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Predictors of relationship satisfaction during the COVID-19 pandemic

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Abstract

Prior work and theory suggest many vulnerabilities, stressors, and adaptive processes shape relationship satisfaction. In the current research, we used machine learning to understand which constructs have greater predictive importance for perceived changes in satisfaction since the pandemic began and satisfaction over the prior week. In a large sample collected at the beginning of the pandemic (*N* = 1873; Study 1), relationship processes were most predictive, explaining up to 70% of variance in satisfaction. Feeling appreciative of one's partner and being satisfied with quality time spent with one's partner were consistently top predictors of satisfaction. We also examined whether these important predictors were associated with changes in relationship satisfaction across the first year of the pandemic in a longitudinal subsample (*N* = 618; Study 2). Appreciation and satisfaction with quality time were associated with high and relatively stable relationship satisfaction over time.

KEYWORDS

COVID-19, machine-learning, relationship satisfaction

1 | INTRODUCTION

The COVID-19 pandemic changed lives. Many cohabiting couples had less contact with others, began working from the same household, and had increased household duties. From early on, researchers warned that such stressors could alter dyadic processes and lower relationship satisfaction (Pietromonaco & Overall, 2021). The Vulnerability-Stress-Adaptation model (VSA), a key model of stress and relationship processes, may help us understand relationship satisfaction during the pandemic (Karney & Bradbury, 1995). This model suggests that stressful events may negatively affect couples' adaptive processes and enduring vulnerabilities may amplify these effects. Researchers adapted this model to the COVID-19 context and suggested that enduring vulnerabilities–both individual (e.g., personality) and contextual (e.g., household income), pandemic-related experiences, stress, and adaptive relationship processes were all likely to shape relationship satisfaction during the pandemic (Pietromonaco & Overall, 2021). However, it is unclear which of these factors mattered most for relationship satisfaction during this historic time. The current research examined the predictive importance of these factors at the beginning and over the first year of the pandemic using machine learning.

In light of VSA, we focus on five broad domains covering vulnerabilities, stressors, and adaptive processes that may have been associated with relationship satisfaction during the pandemic and its changes over time: (1) demographic and environmental factors (e.g., gender, size of home), (2) intrapersonal and interpersonal pandemic-related experiences (e.g., getting COVID-19, partner understanding of COVID-19-related worries), (3) health and wellbeing (e.g., anxiety, exercise), (4) stress and coping (e.g., perceived stress, dyadic coping), and (5) relationship processes (e.g., prior week conflict, attachment). For more details on our theorizing, see Supporting Information S1.

In Study 1, we aimed to examine the importance of various constructs in these five domains in predicting relationship satisfaction. Previous research using machine learning identified attachment, age, and conflict as the top predictors of relationship quality during the pandemic (Eder et al., 2021). We extended this research in a large sample by examining a wider range of predictors, evaluating their predictive power within five broad domains, as well as including two indicators of relationship satisfaction: perceived changes in relationship satisfaction since the pandemic started and relationship satisfaction in the past week. In Study 2, we aimed to examine whether the machine learning-identified predictors from the beginning of the pandemic were associated with *changes* in relationship satisfaction across the subsequent year.

2 | METHODS

2.1 | Participants & procedure

Figure 1 summarizes the data collection procedure and analytical samples for Studies 1 and 2. We collected two samples: Sample A and B. Data collection methods differed, but the survey items were nearly identical.

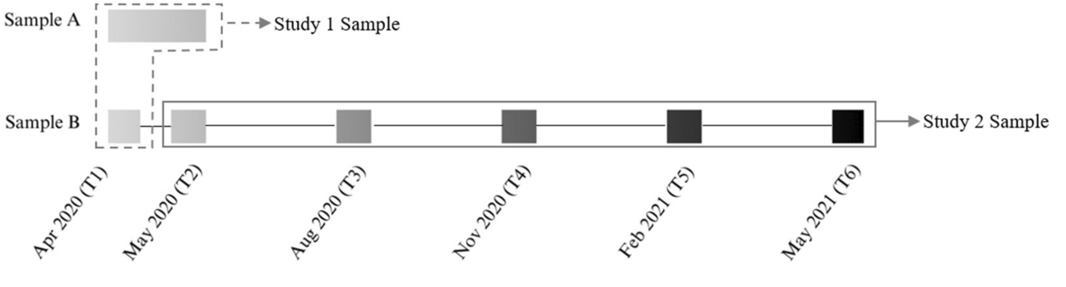


FIGURE 1 Summary of data collection procedures and analytical samples.

Sample A was cross-sectional and collected primarily between April 2020 and 2 May020.[1] We shared a survey on social media (e.g., Twitter, Reddit) to recruit volunteers from the U.S. and Canada. We also used paid Facebook ads to reach potential volunteers. Interested individuals completed an eligibility survey. Eligible participants were 18 or older, in a cohabiting relationship, and living in the U.S. or Canada. Eligible participants completed the survey and were encouraged to invite their partners to complete the same survey. Sample A participants were not compensated and we did not collect any contact information. We aimed for 1000 individuals and 100 couples based on feasibility. A total of 1255 participants completed the study; 957 participated in the survey individually and 149 couples participated (298 individuals).

Sample B was longitudinal and collected at six time points between April 2020 and May 2021. We shared an eligibility survey through Prolific.co and invited eligible participants to complete the same survey as Sample A. Eligible participants were 18 or older, living in the U.S., and sheltering-in-place with their romantic partner at baseline (i.e., both partners not leaving home except for essential business and exercise and not working outside the home; if one partner worked outside the home, the couple was not eligible).[2] Sample B participants received $3 for participating in this survey and were encouraged to invite their partners to complete the same survey (and receive $3). Sample B participants were informed that they would be contacted through Prolific for follow-up surveys. Those who participated in follow-ups received $1.50 for each additional survey. Because we aimed to collect longitudinal data from these participants, we determined the sample size based on a priori power analyses (see Supporting Information S1). The baseline survey was collected in April 2020 (Time 1; $N = 618$); 316 participants completed the study individually and 151 couples completed it (i.e., 302 individuals). They were invited to participate in follow-ups starting in May 2020 (Time 2; $N = 558$) and every 3 months thereafter: August 2020 (Time 3; $N = 429$), November 2020 (Time 4; $N = 365$), February 2021 (Time 5; $N = 297$), and May 2021 (Time 6; $N = 222$). Participants who completed the first four surveys received a $1.50 bonus.

Across samples A and B, at baseline, 1273 individuals and 300 couples participated ($N = 1873$). The study was reviewed by the University of Michigan Institutional Review Board and received exempt status.

2.2 | Measures

2.2.1 | Relationship satisfaction

We measured *perceived changes in relationship satisfaction* using the single item 'Your overall relationship satisfaction' in response to the prompt: 'How has your relationship changed since you and your partner have been sheltering-in-place together…?' Responses were measured on a scale using anchors relevant to multiple items (0 = *Less/Lower*, 5 = *No change*, 10 = *More/Higher*). In Sample A, participants not sheltering-in-place together were instructed to consider changes since the pandemic began. We measured *prior week relationship satisfaction* with the single item: 'In the past week, how satisfied have you been with the following…Your relationship overall?'; 1 = *Not at all*, 5 = *Completely*). These two indicators were correlated at .55 ($p < .001$). Single items were used to minimize survey length and participant attrition. Single-item measures of relationship satisfaction are widely used and perform well (Niehuis et al., 2022).

2.2.2 | Predictors

See Table S1 for a summary of all 90 predictors included in the models.

2.3 | Analytic plan

2.3.1 | Machine learning at baseline

In Study 1, we used Sample A data and Sample B baseline data (Time 1) to understand which variables had the greatest value in predicting relationship satisfaction at the beginning of the pandemic. We used Random Forests (RF): a machine learning method that repeatedly samples random subsets of predictors and participants to build classification or regression trees. It tests the predictive value of each predictor through a process called recursive partitioning and builds decision trees using the strongest predictors. A decision tree is a set of rules that predict the outcome, such as 'if age <25 and parent = 1, then average satisfaction = 4'. It repeats this tree-building process many times using bootstrapping and then averages the resulting trees. Results reveal the predictive metric of each variable and predictors can be rank ordered based on those metrics. We used the Gini Importance metric to select the top predictors. There are several advantages of using RF: It can handle many predictors at once while minimizing overfitting. It is nonparametric, which allows it to capture nonlinear relationships, such as interactions among predictors and complex splits of predictors involving cut-points. Furthermore, it examines the overall predictive power using cross-validation, that is, the resulting tree is evaluated on a subset of data that was not used in the construction of the trees.

We used RF to understand which factors predicted variability in our relationship satisfaction measures at baseline along with their relative predictive values. We ran separate RF on each relationship satisfaction indicator for five categories: (1) demographic and environmental factors, (2) pandemic-related experiences, (3) health and wellbeing, (4) stress and coping, and (5) relationship processes.[3] To account for differences in relationship satisfaction across samples, we included a code for sample (A vs. B) as an additional predictor in all models. Similar to previous work (Joel et al., 2020), we used a subset of predictors identified by a variable selection algorithm. This algorithm may select different numbers of predictors for each model. For more information on the variable selection and RF procedures, see Supporting Information S1.

2.3.2 | Longitudinal growth curve models

In Study 2, we used Time 2 to Time 6 Sample B data to examine whether the top predictors identified in Study 1, that is, the important predictors of relationship satisfaction during the early stages of the pandemic influenced relationship satisfaction over the following year. We took the baseline measures that emerged from the RF analyses and used them as predictors in longitudinal growth curve models assessing changes in satisfaction across new T2–T6 (May 2020–May 2021) data. The models included the linear and quadratic effects of time, and their interactions with the top baseline measures (for more information, see Supporting Information S1). Consistent with prior studies (Joel et al., 2020), we focused on predictors that consistently emerged as important across RF models. We used actor-only models (Kenny et al., 2006) because the data included individuals as well as couples.

2.4 | Study 1 results

2.4.1 | Machine learning analyses

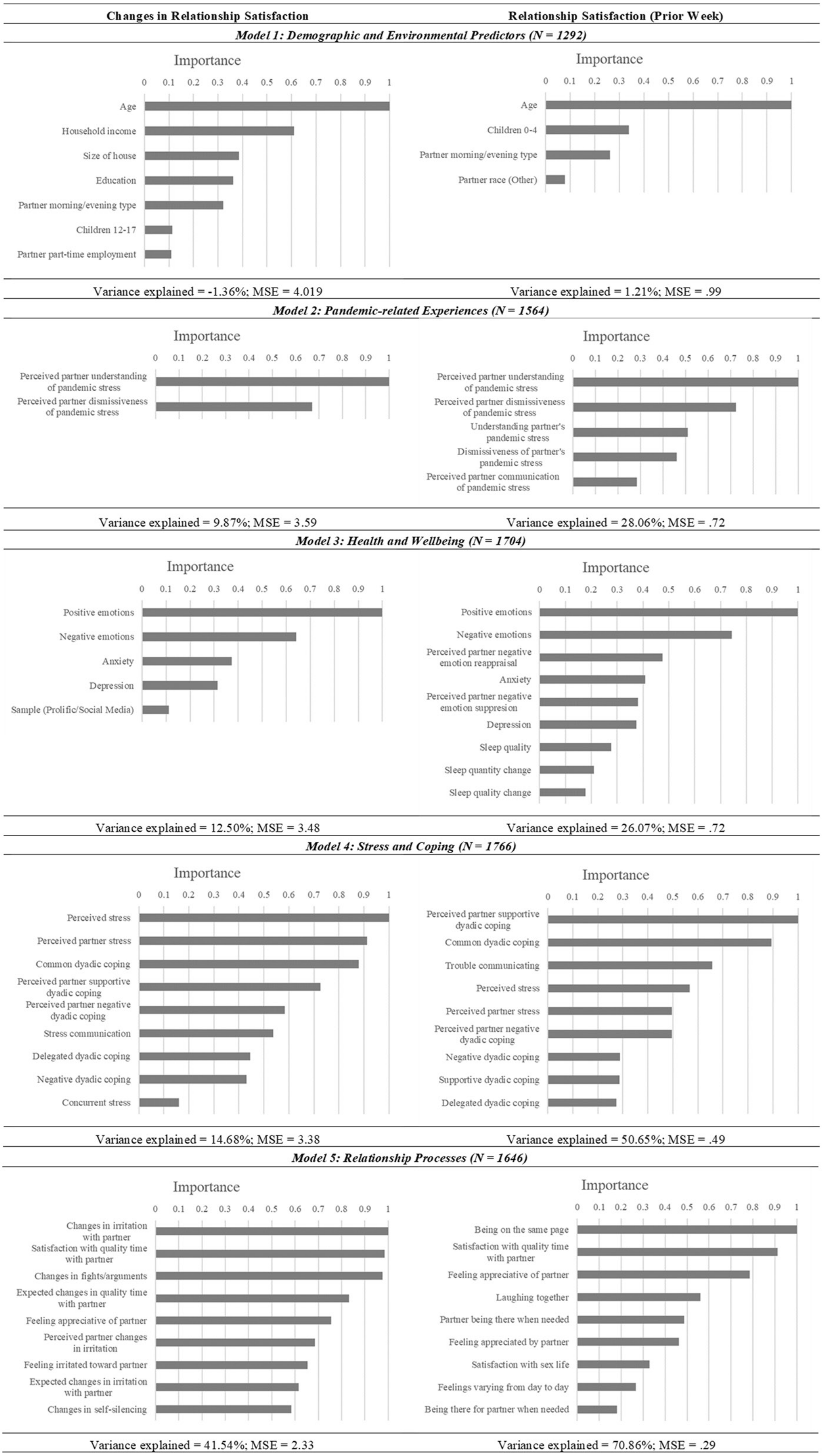
Study 1 used a relatively large dataset to understand which variables had the greatest value in predicting relationship satisfaction at the beginning of the pandemic. Figure 2 summarizes important predictors in each domain, their rankings, and model performance metrics.

Demographic and environmental predictors

This model explained little to none of the variance in perceived changes in relationship satisfaction since the pandemic began (−1.36%) and prior week relationship satisfaction (1.21%). For both outcomes, age was the top predictor.

Pandemic-related predictors

This model explained some variance in perceived changes in relationship satisfaction since the pandemic began (9.87%) and prior week relationship satisfaction (28.06%). For both outcomes, interpersonal aspects of the pandemic


Changes in Relationship Satisfaction
Relationship Satisfaction (Prior Week)
Model 1: Demographic and Environmental Predictors (N = 1292)
Importance
Age
Household income
Size of house
Education
Partner morning/evening type
Children 12-17
Partner part-time employment
Importance
Age
Children 0-4
Partner morning/evening type
Partner race (Other)
Variance explained = -1.36%; MSE = 4.019
Variance explained = 1.21%; MSE = .99
Model 2: Pandemic-related Experiences (N = 1564)
Importance
Perceived partner understanding of pandemic stress
Perceived partner dismissiveness of pandemic stress
Importance
Perceived partner understanding of pandemic stress
Perceived partner dismissiveness of pandemic stress
Understanding partner's pandemic stress
Dismissiveness of partner's pandemic stress
Perceived partner communication of pandemic stress
Variance explained = 9.87%; MSE = 3.59
Variance explained = 28.06%; MSE = .72
Model 3: Health and Wellbeing (N = 1704)
Importance
Positive emotions
Negative emotions
Anxiety
Depression
Sample (Prolific/Social Media)
Importance
Positive emotions
Negative emotions
Perceived partner negative emotion reappraisal
Anxiety
Perceived partner negative emotion suppresion
Depression
Sleep quality
Sleep quantity change
Sleep quality change
Variance explained = 12.50%; MSE = 3.48
Variance explained = 26.07%; MSE = .72
Model 4: Stress and Coping (N = 1766)
Importance
Perceived stress
Perceived partner stress
Common dyadic coping
Perceived partner supportive dyadic coping
Perceived partner negative dyadic coping
Stress communication
Delegated dyadic coping
Negative dyadic coping
Concurrent stress
Importance
Perceived partner supportive dyadic coping
Common dyadic coping
Trouble communicating
Perceived stress
Perceived partner stress
Perceived partner negative dyadic coping
Negative dyadic coping
Supportive dyadic coping
Delegated dyadic coping
Variance explained = 14.68%; MSE = 3.38
Variance explained = 50.65%; MSE = .49
Model 5: Relationship Processes (N = 1646)
Importance
Changes in irritation with partner
Satisfaction with quality time with partner
Changes in fights/arguments
Expected changes in quality time with partner
Feeling appreciative of partner
Perceived partner changes in irritation
Feeling irritated toward partner
Expected changes in irritation with partner
Changes in self-silencing
Importance
Being on the same page
Satisfaction with quality time with partner
Feeling appreciative of partner
Laughing together
Partner being there when needed
Feeling appreciated by partner
Satisfaction with sex life
Feelings varying from day to day
Being there for partner when needed
Variance explained = 41.54%; MSE = 2.33
Variance explained = 70.86%; MSE = .29

experience were most predictive, specifically partner's perceived understanding and dismissiveness of pandemic stress.

Health and wellbeing predictors

This model also explained some variance in perceived changes in relationship satisfaction since the pandemic began (12.50%) and prior week relationship satisfaction (26.07%). For both outcomes, positive and negative emotions were most predictive.

Stress and coping predictors

This model explained some variance in perceived changes in relationship satisfaction since the pandemic began (14.68%) and half of the variance in prior week relationship satisfaction (50.65%). Top predictors differed across outcomes, but for both outcomes, important predictors included perceived stress, perceived partner stress, and multiple aspects of dyadic coping.

Relationship processes predictors

This model explained the most variance, explaining 41.54% of the variance in perceived changes in relationship satisfaction since the pandemic began and 70.86% of the variance in prior week relationship satisfaction. Top predictors differed across the outcomes, but for both outcomes, important predictors included feeling appreciative of one's partner and satisfaction with quality time spent with the partner in the past week.

2.5 | Study 2 results

2.5.1 | Longitudinal growth curve models

Study 2 aimed to examine whether the machine learning-identified predictors at the beginning of the pandemic were associated with *changes* in (prior week) relationship satisfaction across the subsequent year. Therefore, we used key predictors from T1 (identified in Study 1) to predict relationship satisfaction across T2–T6. In our RF analyses, two relationship processes predictors consistently emerged as important for relationship satisfaction: feelings of appreciation and satisfaction with quality time spent with one's partner. Thus, these two variables were included as simultaneous predictors of change in satisfaction over time in the subsequent growth curve models. The findings are summarized in Table S3. Overall, those who were more appreciative of their partner or satisfied with quality time at baseline were more satisfied with their relationship across timepoints.

There was also a significant interaction between appreciation and time. Specifically, those who were more appreciative at baseline had high levels of prior week relationship satisfaction that remained high throughout the year, whereas those who were less appreciative at baseline had *increased* prior week relationship satisfaction over time that later *plateaued* (Figure 3). There was also a significant interaction between satisfaction with quality time and time (Figure 3). Those who were more satisfied with quality time at baseline experienced increases followed by decreases in prior week relationship satisfaction. For those who were less satisfied with quality time, changes in prior week relationship satisfaction were not significant.

FIGURE 2 Summary of RF. Each bar represents the variable importance. Importance refers to Gini Importance values rescaled to show relative importance of predictors within each model (i.e., the most important predictor is set to 1); MSE refers to mean squared error.

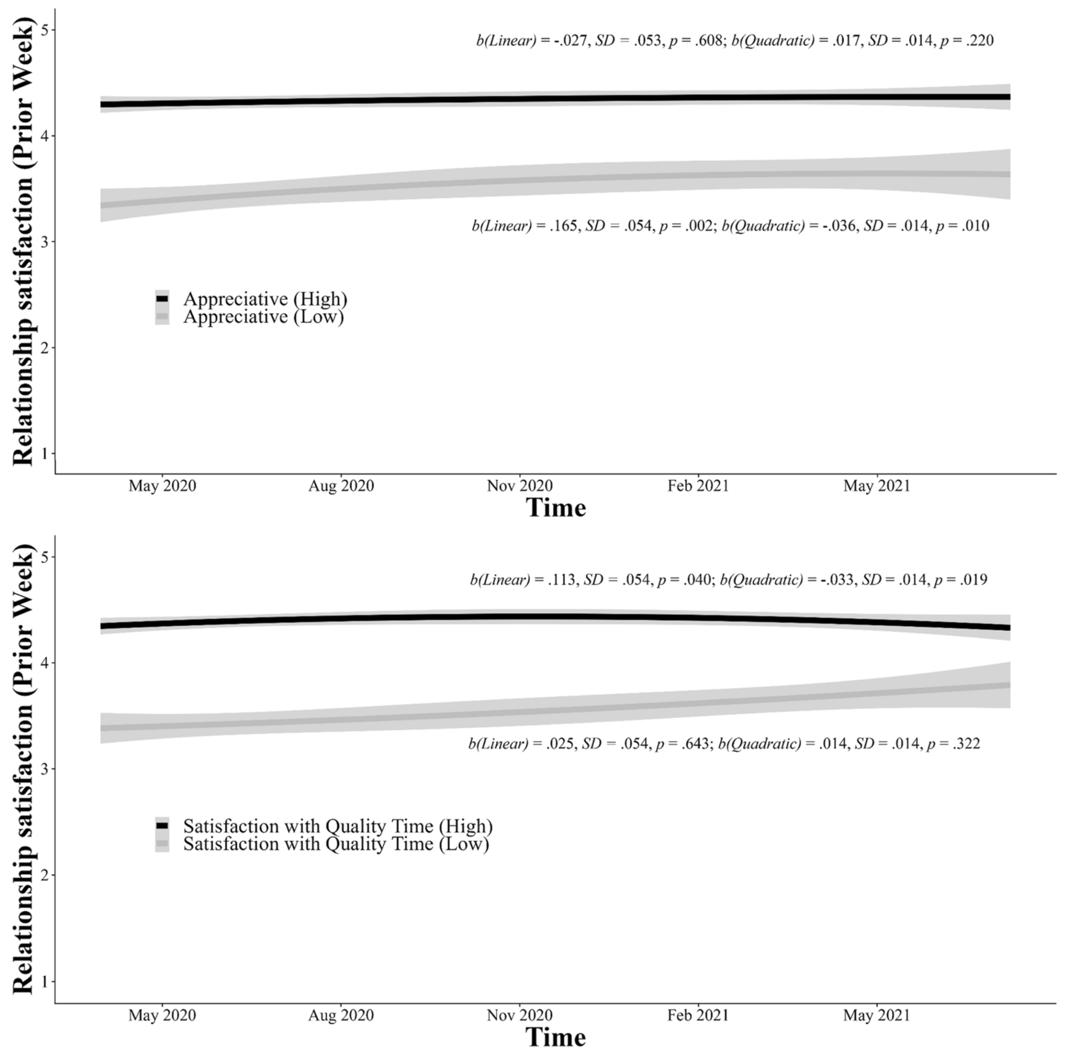


FIGURE 3 Growth curve of relationship satisfaction at low and high levels of predictors.

3 | DISCUSSION

We used machine learning to identify factors that explained cohabiting couples' relationship satisfaction (i.e., perceived changes in satisfaction since the pandemic began and prior week satisfaction) at the start of the COVID-19 pandemic. The identified top predictors were then used in longitudinal growth curve analyses. Variability in relationship satisfaction was best explained by proximal relationship processes such as appreciation and satisfaction with quality time, explaining up to 70% of the variance. This finding suggested that adaptive processes, as outlined in the VSA model, had the highest predictive importance for relationship satisfaction.

Although there was overlap in the top predictors across the two indices of relationship satisfaction, there was also strong evidence for differentiation. For example, in the stress and coping model, perceptions of own and partner stress were the top predictors of perceived changes in satisfaction, whereas dyadic coping was more predictive of prior week relationship satisfaction. Similarly, in the relationship processes model, negative relationship processes (e.g., conflict, irritation) were more predictive of perceived changes in relationship satisfaction, whereas prior week relationship satisfaction was best predicted by positive relational processes (e.g., being on the same page, satisfaction with sex life). These findings suggest that the two outcomes differed in a meaningful way: people may focus more on negative aspects of their relationship when reflecting back on the past, but be more influenced by the positive aspects when evaluating their relationship in the present.

The factors *not* identified as top predictors may be as revealing as those that were. For example, despite the attention paid to it (e.g., Waddell et al., 2021), division of labor during the pandemic did not emerge as an important predictor of relationship satisfaction in these samples. This may be because the association between division of labor and relationship satisfaction depends on how appreciated people feel (Gordon et al., 2022), a factor that did emerge as an important predictor. Our findings are also inconsistent with another machine learning project that identified attachment as a top predictor of relationship quality at the beginning of the pandemic (Eder et al., 2021). This discrepancy could be because our top predictors are more proximal relationship processes that can be influenced by attachment, capturing the mechanisms through which attachment ultimately shapes relationship satisfaction.

Using longitudinal growth curve models, we also examined changes in the prior week satisfaction over the first year of the pandemic. Feeling more appreciative of one's partner and more satisfied with partner quality time at baseline were both associated with high relationship satisfaction.

In considering these findings, there are a few limitations to note. First, some of the top predictors shared similar wording with the corresponding measure of satisfaction (e.g., changes in irritation predicted changes in satisfaction). This makes conceptual sense, but may also represent a measurement issue, particularly since similar items were presented together in matrices. However, there were also relationship processes with consistent wording that did not appear as top predictors (e.g., change in quality time was not an important predictor of change in relationship satisfaction). Moreover, some processes emerged as consistently important across outcomes regardless of wording.

The current RF methods have previously been used with dyadic data (e.g., Joel et al., 2020), however newer methods that account for interdependence (e.g., mixed-effects RF) may be used in future research. Also, we used single-item measures to maximize participation; however, multiple-item measures may perform better. As with any survey, patterned responses are also a potential limitation. To minimize this possibility, we randomized the presentation of items within question matrices. Finally, despite being large, our sample was majority White, educated, higher-income, and Western. This limits the generalizability of our findings to other demographics and countries that experienced a more severe pandemic or had stricter lockdown measures.

In sum, in a large sample of people living with a romantic partner during the COVID-19 pandemic, relationship-relevant processes explained the most variance in relationship satisfaction. Feeling appreciative of one's partner and satisfied with the quality time spent together emerged as important predictors of both indicators of relationship satisfaction, and being more appreciative of one's partner and more satisfied with quality time spent with one's partner were associated with higher relationship satisfaction over time.

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CONFLICT OF INTEREST STATEMENT

The authors have no conflicts of interest to report.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in OSF at https://osf.io/685ta/?view_only=fad8c70425f445ebb862631e9d419f84.

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ENDNOTES

[1] 41 participants completed the survey after May 2020, with the final participant in March 2021.

[2] 60 Sample B baseline respondents reported not sheltering-in-place together and were moved to Sample A. Sample sizes reported above were adjusted accordingly (*N* = 1255 includes these participants).

[3] We also ran additional RFs examining all predictors simultaneously. The results were consistent with the models that explained the most variance (see Supporting Information S1).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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