5	I trusted the facilitators; I felt accepted by the facilitators	1=Strongly Disagree to 5=Strongly Agree	0.96
Family Life Educator Class	Adler-Baeder, F., Futris, T.G., Higginbotham, B., Cooper, E., Gregson, K.,	Co-facilitators	5	The facilitators communicated well with each other; The facilitators respected each other.	1=Strongly Disagree to	0.97

Environment Scale (Co-facilitator relationship quality subscale)	Bailey, Z., Turner, J. Developing the class environment scale for couples in community education. Manuscript under development.	Relationship quality			5=Strongly Agree	
Family Life Educator Class Environment Scale (Facilitator-participant coregulation subscale)	Adler-Baeder, F., Futris, T.G., Higginbotham, B., Cooper, E., Gregson, K., Bailey, Z., Turner, J. Developing the class environment scale for couples in community education. Manuscript under development.	Facilitator-participant coregulation	5	The facilitators provided verbal praise and positive feedback that made us feel comfortable; The facilitators noticed when we needed a break or were not engaged and needed to move on to the next topic	1=Strongly Disagree to 5=Strongly Agree	0.94
Family Life Educator Class Environment Scale (Individual and partner engagement)	Adler-Baeder, F., Futris, T.G., Higginbotham, B., Cooper, E., Gregson, K., Bailey, Z., Turner, J. Developing the class environment scale for couples in community education. Manuscript under development.	Individuals and partners' levels of engagement	6	The facilitators provided verbal praise and positive feedback that made us feel comfortable; The facilitators noticed when we needed a break or were not engaged and needed to move on to the next topic	1=Strongly Disagree to 5=Strongly Agree	0.90
Cross-Cultural Counseling Inventory Revised	Adapted from LaFromboise, T. D., Coleman, H. L., & Hernandez, A. (1991). Development and factor structure of the Cross-Cultural Counseling Inventory—Revised. *Professional*	Facilitators' cultural competency	11	They were aware of their own cultural heritage; Their communication was culturally appropriate for me	1=Strongly Disagree to 7=Strongly Agree	0.96

	psychology: Research and practice, *22*(5), 380.					

Figure 1. Confirmed Features from Random Forest Model Using Self-Reported Variables Predicting Individuals' Post-Program Levels of Relationship Quality

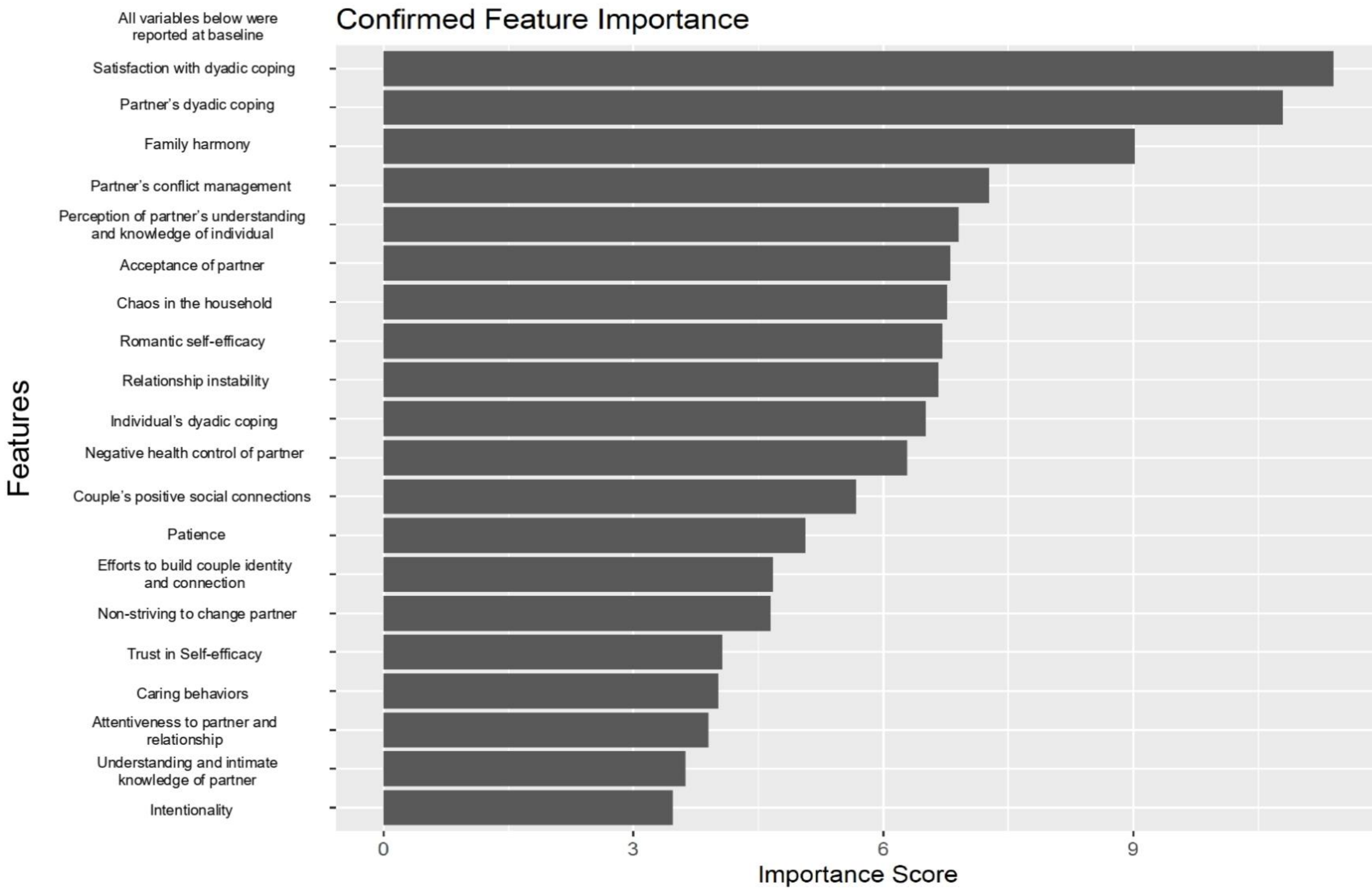

Figure 2. Confirmed Features from Random Forest Model Using Partner-Reported Variables Predicting Individuals' Post-Program Levels of Relationship Quality

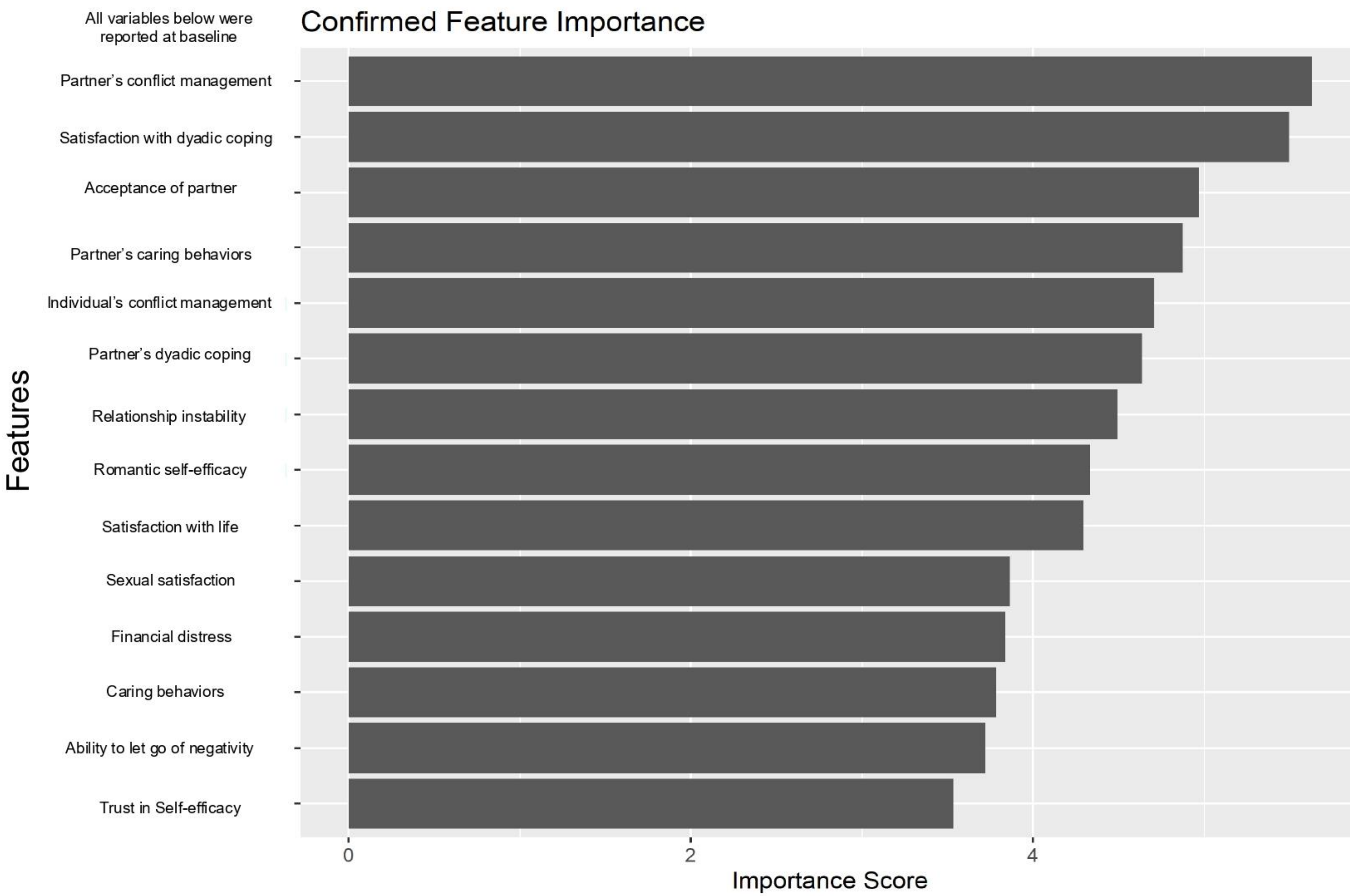

Figure 3. Confirmed Features from Random Forest Model Using Combined Actor- and Partner-Reported Variables Predicting Individuals' Post-Program Levels of Relationship Quality

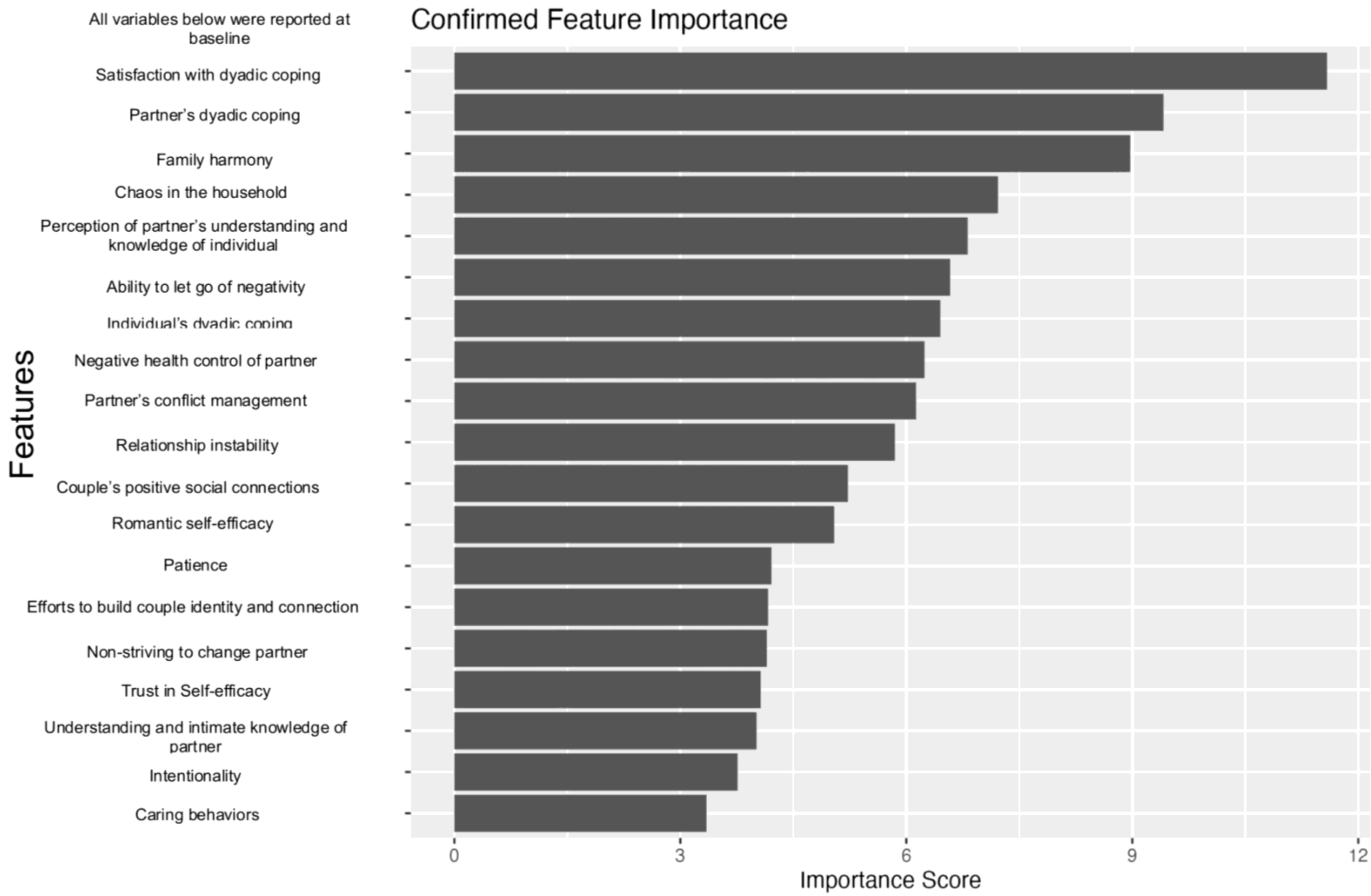

Figure 4. Confirmed Features from Random Forest Model Using Self-Reported Variables Predicting Individuals' Changes in Relationship Quality

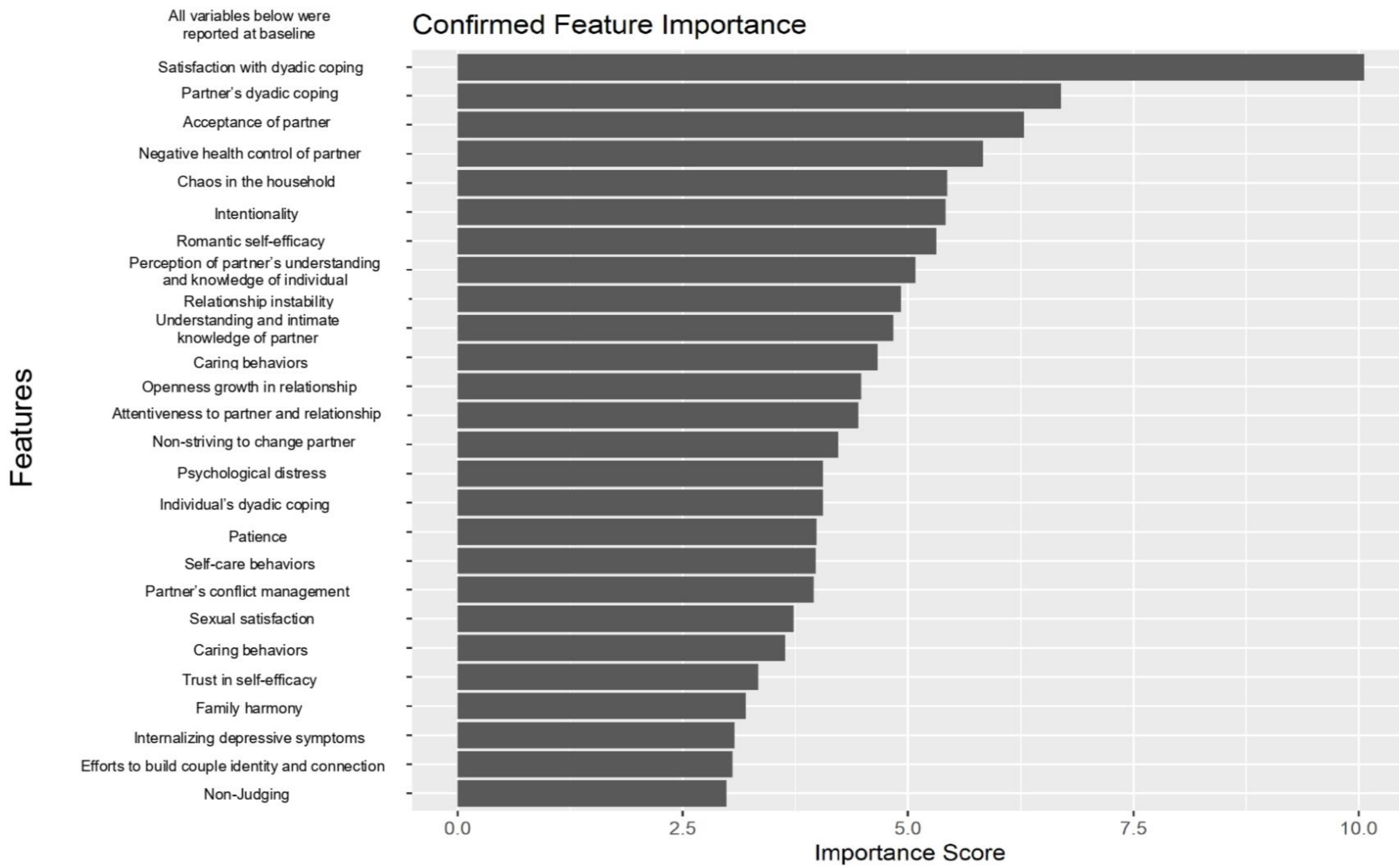

Figure 5. Confirmed Features from Random Forest Model Using Partner-Reported Variables Predicting Individuals' Changes in Relationship Quality

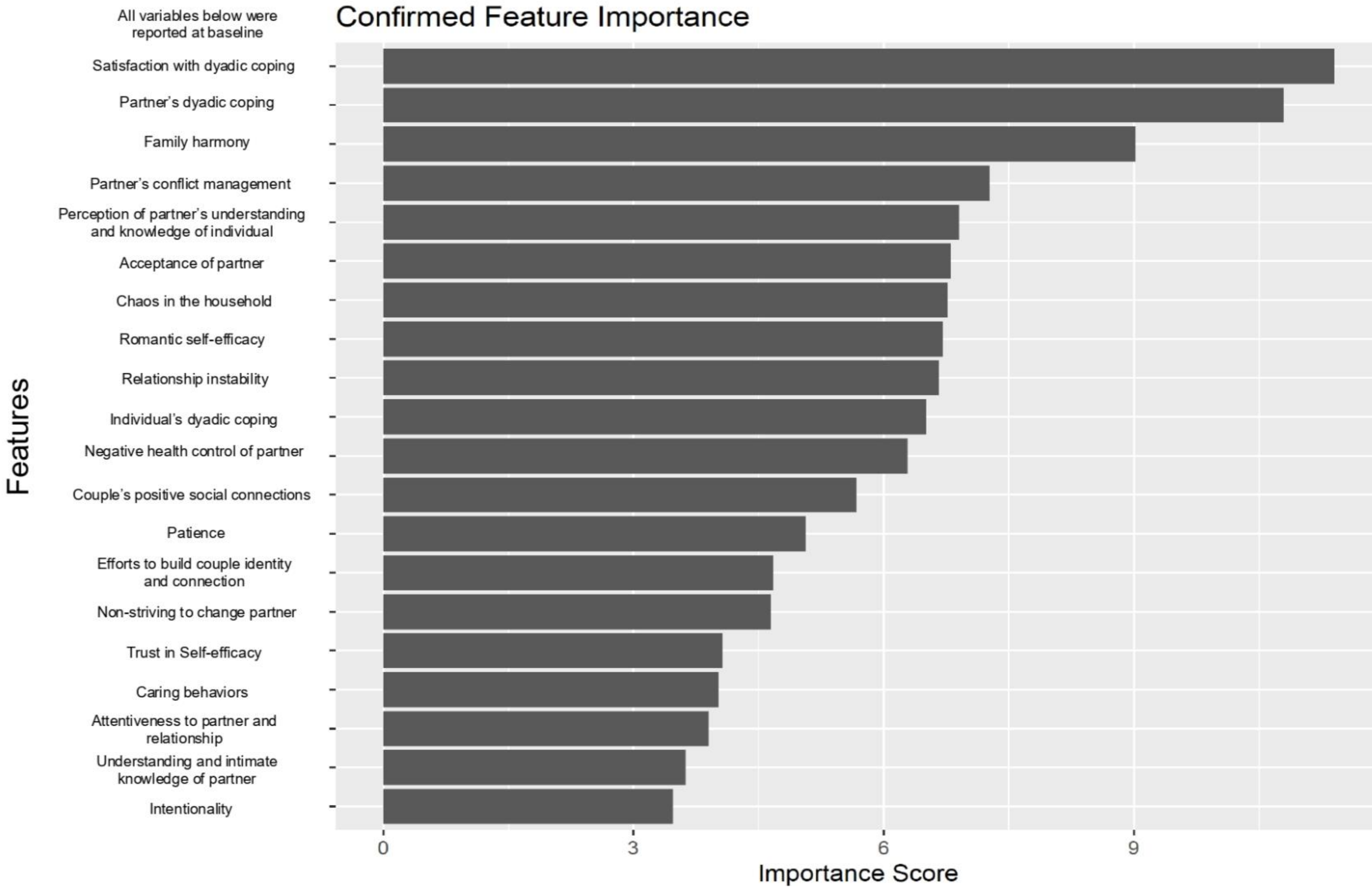

Figure 6. Confirmed Features from Random Forest Model Using Actor- and Partner-Reported Variables Predicting Individuals' Changes in Relationship Quality

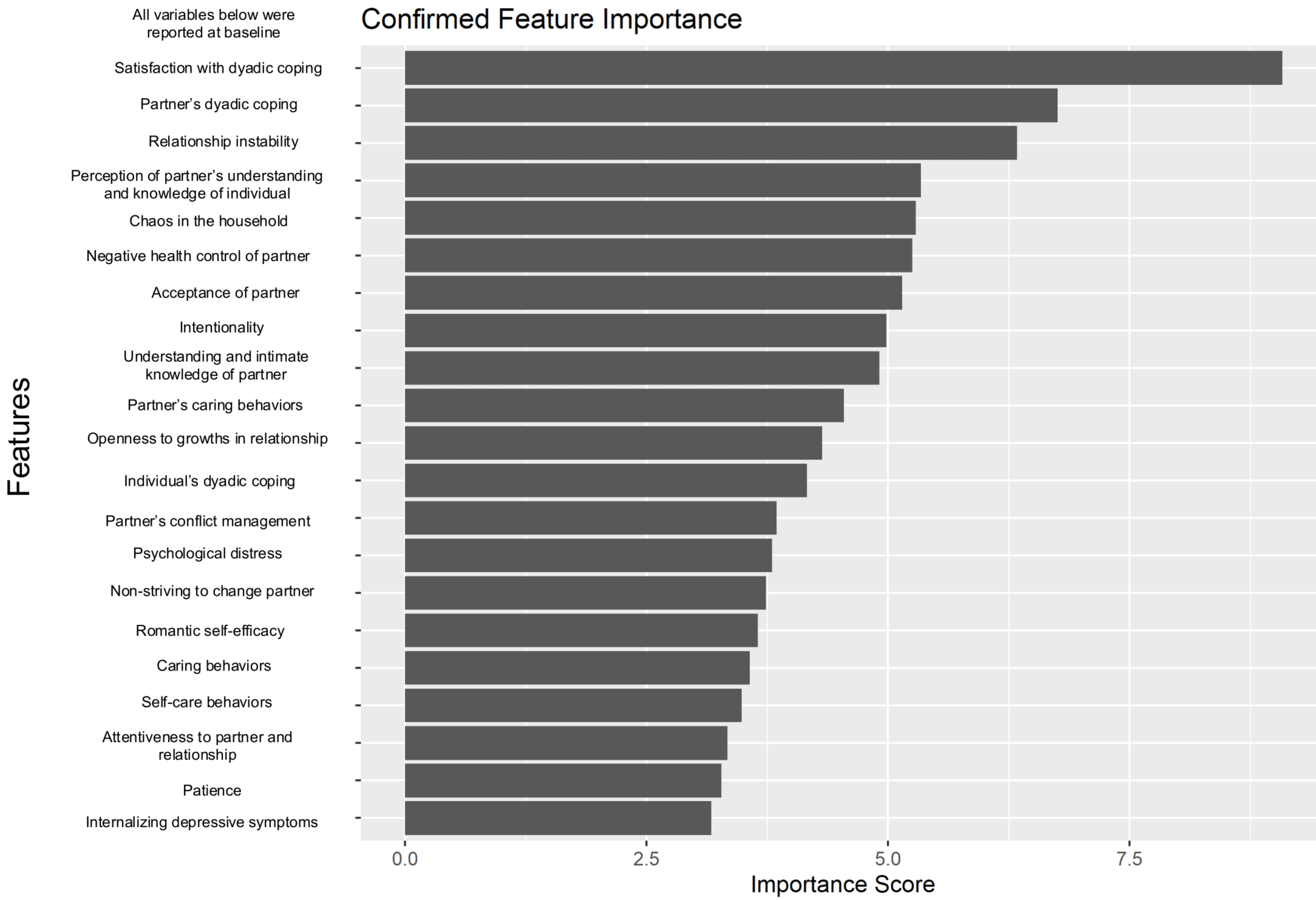

Table 2. Model Performance Comparison Between Post-Program Models			
Self-reported predictor model			
Random forest	$R^2 = 0.33$	RMSE = 9.05	N = 20
Linear multiple regression	$R^2 = 0.30$	RMSE = 9.20	N = 6
Elastic net	$R^2 = 0.31$	RMSE = 9.18	N = 20
Partner-reported predictor model			
Random forest	$R^2 = 0.02$	RMSE = 11.20	N = 14
Linear multiple regression	$R^2 = 0.01$	RMSE = 11.05	N = 1
Elastic net	$R^2 = 0.01$	RMSE = 10.97	N = 14
Combined Self- and Partner-reported predictor model			
Random forest	$R^2 = 0.29$	RMSE = 9.23	N = 19
Linear multiple regression	$R^2 = 0.28$	RMSE = 9.25	N = 7
Elastic net	$R^2 = 0.29$	RMSE = 9.20	N = 11

Table 3. Model Performance Comparison Between Change Models			
Self-reported predictor model			
Random forest	$R^2 = 0.16$	RMSE = 0.80	N = 26
Linear multiple regression	$R^2 = 0.16$	RMSE = 0.81	N = 4
Elastic net	$R^2 = 0.16$	RMSE = 0.80	N = 26
Partner-reported predictor model			
Random forest	$R^2 = 0.01$	RMSE = 0.89	N = 24
Linear multiple regression	$R^2 = 0.01$	RMSE = 0.88	N = 3
Elastic net	$R^2 = 0.01$	RMSE = 0.87	N = 24
Combined Self- and Partner-reported predictor model			
Random forest	$R^2 = 0.17$	RMSE = 0.78	N = 21
Linear multiple regression	$R^2 = 0.16$	RMSE = 0.80	N = 7
Elastic net	$R^2 = 0.17$	RMSE = 0.78	N = 21

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Appendix

Section 1. Elastic Net Regression

Elastic net (Zou & Hastie, 2005) is one of the penalized or regularized regression models that is based on Ridge regression (Hoerl & Kennard, 1970) and Least Absolute Shrinkage and Selection Operator (LASSO; Tibshirani, 1996) regression. These three methods are all considered methods to restrict the linear regression models by controlling or adding a penalizing effect to the parameter estimates, but differ from each other in the ways that the penalty is applied to the parameter estimates. Ridge regression achieves the effects of penalty by using a second-order penalty (L_2), a proportional shrinkage method where a tuning factor λ is introduced and the larger the λ is, the more shrinkage occurs in the model, the closer the estimates shrink toward zero (Hastie et al., 2009). The main issue with applying Ridge regression to the current project would be that Ridge regression does not perform feature selection because no coefficients will be zero. Different from the Ridge regression, LASSO regression uses first-order-penalty (L_1), when λ is sufficiently large, LASSO will set some coefficients to be zero, which makes feature selection possible. When there are highly correlated predictor variables in the data, which is the case of the current study, the Ridge regression tends to shrink the estimates of these correlated variables toward each other, whereas the LASSO regression tends to randomly select a predictor among a group of highly correlated predictors and ignore the others. As such, the LASSO regression is likely to be compromised when multicollinearity is high. Elastic net is the combination of Ridge and LASSO regression where it limits the impact of predictor variables like Ridge and allows feature selection like LASSO, which makes it an ideal method for feature selection when there are highly correlated variables present in the data.

Section 2. Linear Multiple Regression Models and Elastic Net Models Results

Supplemental Table 1. Post-Program Models: Linear Multiple Regression Model Significant Variable Coefficiants								
Self-reported predictors model			Partner-reported predictors model			Combined Self- and partner-reported predictors model		
Variable	**β**	**p**	**Variable**	**β**	**p**	**Variable**	**β**	**p**
Choose	0.13	0.25	CareSR	-0.003	0.97	Choose	0.16	0.18
KnowSR	0.15	0.17	CarePR	-0.02	0.84	**KnowSR**	**0.25**	**0.03***
KnowPR	-0.01	0.89	ManageSR	0.03	0.79	KnowPR	0.05	0.65
Share	0.18	0.07	ManagePR	0.05	0.5	Share	0.12	0.3
CareSR	**0.17**	**0.03***	Rel Instability	-0.06	0.76	CareSR	-0.16	0.1
ManageSR	0.11	0.11	MCRSTrust	-0.04	0.81	ManagePR	0.09	0.22
Connect	**0.19**	**0.02***	**MCRSAccept**	**0.43**	**0.01****	Connect	0.12	0.21
Rel Instability	**-0.42**	**0.01****	MCRSLet go	-0.12	0.22	**Rel Instability**	**-0.5**	**0.004****
MCRSPatience	0.03	0.79	DCIPartner	-0.07	0.64	MCRSPatience	-0.03	0.78
MCRSTrust	-0.16	0.37	DCIOverall	-0.25	0.46	MCRSTrust	-0.22	0.26
MCRSNonStriving	0.17	0.32	Sexual Satisfaction	0.01	0.96	**MCRSNonStriving**	**0.34**	**0.03***
MCRSLet go	0.21	0.01	Rom Self-Eff	-0.07	0.29	MCRSLet go	0.04	0.83
MCFSNotice	-0.13	0.14	Satisfaction w/ Life	-0.14	0.06	**DCIPartner**	**0.29**	**0.04***
DCIPartner	**0.29**	**0.03***	Financial Wellbeing	0.04	0.053+	DCISelf	-0.41	0.06
DCISelf	-0.38	0.06				**DCIOverall**	**1.09**	**<0.001*****
DCIOverall	0.52	0.09				**Rom Self-Eff**	**0.19**	**0.002****
Rom Self-Eff	0.11	0.052+				HlthCnt_Neg	-0.02	0.79
HlthCnt_Neg	-0.02	0.77				**Family Harmony**	**0.31**	**0.006****
Fam Harmony	**0.46**	**<0.001*****				Fam CHAOS	-0.1	0.18
Fam CHAOS	0.11	0.13						

Supplemental Table 2. Post-Program Models: Elastic Net Model Significant Variable Coefficiants					
Self-reported predictors model		Partner-reported predictors model		Combined Self- and partner-reported predictors model	
Variable	***β***	**Variable**	***β***	**Variable**	***β***
DCIOverall	0.422	DCIOverall	-0.009	DCIOverall	0.711
Rel Instability	-0.354	Sexual Satisfaction	-0.007	Rel Instability	-0.396
FamilyHarmony	0.268	MCRSAccept	0.005	DCIPartner	0.214
DCIPartner	0.215	DCIPartner	-0.004	MCRSNonStriving	0.210
Share	0.168	Satisfaction w/ life	-0.003	CareSR	0.149
MCRSLet go	0.146	MCRSLet go	-0.003	Family Harmony	0.133
Connect	0.143	Rom Self-Eff	-0.003	Choose	0.122
CareSR	0.137	Rel Instability	0.002	KnowPR	0.102
DCISelf	-0.128	CarePR	-0.002	Rom Self-Eff	0.093
MCRSNon Striving	0.125	CareSR	-0.002	ManagePR	0.092
ManagePR	0.106	ManagePR	-0.001	Fam Chaos	-0.038
Choose	0.104	MCRSTrust	-0.001	MCRSPatience	0
KnowSR	0.098	ManageSR	-0.001	MCRSTrust	0
Rom Self-Eff	0.072	Financial Wellbeing	0.001	MCRSLet Go	0
KnowPR	0.067			DCISelf	0
MCRSNotice	-0.061			HlthCnt_Neg	0
MCRSTrust	-0.056			Connect	0
HlthCnt_Neg	-0.006			Share	0
Fam Chaos	-0.005			KnowSR	0
MCRSPatience	-0.003				

Supplemental Table 3. Changes Models: Linear Multiple Regression Model Significant Variable Coefficiants

Self-reported predictors model				Partner-reported predictors model				Combined Self- and partner-reported predictors model		
Variable	*β*	*p*		Variable	*β*	*p*		Variable	*β*	*p*
Self Care	-0.002	0.53		Choose	-0.014	0.14		Self Care	-0.002	0.59
Choose	-0.010	0.18		KnowPR	-0.008	0.92		Choose	-0.016	0.12
KnowSR	0.006	0.54		Share	0.102	0.22		KnowSR	0.014	0.15
KnowPR	**-0.021**	**0.009****		ManageSR	0.002	0.84		**KnowPR**	**-0.027**	**0.002****
Share	0.002	0.76		ManagePR	0.009	0.19		CarePR	0.007	0.42
CareSR	0.006	0.52		**Connect**	**0.016**	**0.03***		**CareSR**	**-0.023**	**0.005****
CarePR	**-0.018**	**0.03***		Rel Instability	-0.010	0.51		ManagePR	0.001	0.84
ManagePR	0.004	0.45		MCRSNon Judging	0.001	0.92		**Rel Instability**	**0.047**	**0.002****
Rel Instability	**0.043**	**0.004****		MCRSPatience	-0.008	0.41		MCRSPatience	0.010	0.3
MCRSNon Judging	0.010	0.28		MCRSBeginnerMd	0.011	0.48		MCRSBeginnerMd	-0.016	0.21
MCRSPatience	0.008	0.42		MCRSTrust	0.002	0.89		MCRSNonStriving	0.003	0.8
MCRSBeginnerMd	-0.015	0.35		MCRSNonStriving	-0.007	0.6		MCRSAccept	-0.021	0.15
MCRSTrust	-0.016	0.3		**MCRSAccept**	**0.030**	**0.04***		MCFSNotice	-0.012	0.14
MCRSNonStriving	-0.001	0.97		MCRSLet go	-0.004	0.61		DCIPartner	0.002	0.86
MCRSAccept	-0.026	0.08		MCRSNotice	-0.003	0.75		DCISelf	0.007	0.69
MCFSNotice	-0.013	0.12		DCIOverall	-0.007	0.6		DCIOverall	-0.036	0.2
DCIPartner	0.007	0.56		DCISelf	-0.009	0.6		Rom Self-Eff	0.007	0.2
DCISelf	0.011	0.53		DCIOverall	0.020	0.61		HlthCnt_Neg	-0.006	0.33
DCIOverall	-0.045	0.1		Sexual Satisfaction	0.006	0.89		Psychological distress	0.004	0.3
Sexual Satisfaction	**-0.063**	**0.011***		Rom Self-Eff	-0.007	0.16		Internalizing Sym	0.021	0.16
Rom Self-Eff	0.010	0.058		**Satisfaction w/ Life**	**-0.012**	**0.05***		Fam CHAOS	-0.005	0.43
HlthCnt_Neg	-0.009	0.18		Internalizing Sym	-0.009	0.47				
Psychological distress	0.005	0.34		Fam Harmony	-0.001	0.96				
Internalizing Sym	0.014	0.32		Fam CHAOS	0.006	0.4				
Fam Harmony	-0.001	0.96								
Fam CHAOS	-0.003	0.68								

Supplemental Table 4. Changes Models: Elastic Net Model Significant Variable Coefficiants

Self-reported predictors model			Partner-reported predictors model			Combined Self- and partner-reported predictors model	
Variable	***β***		**Variable**	***β***		**Variable**	***β***
Sexual Satisfaction	-0.040		MCRSAccept	0.005		Rel Instability	0.031
Rel Instability	0.026		Rel Instability	-0.004		DCIOverall	-0.027
DCIOverall	-0.026		DCIOverall	0.004		KnowPR	-0.015
MCRSAccept	-0.014		Connect	0.004		MCRSAccept	-0.014
KnowPR	-0.012		Sexual Satisfaction	0.003		Internalizing Sym	0.012
MCRSTrust	-0.012		MCRSBeginnerMd	0.003		CarePR	-0.011
MCRSBeginnerMd	-0.010		Share	0.002		MCRSBeginnerMd	-0.011
Internalizing Sym	0.009		DCISelf	-0.002		Choose	-0.009
CarePR	-0.008		Rom Self-Eff	-0.002		DCIPartner	-0.006
Choose	-0.008		Choose	-0.002		MCRSNotice	-0.005
MCRSNotice	-0.006		Satisfaction w/ Life	-0.002		MCRSPatience	0.005
MCRSNonStriving	-0.005		ManagePR	0.002		HlthCnt_Neg	-0.004
HlthCnt_Neg	-0.005		MCRSPatience	-0.002		Psychological distress	0.004
MCRSPatience	0.004		Fam CHAOS	0.001		MCRSNonStriving	-0.003
Psychological distress	0.004		MCRSNotice	-0.001		CareSR	-0.003
DCISelf	0.004		DCIPartner	0.001		ManagePR	-0.003
Rom Self-Eff	0.003		KnowPR	0.001		Rom Self-Eff	0.003
DCIPartner	-0.003		MCRSNon Judging	0.001		DCISelf	0.002
Share	-0.003		ManageSR	0.001		Self Care	-0.002
KnowSR	-0.003		Fam Harmony	-0.001		KnowSR	0.001
CareSR	-0.002		Internalizing Sym	0.001		Fam CHAOS	-0.001
SelfCare	-0.002		MCRSNonStriving	<0.001			
MCRSNon Judging	0.002		MCRSTrust	<0.001			
Fam Harmony	-0.001		MCRSLet go	<0.001			
ManagePR	<0.001						
Fam CHAOS	<0.001						