RUNNING HEAD: Early Relationship Prediction

**Predicting Romantic Interest during Early Relationship Development:
A Preregistered Investigation using Machine Learning**

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Word count: 17,053

Link to materials, data: https://osf.io/6zkjt/?view_only=b5e6d8512f604e448acf43749cd874f7

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Abstract

There are massive literatures on initial romantic attraction and established, “official” relationships. But there is a gap in our knowledge about early relationship development: the interstitial stretch of time in which people experience rising and falling romantic interest for partners who have the potential to—but often do not—become sexual or dating partners. In the current study, 208 single participants reported on 1,065 potential romantic partners across 7,179 data points over seven months. In stage 1 of the analyses, we used machine learning (specifically, Random Forests) to extract estimates of the extent to which different classes of predictors (e.g., individual differences vs. target-specific constructs) accounted for participants’ romantic interest in these potential partners (12% vs. 36%, respectively). Also, the machine learning analyses offered little support for *perceiver × target moderation accounts of compatibility*: the meta-theoretical perspective that some types of perceivers are likely to experience greater romantic interest for some types of targets. In stage 2, we used traditional multilevel-modeling approaches to depict growth-curve analyses for each predictor retained by the machine learning models; robust (positive) main effects emerged for many variables, including sociosexuality, gender, the potential partner’s positive attributes (e.g., attractive, exciting), attachment features (e.g., proximity seeking, separation distress), and perceived interest. We also directly tested (and found no support for) ideal partner preference-matching effects on romantic interest, which is one popular *perceiver × target moderation account of compatibility*. We close by discussing the need for new models and perspectives to explain how people assess romantic compatibility.

Keywords: attraction, romantic relationships, hookups, compatibility, random forests

Predicting Romantic Interest during Early Relationship Development: A Preregistered Investigation using Machine Learning

Our collective understanding of the psychological process by which people evaluate romantic partners has traditionally derived from two disconnected literatures. First, initial attraction approaches (in both the social and evolutionary psychological traditions) examine how people evaluate a potential romantic partner depicted in a photograph or a vignette (e.g., Brandner et al., 2020; Hitsch et al., 2010; Lee et al., 2008; Townsend & Levy, 1990) or in a face-to-face interaction in the laboratory or on a speed-date (e.g., Back et al., 2011; Eastwick et al., 2011; Olderbak et al., 2017; Luo & Zhang, 2009). In virtually all cases, however, studies of initial attraction conclude after the participant reports a single evaluative judgment; there is no information about how these relationships might have changed and developed over time. Second, close relationships approaches (in both the social psychological and family studies traditions) often examine the way people evaluate their dating or married partners longitudinally (for reviews, see Berscheid, 1999; Finkel et al., 2017; Reis, 2007). But the near-universal inclusion criterion for a close relationships study is that participants need to indicate that they are involved in a committed, “official” relationship. In other words, people’s experiences are only included in the close relationships literature when they can report on a specific partner whom they are (at least) dating; relationships that never make it that far are empirical ghosts.

These two approaches combine to create a published knowledge base that largely omits whatever takes place after an initial interaction and before relationship formation (Campbell & Stanton, 2014; Eastwick et al., 2019b). Critically, this *early relationship development* period is likely to be more than a few days: Typically, people report retrospectively that they knew their partners as friends or acquaintances—often getting to know them over a period of weeks or months—before the relationship became romantic or sexual (Eastwick et al., 2018; Hunt et al.,

2015; Kaestle & Halpern, 2005; Manning et al., 2006; Walsh et al., 2014). Presumably, it is during this understudied period that single individuals' waxing and waning romantic interest functions as a critical factor that determines which relationships have a chance to mature and which will remain in a perpetual state of "what if?"

The current study tracked fluctuations in romantic interest of more than 200 single participants over a period of seven months as they considered over 1,000 different potential romantic partners. No prior work had examined this portion of the relationship arc in such detail. Therefore, rather than applying any specific existing model of close relationship processes, we began our investigation by examining the relative explanatory power of two broad classes of constructs: individual differences (e.g., relationship-relevant traits and motivations), and target-specific constructs (e.g., participants' judgments about a particular potential partner). We also examined the meta-theoretical perspective that certain perceivers are especially *compatible* with certain targets (e.g., perceiver $\times$ target moderation approaches). To perform these tests, we used machine learning to extract estimates of how strongly different batches of variables predict initial-report, peak, final-report, and change in romantic interest (see "analysis plan stage 1" below).

Machine learning is a novel way to identify which predictors are likely to be especially robust, but by themselves, such methods do not yield a user-friendly visualization of growth curves and effect sizes. Thus, in an effort to bridge the new and classic approaches, we further examined each predictor that emerged in (at least) one of the machine learning models using multi-level models (see "analysis plan stage 2" below). In this stage, we also performed a focused test of a perceiver $\times$ target perspective by analyzing whether participants were especially interested in potential partners whose attributes matched their *a priori* ideal partner preferences—a hypothesis that had never been examined in this context. We ground our investigation in classic

and novel theories that have discussed the processes by which people gauge whether or not they are romantically compatible with a specific romantic partner.

Early Relationship Development

Theoretical Conceptualizations and Challenges

Relationship science is home to a variety of theories that depict the process by which people develop and maintain romantic relationships (for reviews, see Bradbury & Karney, 2019; Finkel et al., 2017). Even though these many theories were primarily developed using data on established couples, the theories themselves typically do not posit a switch that turns components of the theory “off” prior to the official formation of the relationship and “on” afterwards. For example, the gradual process of building intimacy via self-disclosure (Reis & Shaver, 1988) likely begins prior to the formation of a dating relationship, the vulnerabilities associated with low self-esteem or high attachment anxiety (Murray, Holmes, & Collins, 2006) should presumably cause someone to be wary of both initiating a new relationship and deepening an existing relationship, and the “investment” construct in the investment model of commitment (Rusbult, Agnew, & Arriaga, 2012) is a continuous variable that can range from very low (e.g., a plan to meet up for coffee) to very high (e.g., raising children and owning a home together). It is even common for scholars to derive new insights about people’s first impressions of strangers by drawing from close relationships theories on attachment (McClure & Lydon, 2014), social exchange (Sprecher et al., 2013), capitalization, (Reis et al., 2010), and self-expansion (Vacharkulksemsuk & Fredrickson, 2012), just to name a few. In this light, it is reasonable to conceptualize the decision to form an official relationship as one step in the multistep process of creating a long-term, stable, happy partnership (Baxter & Bullis, 1986; Lloyd & Cate, 1985), and so major relationship theories could presumably retain some applicability to the portions of the relationship trajectory that precede this event (see also Sprecher et al., 2008).

Of course, some perspectives do contain a specific focus on the way that relationships might develop (or fail to develop) during this stretch of time. Knapp's (1978; Knapp et al., 2013) classic relational development model proposes that prospective romantic partners move through stages of escalating self-disclosure and interdependence when forming a relationship, and two of these stages—*experimenting* with self-disclosure and *intensifying* through expressions of affection—take place after an initial interaction but before a couple-level identity has coalesced. A more recent example of this approach is the ReCAST model (Eastwick et al., 2018, 2019b), which proposes that prospective partners attempt to assess compatibility during early relationship development, and it takes time for people to ascertain whether a given relationship has short-term (i.e., only sexual) potential, long-term (i.e., sexual and attachment) potential, or no potential at all. Qualitative work on the hookup culture of college campuses suggests that students often feel compelled to suppress intimacy in casual sexual relationships, which consequentially limits their opportunity to form relationships that are both sexual and attached (Wade, 2017). These (early-relationship-specific) perspectives collectively suggest that early relationship development is a volatile period of discovery and uncertainty (Clark et al., 2019; Tennov, 1979) such that people's feelings about a potential partner may be in flux as new information emerges and new experiences occur.

Nevertheless, very little empirical evidence exists regarding the trajectory of romantic interest during the time period that precedes actual relationship formation, and even less evidence exists on such trajectories in relationships that never actually become dating relationships. A number of studies (primarily in the sexuality and adolescent health literatures) examine college hookups, "friends-with-benefits," and related phenomena (e.g., Calzo, 2013; Harden, 2014; Fiedler et al., 2013; Garcia et al., 2012; Jonason et al., 2010; Lehmiller et al., 2014; Owen & Fincham, 2012; Wesche et al., 2018). But these studies do not typically track people's

relationships with the same hookup partners over multiple time points (for an exception, see Machia et al., 2020). One set of studies managed to plot ~700 romantic interest trajectories, beginning with the participants' initial encounter with the partner and continuing through the end of the relationship (Eastwick et al., 2018, 2019b). However, these studies were limited in that (a) they were retrospective, and (b) the relationships had to become “long-term” or “short-term” at some point to merit inclusion. There are few if any longitudinal studies of early relationship development that are (a) tracked prospectively and (b) conditioned simply on the experience of romantic interest in a particular person (rather than the later occurrence of an event like sexual contact or forming a relationship). The current study uses exactly such an approach in an attempt to document the nature of early relationship development in real time.

Individual Differences, Target-Specific Constructs, and Perceiver × Target Moderation

A major strength of the myriad theories of close relationships described above is that they are tightly connected to a wide array of constructs and measures. Theories vary in the constructs they highlight, but they generally depict the interpersonal process by which (a) individual differences and (b) target-specific perceptions of a partner or the relationship as whole intersect to predict behavioral and evaluative outcomes (Joel et al., 2020).

Individual differences refer to constructs like personality, temperament, beliefs, resources, or abilities; for these variables, participants are asked to report on some aspect of themselves that is (purportedly) independent of any relationship partner. In the existing literature, common theoretically central individual differences include: anxiety and avoidance within attachment theory (Mikulincer & Shaver, 2016); expectations and standards within interdependence theory (Arriaga et al., 2008); chronic concerns about rejection (e.g., self-esteem, rejection sensitivity) within the risk regulation model (Murray et al., 2006); sex, mate value, and sociosexuality within sexual strategies theory (Buss & Schmitt, 1993); vulnerabilities (e.g., family income and history,

emotional instability) within the stress-vulnerability-adaptation model (Karney & Bradbury, 1995); ideal partner preferences within the ideal standards model (Fletcher et al., 1999); and implicit theories of relationships (e.g., destiny and growth beliefs; Knee, 2001). Broadly speaking, some models posit a form of *direct influence* such that certain individual differences are associated with boosts in romantic interest for potential partners in general, unmediated by any particular target-specific process (e.g., sex; Buss & Schmitt, 1993; sociosexuality; Eastwick et al., 2019b; Penke & Asendorpf, 2008). Other models posit that individual differences operate via *mediated expression*: That is, they predict the likelihood that participants engage in a particular target-specific process that subsequently influences romantic evaluation (e.g., individual differences in ideals predict that participants project positive attributes onto a partner, which subsequently predicts higher relationship satisfaction; Murray et al., 1996a). Both direct influence and mediated expression pathways are common in close relationships theories, and theories often make room for both possibilities.

Target-specific constructs refer to participants' judgments about a relationship (e.g., perceptions of specific relationship processes, like levels of self-disclosure or trust) or judgments about a partner (e.g., perceptions of the partner's attributes, like "attractive" or "supportive"); for these variables, a target partner must be specified, usually as a part of each item. Common theoretically central target-specific constructs include: proximity seeking, safe haven, secure base, and separation distress within attachment theory (Tancredy & Fraley, 2006), investments and alternatives within the investment model of commitment (Rusbult et al., 1998, 2012), self-disclosure within the intimacy process model (Reis & Shaver, 1988); perceived regard within the risk regulation model (Murray et al., 2006), or perceptions of the partner's desirable traits in evolutionary models (Brandner et al., 2020). These particular variables all tend to exhibit main effects on romantic evaluations in both initial attraction and established relationships contexts; it

seems plausible that they would exert comparable effects during early relationship development, although their effect sizes and relative importance remain unknown.

In addition, an implicit meta-theory in the attraction and close relationships literatures is that romantic evaluations are determined by the interaction of features of the perceiver with the features of the target, which we call the *perceiver $\times$ target moderation account of compatibility*. Common examples include ideal-partner preference matching (e.g., Lawrence likes Issa because he ideally wants a partner who is funny and she is funny; Fletcher et al., 1999), similarity-matching (e.g., Lawrence likes Issa because both of them enjoy martial arts movies; Montoya et al., 2008), and mate-value matching (e.g., Lawrence likes Issa because they are similarly attractive; Conroy-Beam et al., 2016). Other, more narrow empirical illustrations of perceiver $\times$ target moderation effects are pervasive in the literature, and they are commonly pitched as extensions of established frameworks like attachment theory (e.g., Eastwick & Finkel, 2012; Hadden et al., 2014), the risk regulation model (e.g., Luerksen et al., 2017), evolutionary models (e.g., Lamela et al., 2020; Meltzer et al., 2014), and implicit theories of relationships (e.g., Hui et al., 2012). Collectively, these examples are linked by the meta-theoretical proposition that certain people evaluate certain other people positively—that perceivers with features like Lawrence (e.g., those who ideally want a funny partner/who enjoy martial arts movies) should like targets with features like Issa (i.e., targets who they perceive as funny/who enjoy martial arts movies).

Some perceiver $\times$ target moderation accounts of compatibility have recently encountered empirical challenges in the initial attraction and close relationships literatures: Many studies on ideal partner preference-matching, similarity-matching, and mate-value matching reveal near-zero effect sizes (e.g., Chopik & Lucas, 2019; Eastwick et al., 2019a; Luo & Zhang, 2009; Sparks et al., 2020; Tidwell et al., 2013; Watson et al., 2004; Van Scheppingen et al., 2019; Wurst et al., 2018). But even if all of these particular moderation effects proved to be tiny, the broader meta-

theory that romantic evaluations can be explained by perceiver $\times$ target effects could still be true. It is always possible that researchers have not yet derived the right combination of theory-relevant features to test (e.g., perhaps Lawrence uniquely likes Issa because insecure men uniquely like strong women). Therefore, a test of the meta-theoretical perceiver $\times$ target perspective could benefit from a robust and principled way of exploring a dataset that examines both intuitive and counterintuitive interactions among predictors.

In summary, the voluminous literatures on initial attraction and established relationships include a variety of individual differences and target-specific processes that are also potentially relevant for early relationship development. A study examining this period of time could be informative by attempting to ascertain the relative importance of these two classes of constructs, and perhaps also by identifying some specific examples of each that are particularly impactful—both initially and over time. A study could also be informative by weighing the evidence for whether individual differences (a) have direct effects on romantic interest, (b) exert effects on romantic interest that are mediated by target-specific processes, and (c) moderate the influence of target-specific processes (i.e., the perceiver $\times$ target moderation accounts of compatibility). A machine learning approach can accomplish all of these goals.

Machine Learning

Advantages of Machine Learning

An underappreciated feature of common psychological statistical approaches (e.g., regression) and research practices is that they can render accurate prediction difficult (Schmueli, 2010; Yarkoni & Westfall, 2017). The largest contributor to this problem is *statistical overfitting* (Hawkins, 2004; McNeish, 2015). When scholars estimate associations between variables in an initial sample, those associations will always be influenced by sampling and measurement error. Given that sampling and measurement error will have different effects on subsequent samples, a

statistical model that fits the initial sample well will almost always perform worse in subsequent samples—especially insofar as the model is complex (e.g., regressions with statistical interactions or other higher-order polynomial terms; Yarkoni & Westfall, 2017). In other words, when researchers fit models too closely to the data in the initial published studies, they will commonly encounter challenges finding support for the model in new data.¹

Machine learning can reduce scholars' reliance on overfitted regression equations, making accurate prediction easier (Domingos, 2012; Strobl, Malley, & Tutz, 2009). Machine learning iteratively “recycles” an existing dataset so that part of the data is used to fit an original model, and part of it is used to test the predictive utility of that model (Yarkoni & Westfall, 2017). Specifically, machine learning techniques repeatedly test predictor variables in different subsets of cases (i.e., rows in the dataset), thereby documenting which predictors are especially robust—and therefore more likely to emerge again in subsequent data collection efforts. Machine learning has a second, related advantage: Because the iterative recycling of data also uses different subsets of *predictors* in each round, it is able to test the importance of a very large number of predictors without inflating Type I error. This feature is extremely useful in large datasets, where choices about which predictor variables to highlight are traditionally constrained by the preferences and the imagination of the researcher. That is, researchers might typically wish to highlight the variables (or combinations thereof) that currently happen to be in vogue in their own area of expertise. Machine learning reduces this human bias and can provide an assessment of the relative

¹ The common “replicate in Study 2 what you found in Study 1” approach can address this concern in some areas of scholarship. For example, when developing new scales, scholars often conduct an exploratory factor analysis in Study 1 and use those path estimates to perform a confirmatory factor analysis in Study 2. However, most Study 1/Study 2 pairs do not facilitate strong prediction in this way because researchers do not actually test the fit of *the identical Study 1 model* in Study 2 (e.g., they do not fix Study 2 path parameters to equal the Study 1 parameters and then evaluate model fit). Rather, researchers are primarily interested in whether a given parameter is significantly different from zero in both studies to see whether it “replicates.” To illustrate this distinction: If a Study 1 parameter is $B = .10$ ($p = .020$), a Study 2 parameter of $B = .70$ ($p < .001$) is likely to be considered a more successful replication than a Study 2 parameter of $B = .02$ ($p = .500$), yet the latter result would result in better fit to the predicted value from the Study 1 model.

value of a wide variety of predictor variables to inform future theory development (Yarkoni, in press).

The ability to test different combinations of predictors also means that machine learning could conceivably test a broader version of the perceiver $\times$ target moderation account of compatibility. It is straightforward to preregister and test specific, theoretically derived perceiver $\times$ target moderation accounts of compatibility—indeed, we directly test predictions deriving from theories of ideal partner preference-matching (Fletcher et al., 1999) later in this article. But machine learning can test whether compatibility is generated by nonintuitive forms of statistical interactions that would elude most researchers, as long as the variables that comprise those interactions are present in the dataset. Machine learning accomplishes this feat because, in addition to testing myriad combinations of different predictor variables, it also tests myriad interactions among those predictors (McKinney et al., 2006). Thus, in the context of early relationship development, a machine learning analysis could reveal (a) the relative contribution of individual differences and target-specific constructs in predicting romantic interest, (b) the specific individual-difference and target-specific variables that are the most robust predictors, and (c) the extent to which the perceiver $\times$ target moderation account of compatibility is an important influence on early relationship development.

Applying Prior Machine Learning Findings to Early Relationship Development

Previous research has produced several examples of these types of machine learning contributions at later stages of close relationship development. One recent study applied machine learning to 43 datasets of long-term established couples to predict relationship satisfaction at baseline and longitudinally (Joel et al., 2020). Results showed that, first, both individual differences and target-specific constructs independently accounted for meaningful variance, and consistent with models positing a distal role for individual differences (e.g., Karney & Bradbury,

1995; Rusbult et al., 2001), target-specific reports accounted for approximately twice as much variance as individual differences when predicting one's own current relationship satisfaction. Second, the individual differences were unable to explain any variance above and beyond the target-specific reports. This finding implies that, in contrast to a variety of theories of attraction and close relationships, there were few robust examples of direct, unmediated individual difference predictors and few individual differences moderating target-specific reports; if either of these types of influences had been common, adding individual difference variables to the model would have accounted for additional variance. These two findings were also echoed in other machine learning studies in speed-dating (Joel et al., 2017; Paraschakis & Nilsson, 2020) and established relationship (Großmann et al., 2019) contexts. Third, the models accounted for 2-3 times more variance in baseline relationship satisfaction than follow-up satisfaction (i.e., satisfaction assessed $M = 14$ months later). Fourth and finally, despite the fact that the slope of relationship satisfaction over time is a common dependent measure in the close relationships literature, the models were unable to predict any variance in this parameter at all.

In the present study, we attempt to derive similar insights concerning individual differences and target-specific processes during early relationship development—the understudied context in which participants are considering different potential romantic partners prior to the formation of an official relationship. With so few studies examining this stretch of time, we know little about whether prior machine learning findings should generalize (e.g., will target-specific constructs again outperform individual differences, and if so, by how much?). Critically, some perspectives suggest that perceiver $\times$ target accounts of compatibility should be particularly *likely* to emerge during this period. For example, perhaps perceiver $\times$ target accounts perform poorly in initial attraction contexts because participants doubt the accuracy of their judgments about novel partners; they may resist making an especially positive evaluation until they get to know whether a

given partner is really a strong match to their ideals (Fletcher et al., 2014). Similarly, relationship effects might be initially unstable because they are influenced by the (somewhat random) flow of early conversations and events; friends and acquaintances should have had more opportunities to assess the fit between stable features of the perceiver and the target. Furthermore, people often feel motivated to defend established relationships against the sense that partners are less-than-ideal (Gagne & Lydon, 2004; Murray & Holmes, 1993). But, they should be more willing to deliberate carefully about whether partners are a good match as they consider whether to spend time with one potential partner rather than another before making any official commitments. For these reasons, early relationship development is exactly when perceiver $\times$ target effects like ideal partner preference-matching and similarity-matching could come to the fore (Bahns et al., 2017; Campbell & Stanton, 2014).

The Current Research

This article reports analyses of 208 single undergraduate participants who reported on 1,065 potential romantic partners, providing a total of 7,179 partner-specific ratings from October through April of their first year at university. This study included a wide array of individual-difference and target-specific constructs and measures that are commonly assessed in the close relationships literature and are tightly connected to the myriad theoretical perspectives described above.

We preregistered the analysis plan in two stages. We preregistered stage 1 (machine learning) on August 29, 2019, and we then conducted the analyses described in that preregistration. These analyses allowed us to identify the relative power of individual-differences vs. target-specific constructs, as well as the likelihood that individual differences exert their effects via direct influence and/or the perceiver $\times$ target moderation account of compatibility. They also could be used to determine how well these variables explained romantic interest initially versus

over time. After reviewing the results, we preregistered stage 2 (specific predictors) on October 3, 2019. In stage 2, we used multilevel modeling to graph every predictor that was retained by at least one of the machine learning analyses in stage 1 (that explained a meaningful portion of the variance in romantic interest). We also tested a specific perceiver $\times$ target account of compatibility that follows from the ideal standards model (Fletcher et al., 1999, 2000; see more detail in the section Stage 2 below). The preregistered analysis plans, as well as a full codebook of all measures assessed in this study can be found at this [osf link](#).

Stage 1

In Stage 1, we conducted a wide array of non-machine-learning descriptive analyses that illuminated the nature of the rarely studied context of early relationships development. In addition, the stage 1 preregistration included four machine learning analyses modeled off the Joel et al. (2020) study of established relationships. We stated in that preregistration that we would consider those findings to have generalized to the current early relationship development context if:

Hypothesis 1: Target-specific reports accounted for more variance than individual-differences.

Hypothesis 2: Adding individual-difference reports to the machine learning models did not increase the amount of variance explained over and above target-specific reports alone (i.e., perceiver $\times$ target accounts of compatibility and direct influence effects were very small).

Hypothesis 3: Models predicting initial romantic interest (i.e., when the target first enters the dataset) explained more variance than models predicting final-wave romantic interest.

Hypothesis 4: Change in romantic interest was difficult to predict ($\leq 5\%$ of explained variance).

However, note that the aim of these four hypotheses was not to serve as a “severe test” of a singular theory (Mayo, 1991), but rather to provide specific estimates that could facilitate more

precise, streamlined thinking about the relative contributions of different kinds of variables (Kenny, 2004; 2019; Luce, 1995; MacInnis & Page-Gould, 2015).

Method

Participants. This sample consists of $N = 208$ individuals (91 men, 117 women) who participated in a study of relationship initiation at a midwestern university. Participants were recruited in late September via flyers posted around campus and emails sent to students in various introductory-level courses. To be eligible for the study, the participant had to be at least 18 years old, enrolled as a freshman at the university, single, heterosexual², and a native English speaker (or have been fluent in English for at least 10 years). The participants were $M = 18.1$ years old ($SD = 0.3$); in terms of race, 0.5% of participants identified as American Indian or Alaskan Native, 21.2% Asian, 3.8% Black or African-American, 0.5% Native Hawaiian or Other Pacific Islander, 63.9% White, 1.9% “some other race,” 7.2% “two or more races,” and 1.0% declined to respond. Also, 9.6% responded that they were of Hispanic, Latino, or Spanish origin, whereas the remaining 90.4% responded that they were not of Hispanic, Latino, or Spanish origin. Participants received \$100 for completing the study (i.e., \$10 for completing the online questionnaire, \$25 for attending the in-lab session, \$4 for completing each of the 10 longitudinal questionnaires, and a \$25 bonus if they completed at least 9/10 longitudinal questionnaires). This study was approved by the university IRB.

Procedure.

Online and in-lab intake questionnaires. Participants first completed a one-hour online questionnaire, which consisted of ~75 self-reported individual difference and personality measures. Approximately one week later, participants attended a two-hour in-lab session, which

² We recruited heterosexual individuals given that (a) we did not have the ability to recruit a large, comparable sample of nonheterosexual students, and (b) an unrelated and purposefully nonromantic part of the study examined same-sex friendships.

consisted of ~90 additional self-reported individual difference and personality measures.

Participants then learned additional details about the study procedure.

Ten-wave longitudinal questionnaires. At the end of the in-lab session, participants completed the first of ten longitudinal questionnaires. Each follow-up questionnaire was administered every three weeks, meaning that the longitudinal portion ran from early October to mid-April and captured most of participants' first-year experience at the university. These questionnaires contained a set of items about each participant's own personal *potential partners*—that is, acquaintances and friends whom they identified as people who could possibly become romantic partners for them. (These questionnaires also contained items about platonic friends and a manipulation of regulatory focus that are not relevant to the present report.) Eighty percent of participants completed all 10 of the online wave questionnaires, and 87% completed at least 9 of the 10.

On the first longitudinal questionnaire, participants identified two potential partners in response to the following prompt: “Now, please list the first name and last initial of the two people you've met since coming to [university name] with whom you are most interested in forming a romantic relationship.” In listing their romantic interests, participants further specified the “person I'm most interested in” and the “person I'm second most interested in” and provided a description of where they met each person. On this and all subsequent longitudinal questionnaires, the prompt for each potential partner drew from these two pieces of information to read: “The following questions refer to _____ who you met at _____.”

On each subsequent questionnaire, participants were again asked to list and rank the two people with whom they were most interested in forming a romantic relationship. For each person listed, they were asked to specify whether this was someone they had ever listed in a previous wave, and, if so, to select the person's name from a drop-down list of all of their previous

responses over the course of the study. However, regardless of whether a potential romantic interest was still listed among participants' top two choices, they continued to answer questions regarding that person for all the remaining waves of the study after when the person was initially nominated. Therefore, at every wave, participants reported on at least two romantic interests, but up to as many different individuals they had ever nominated over the course of the study thus far. Over the ten-wave longitudinal portion of the study, participants nominated $M = 5.1$ potential partners ($SD = 2.2$, range = 2-14), for a total of $N = 1,065$ potential partners. Participants completed $M = 6.7$ reports about each potential partner ($SD = 2.9$, range = 1-10), for a total of $N = 7,179$ reports. Unless otherwise indicated, analyses reported below use this full sample of reports.

Each time participants reported on a potential partner on each wave, they answered the item "How would you describe the current status of your relationship with this person?" They were provided with the following mutually exclusive response options (from Finkel et al., 2007): "I do not have any sort of relationship with this person" (selected 758 times out of 7,179 reports; 10.6%), "acquaintance WITHOUT romantic potential" (21.5%), "acquaintance WITH romantic potential" (14.9%), "friend WITHOUT romantic potential" (25.6%), "friend WITH romantic potential" (19.4%), "dating casually" (2.8%), and "dating seriously" (2.3%).³

In the Supplemental materials, a set of "dating subset" analyses focuses on the participants who reported that they were dating one (or more) of their potential partners: If participants reported that they were "dating casually" or "dating seriously" a given potential partner *on at least one wave* during the course of the 10-wave study, all reports about that potential partner were used in these dating-subset analyses. Over the entire ten-wave longitudinal portion of the study, $N = 79$

³ Participants tended to believe the potential partners had more romantic potential on the wave that the partner *first* entered the database: "I do not have any sort of relationship with this person" (selected 69 times out of 1,065 first-reports; 6.5%), "acquaintance WITHOUT romantic potential" (14.7%), "acquaintance WITH romantic potential" (29.1%), "friend WITHOUT romantic potential" (16.5%), "friend WITH romantic potential" (17.4%), "dating casually" (3.5%), and "dating seriously" (0.5%). The target-specific reports described below all derive from this initial report.

participants (i.e., 38% of the total sample of participants; 31 men, 48 women) dated $M = 1.4$ potential partners ($SD = 0.7$, range = 1-4), for a total of $N = 112$ dating partners (i.e., 11% of the total sample of partners). Participants completed $M = 7.1$ reports about each dating partner ($SD = 2.9$, range = 1-10), for a total of $N = 794$ dating reports.

Materials. For the purposes of the present study, the questionnaire items are separated into three groups: individual-difference reports, target-specific reports, and the romantic interest dependent measure. We selected these variables primarily by consulting the *Handbook of Relationship Initiation* (Sprecher et al., 2008)—especially the many chapters that extend theories of established relationships (e.g., attachment theory, interdependence theory, evolutionary theories, the ideal standards model, implicit theories) to relationship initiation contexts. We also drew from prior longitudinal studies of established relationships that we ourselves had conducted (e.g., Finkel et al., 2013; Luchies et al., 2013). Although no prior research had empirically identified the most prevalent close-relationships constructs at the time we launched this study, a subsequent investigation revealed that we had assessed a full two-thirds of the most commonly assessed individual differences in this literature (Joel et al., 2020; see the section “Removing rare individual difference measures” below). We also added a handful of measures from the broader social psychological literature that we believed could be important for predicting who might be more likely to prefer particular types of partners or who might be more engaged in identifying or pursuing new relationship partners (e.g., regulatory focus, values, relationship initiation goals).

Individual-difference reports. On the online intake questionnaire and in-lab questionnaire, participants completed questionnaires designed to measure 164 constructs about themselves. These constructs include personality measures (e.g., the Big Five), attachment style, ideal partner preferences, and a wide variety of individual-difference constructs commonly used in the close

relationships, evolutionary psychological, and social psychological literatures. See Appendix A for a compilation of all constructs used in the individual-difference reports analyses.

Target-specific reports. On the longitudinal questionnaires, participants completed questionnaires designed to measure 30 constructs about each potential partner when that partner entered the database (i.e., on the first wave that the participant nominated the potential partner). These constructs include trait ratings of the potential partner (e.g., physical attractiveness, dependable, exciting, optimistic), perceived reciprocal interest, self-disclosure, attachment features and functions (e.g., proximity seeking, separation distress), and several other commonly assessed relationship-specific constructs. For the analyses reported in this manuscript, all target-specific reports come from the wave that the potential partner entered the database for the first time (participants completed some of these items about each potential partner at each wave). See Appendix B for a compilation of all constructs used in the target-specific reports analyses.

Romantic interest dependent measure. The dependent measure was the item “I am romantically interested in this person.” Participants completed this item on a 1 (*strongly disagree*) to 7 (*strongly agree*) scale at each wave about each potential partner. For the machine learning analyses reported below, we use four different versions of this dependent measure. *Initial report* refers to romantic interest value when the participant first nominated the potential partner (i.e., when the potential partner entered the dataset); *peak* refers to the highest romantic interest value reported by the participant about the potential partner, regardless of which wave that value occurred; *final report* refers to the romantic interest value when the participant reported on the potential partner for the last time (as long as the participant reported on the potential partner at least twice); and *slope* refers to the target-specific regression slope of romantic interest across all of the romantic interest values the participant reported for that potential partner (as long as the participant reported on the potential partner at least twice).

Analysis plan stage 1: Machine learning. As in Joel et al. (2017, 2020), we analyzed these data using Random Forests (Breiman, 2001), which is a machine learning technique that can handle many predictors at once. Random Forests builds on a recursive partitioning technique called decision trees (Breiman et al., 1984; see Berk, 2008 for review). Decision trees are built from a stage-wise process of splitting the dataset into smaller and smaller subsets, or nodes, that differ from each other on an outcome variable; in our case, nodes might cluster around high or medium or low values of romantic interest. Specifically, decision trees involve splitting the dataset at each scale value for all available predictors, until the best predictor and split value combination is found—that is, the one that improves model fit the most. This process is repeated until model fit cannot be improved any further. In the end, a single decision tree might depict effects that resemble a combination of main effects and/or interaction effects that should be familiar to scholars who use multiple regression. For example, Figure 1 depicts a hypothetical decision tree suggesting that perceiving a potential partner to be attractive interacts with sociosexuality to predict romantic interest (Simpson & Gangestad, 1992). It also contains positive main effects of both variables.

Figure 1: One Hypothetical Decision Tree

Note: This decision tree classifies each data point into a low, medium or high romantic interest grouping. There are two decision splits. At the first, the participant perceives the potential partner to be either low (low interest group) or high in attractiveness. If the participant perceives the partner to be high in attractiveness, then the decision at the second split depends on whether the participant him/herself is low (medium interest group) or high (high interest group) in sociosexuality. This decision tree would likely fit a dataset that contained (in regression terms) a positive main effect for both variables (high values for attractiveness and sociosexuality lead to the higher romantic interest groups, on average) as well as a positive interaction between those variables (sociosexuality only has an effect at high attractiveness values).

A single decision tree is likely to overfit a given dataset; Random Forests addresses this problem. The Random Forests approach first builds a decision tree from a random subset of predictors and 2/3 of the cases (rather than the entire dataset). Next, it tests the tree's overall predictive power on the remaining 1/3 of cases that were not used to construct the original decision tree (i.e., the “out of bag” sample). Then, these steps are repeated across several thousand

trees. Predictors and splits are likely to differ from one tree to the next, but given that repeatedly testing predictors in different subsamples of a common dataset is an especially robust way of culling a set of predictors (see simulations in Breiman, 2001), predictors (and combinations thereof) that truly matter will end up being retained across many trees. Finally, the results are averaged together, and the output reveals (a) how much variance in the dependent measure was predictable (across the several thousand trees) and (b) which predictors reliably made contributions to the model. Again, given that decision trees themselves capture any main effects, nonlinear effects, and interactions among predictors that happen to be present, Random Forests should capture these effects, too. Importantly, however, there is no single final output tree that depicts how all the variables fit together in a single algorithm. Rather, the output is a forest, in which some types of trees are more common than others.

Each model was conducted using the “randomForest” package for R using tuning parameters from Joel et al. (2017, 2020; $n_{tree} = 5000$, $m_{try} = p/3$). Also, the widely used “VSURF” package for R determines which specific predictors should be retained (Genuer et al., 2015). VSURF cuts predictors sequentially across three steps: threshold → interpretation → prediction. That is, at the *threshold* step, VSURF is very liberal with the variables it retains: it only cuts variables that never contribute to the model. Then, at the *interpretation* (i.e., moderate) and *prediction* (i.e., conservative) steps, VSURF increases the standards for which variables to retain until only the variables that make a substantial contribution remain. Colloquially, the threshold (liberal) step only drops variables that are primarily noise, the prediction (conservative) step tries to use as few predictors as possible, and the interpretation (moderate) step falls in between. Our stage 1 preregistration emphasized the interpretation (moderate) step, and therefore only variables retained at the interpretation step were examined in stage 2 of the analysis plan. However, for

completeness, we present overall model performance for all three steps in the stage 1 Results section below.

In the current study, the predictors are the individual-difference reports (164 measures) and target-specific reports (30 measures), and each case is a participant's romantic interest dependent measure (initial-report, peak, final-report, or slope) regarding one potential partner ($N = 1,065$ in the primary analysis; $N = 112$ in the dating subset analysis in the Supplemental materials).⁴ We conducted models with three different sets of predictors: (a) all the individual-difference reports, (b) all the target-specific reports, and (c) all individual-difference reports and target-specific reports combined (i.e., a “stacked” analysis; Großmann et al., 2019; Joel et al., 2020). Intuitively, it seems as though adding all the individual-difference reports to the target-specific reports (i.e., analysis c) would surely explain more variance than the models containing the target-specific reports alone (i.e., analysis b). But for the variance explained to be higher in analysis (c), one or both of two conditions must be true: Either the target-specific reports must be moderated by individual differences (i.e., the perceiver $\times$ target moderation account of compatibility), or the individual differences must exert direct effects on romantic interest that are completely unmediated by any target-specific reports (i.e., the direct-influence model). If the addition of individual-difference reports accounts for approximately the same variance as the target-specific reports alone, then neither of these conditions is likely to hold, implying that individual-differences affect romantic interest primarily via mediated expression rather than direct influence or moderation; Joel et al., 2020). Simulations in the Supplemental Materials demonstrate that Random Forest models can recover moderation effects using the stacking approach: The addition

⁴ The full dataset with $N = 7,179$ rows has three levels: time (level 1) nested within target (level 2) nested within participant (level 3). Our four romantic interest DVs aggregate across the lowest level (time) to produce a dataset with $N = 1,065$ rows. Nevertheless, this dataset still has two levels (target nested within participant), and Random Forests and the VSURF predictor selection algorithm do not make adjustments for multilevel structures. For this reason, we use standard multilevel modeling techniques across all three levels in stage 2 of this manuscript. A conventional power analysis would suggest that the $N = 1,065$ row dataset provides 80% power to detect $r = .09$, although it is not clear that sample size affects the ability of random forests (with VSURF) to explain additional variance.

of individual-difference reports indeed explains more variance than target-specific reports alone if moderation effects are built into the data.⁵ Also, it is worth noting that polygenic studies use decision trees and random forests to successfully document gene $\times$ gene interactions using a similar approach (Bureau et al., 2005; McKinney et al., 2006; Pociot et al., 2004).

Results

Basic descriptive information. First, given that datasets examining early relationship development over time are extremely rare, we conducted some basic descriptive analyses on the romantic interest dependent measure. Figure 2 depicts the average romantic interest values across all $N = 1,065$ potential partners at each of the ten time points. Critically, time = 1 is the romantic interest report when the potential partner *entered the dataset* (i.e., the initial-report), not (necessarily) wave 1 of the study itself (i.e., the first week of October). In other words, only potential partners who were nominated on the first longitudinal questionnaire could possibly reach the time = 10 datapoint (hence the error bars are wider for the later timepoints), and potential partners who were nominated on the tenth and final longitudinal questionnaire could only contribute to the time = 1 datapoint. Generally speaking, when participants nominated potential partners for the first time (time = 1), their romantic interest ratings were considerably higher than at subsequent time points. Three weeks after a potential partner was nominated (time = 2), the participant's romantic interest had already dropped by nearly a full scale point.

Figure 3 contains spaghetti plots of this descriptive data over time, along with the average romantic interest values (i.e., the thick black line) corresponding to each time point. Panel A depicts the 112 dating relationships used in the dating subset analyses in the Supplemental

⁵ We also preregistered analyses in stage 1 that involved a set of 37 state-like self-reports (e.g., mood, life satisfaction) that participants reported at each wave but that did not reference any particular potential partner. Models using these variables sometimes performed as well as the target-specific reports, and they sometimes performed quite poorly; see Supplemental materials. We did not have any a priori hypotheses about these variables. Given the ambiguity of these analyses, we do not discuss this set of variables further in the main text.

Materials, whereas Panel B depicts 112 potential partners who were both (a) randomly selected from the “first” potential partners that participants nominated (i.e., the very first potential partner who came to mind on the first longitudinal questionnaire), and (b) never casual or serious dating partners at any point. Romantic interest for the relationships depicted in Panel A is higher than those depicted in Panel B, especially at the later time points. Relatedly, the spaghetti plots suggest that participants’ romantic interest in partners they will date (at some point) often start high and remain high over time (Panel A), whereas romantic interest in the random set of never-dated potential partners start high but decline precipitously at some point (Panel B). In other words, it may be hard to “carry a torch” for someone over many months unless you actually get to date them at some point.

Figure 2: Romantic Interest in Potential Partners over Time

Note: Romantic interest was reported on a 1-7 rating scale. Time = 1 is the wave that the participant first nominated the potential partner. *Ns* for each time point are included at the base of each bar.

Figure 3: Spaghetti Plots for Dated (A) and Never-Dated (B) Potential Partners

Note: Romantic interest was reported on a 1-7 rating scale. Time = 1 is the wave that the participant first nominated the potential partner. Panel A depicts $N = 112$ potential partners that the participant casually or seriously dated at some point; Panel B depicts $N = 112$ random potential partners nominated at the first wave of the study but whom participants never dated at any point.

Figure 4 contains histograms of the number of participants who (a) casually/seriously dated partners during the course of the study (i.e., anyone above 0 comprises the dating subsample; Panel A), and (b) reported engaging in “any romantic physical contact (kissing or other sexual activities)” with a potential partner (Panel B). (This is a target-specific item; see Appendix B.) The subset of participants who engaged in romantic physical contact ($n = 139$, or 67% of the total sample of participants) is nearly double the number who reported having a dating relationship ($n = 79$, or 38%). Also, participants reported having physical contact with $n = 317$ different targets on 1,400 (out of 7,179) reports. Thus, the number of physical contact partners is approximately triple the number of dating partners ($n = 112$), which is consistent with the suggestion that the average college student’s pool of hookup partners is considerably larger than their pool of dating partners (Wade, 2017). (Not surprisingly, nearly all of the dating partners were included in the pool of physical contact partners; $n = 106$, or 94.5%.) Nevertheless, most participants did not have romantic physical contact with a great variety of partners over 7 months (i.e., 87.5% had 0-3 physical contact partners).

Figure 4: Histograms of Total Dating (A) and Physical Contact (B) Partners

Note: Panel A depicts the number of casual/serious dating partners that each participant reported during the course of the study. Panel B depicts the number of partners with whom a given partner had romantic physical contact (kissing or other sexual activities) during the course of the study. Total $N = 208$ for each panel; percentages within a panel add up to 100%.

Machine learning: Full set of predictors. Table 1 contains the associations among the four romantic interest dependent measures used in the machine learning analyses (along with means and *SDs*). Initial and peak romantic interest tended to be strongly associated, which implies that results for those two variables should be quite similar. Indeed, initial-report romantic interest matched peak romantic interest for 74.6% of the 1,065 potential partners. Variability tended to be especially pronounced for the final-report relative to the other DVs.

Table 1: Associations among the Four Romantic Interest DVs

	Initial-report	Peak	Final	Change
Initial-report				
Peak	.80***			
Final	.26***	.42***		
Change	-.23***	-.02	.45***	
<i>Mean</i>	5.19	5.55	3.36	-0.33
<i>SD</i>	1.26	1.16	1.85	0.57

Note: Values reflect standardized β in a multilevel regression with potential partner target nested within participant. Values were assessed with the row variable predicting the column variable (i.e., row = x , column = y); $N = 1,065$.

Figure 5 presents the variance accounted for in the Random Forests analyses (3 sets of variables $\times$ 4 DVs) on the full sample across all three VSURF steps: threshold (liberal), interpret (moderate), and predict (conservative). The four preregistered analyses emerged as follows.

Hypothesis 1. The first pre-registered analysis showed that target-specific reports accounted for more variance than individual-difference reports, as illustrated by the fact that the middle group of bars (target-specific reports) in Figure 5 is generally higher than the left group

of bars (individual differences). This difference (Δ) was more pronounced for the initial-report ($\Delta = 19\%$ across the three VSURF steps) and peak ($\Delta = 17\%$) DVs than the final-report ($\Delta = 3\%$) and change ($\Delta = 0\%$) DVs, and the difference was also more pronounced at the interpret ($\Delta = 14\%$ across the four DVs) and predict ($\Delta = 13\%$) VSURF steps than the threshold ($\Delta = 3\%$) step. Joel et al. (2020) found (at the interpret VSURF step) that individual-difference reports meta-analytically predicted 19% and target-specific reports predicted 45% of one's own current relationship satisfaction; the parallel values here are lower (12% and 36%) but the difference between them is nearly identical.

Hypothesis 2. The second pre-registered analysis showed that the addition of individual-difference reports did not increase the amount of variance accounted for relative to the target-specific reports alone, as illustrated by the fact that the right group of bars in Figure 5 tended to be approximately equivalent to the middle group of bars. Conceptually, these findings suggest that any effects of individual-difference reports on romantic interest in potential partners could be mediated by target-specific reports (i.e., mediated expression models), but they are not likely to exert direct effects or to moderate the effects of target-specific reports (or else individual-differences would have explained more variance when added to the models). These findings are also consistent with Joel et al. (2020), which found that individual-difference reports predicted between 0.0 and 3.5% of the variance above and beyond target-specific reports, depending on the analysis.

Intriguingly, in some cases (e.g., at the interpret and predict step for the initial-report and peak DVs), the models performed several percentage points *worse* when individual-difference reports were added to the model. In other words, the addition of individual differences seemed to lower the variance-accounted-for values. Upon inspection of these outputs (see [here](#)), VSURF

seemed to be cutting out many target-specific variables in the “All variables” analysis that had previously performed well in the “Target-specific reports” analysis. As one example, for the initial-report DV at the interpret step (Figure 5), VSURF selected 16 target-specific reports (i.e., desirable alternatives, mixed signals, partner: attractive, partner: confident, partner: dominant, partner: exciting, partner r’ship status, perceived interest, prevention facilitation, proximity seeking, relative power, secure base, self-disclosure, separation distress, sexual contact, trust), which then accounted for 35.6% of the variance in the random forest models. But when adding individual-differences to the model, VSURF now selected only 2 of these variables (i.e., partner: attractive and relative power) along with 1 individual-difference (sociosexuality attitudes), which then accounted for only 23.5% of the variance in the random forest models. In other words, the addition of individual differences seemed to lower the variance-accounted-for values because the large volume of weak variables made it more difficult for VSURF to “find” the smaller number of high-performing target-specific constructs (see Genuer et al., 2015, for details).

To attempt to adjust for this issue, we reran all the Figure 5 “All variables” analyses after telling the random forest models to “add back” any target-specific variables that had been selected in the “Target-specific reports” analysis. For example, for the initial-report DV at the interpret step, the random forest models now used all 16 target-specific constructs noted above (i.e., not just partner: attractive and relative power) as well as the 1 selected individual-difference (i.e., sociosexuality attitudes). Now, the model accounted for 37.7% of the variance. In other words, now the “All variables” analysis accounted for 2.1% more variance rather than 12.1% less variance. Overall, the “All variables” analysis exceeded the “Target-specific reports” analysis by 2.2% for the initial-report and peak DVs (rather than 5% worse) across all three steps; see the Supplemental Materials for an alternative version of Figure 5 that uses this

approach. This analysis suggests the apparent decline in predictive power depicted in Figure 5 (at the interpret and predict steps) was a function of VSURF overzealously cutting some of the strong target-specific constructs. It also suggests that 2.2% might be one reasonable estimate for the sum total of all robust perceiver $\times$ target moderation effects and direct effects of individual differences. Other sensitivity analyses using smaller sets of focused predictors (as recommended by reviewers) are reported in the Supplemental Materials.

Hypothesis 3. The third pre-registered analysis showed that the models predicting the initial report performed better than the models predicting the final-report, as illustrated by the fact that the bars in the initial-report panel are considerably higher than the parallel bars in the final-report panel ($\Delta = 25\%$ on average). Indeed, our ability to predict final-report romantic interest was fairly poor overall; no analysis exceeded 6%. By way of comparison, Joel et al. (2020) was generally able to predict 10-20% of relationship satisfaction using similar individual-difference reports and target-specific variables $M = 14$ months later. It may be easier to predict the future of established relationships (as in Joel et al., 2020) than it is to predict the future of potential partnerships.

Hypothesis 4. The fourth pre-registered analysis showed that it was challenging to predict slope effects, as evidenced by the fact that none of the change analyses succeeded in predicting even 1% of the variance. Values in Joel et al. (2020) also tended to be quite low (i.e., 5% of the variance or less). It may not be possible to predict the extent to which someone experiences an increase or a decrease in romantic interest in a potential partner from variables assessed at baseline (i.e., prior to or concurrent with the moment that the participant first reports on the partner).

Figure 5: Machine Learning Analyses Predicting Romantic Interest in the Full Sample

Note: Bar colors (blue/red/green) refer to VSURF variable cutpoints that retain many variables (i.e., liberal-threshold), some variables (moderate-interpret), or only the most critical variables (conservative-predict). CIs were generated by converting the variance explained output (R^2) into effect size r , computing the CI around this r (given sample size $N = 1,065$), then converting both the upper and lower 95% CI values of r back to R^2 . See raw output files [here](#).

Recall that participants described 31.2% of their nominated potential partners as “without romantic potential” when those partners first entered the dataset (Footnote 3). It is not clear why

participants thought these nominations had no romantic potential; one possibility is that participants viewed reciprocation from these partners as particularly unlikely or fraught (Afifi & Burgoon, 1998), and another possibility is that some participants might have been adding potential partners to the database simply to comply with experimenter demands. To see if the inclusion of these potential partners affected our conclusions, we reconducted the machine learning analyses with these $N = 333$ cases removed. All four hypothesis tests revealed identical conclusions; see Supplemental Materials. Individual differences performed somewhat worse in this analysis, and so the difference between individual differences and target-specific reports (hypothesis 1) was even stronger (i.e., for initial-report and peak romantic interest, individual differences alone predicted 4% and target-specific reports alone predicted 30%). Values for hypotheses 2-4 were essentially identical to the full analysis.

Discussion

For stage 1 of our analysis plan, we used machine learning to examine the extent to which people's romantic interest in potential partners is predictable. All four preregistered hypotheses received support. Although these hypotheses were not severe tests of a single existing theory and might strike many readers as intuitively obvious (Mayo, 1991), they provide estimates of the relative importance of different classes of variables that will facilitate our ability to develop robust mathematically-informed models (e.g., Kenny, 2004; MacInnis & Page-Gould, 2015). Also, these data tested a generalizability question: Do the findings of Joel et al. (2020) apply to this (rarely studied) early relationship development context? The results suggest that the answer is "yes," and because the hypotheses were preregistered and the data themselves did not inform the hypotheses, we can adjust our confidence in the generalizability of these findings upward (Ledgerwood, 2018). The findings were consistent regardless of whether we examined

the full sample or the dating subset (see Supplemental Materials), although estimates in the dating subset proved more variable given the smaller sample size.

First, target-specific reports accounted for more variance than individual-difference reports. This difference, which ranged from 15-20% depending on the analysis, is consistent with a common assumption among (social psychological) close relationships researchers that measures of the relationship itself provide the best insights into the nature of human mating (Van Lange, 2010). This finding is also consistent with many theories in the close relationships literature positing that individual differences play a more distal role than people's private perceptions of their partners in affecting relational outcomes (e.g., Karney & Bradbury, 1995; Rusbult et al., 2001). Of course, some proportion of this effect could be due to common method variance (e.g., participants completed the target-specific measures and the romantic interest DV at the same time; Podsakoff et al., 2003).

Second, in the preregistered analyses, the addition of individual-difference reports did not reliably contribute beyond target-specific reports in predicting romantic interest. In another version of this analysis (e.g., an analysis that encouraged the machine learning models to “add back” target-specific constructs that emerged in earlier analyses), the best reasonable estimate of the incremental predictive effect of all individual differences was ~2%. If individual-difference constructs (a) exerted unmediated direct influence on romantic interest, or (b) reliably moderated the effects of target-specific reports (e.g., the meta-theoretical perceiver $\times$ target moderation account of compatibility), then the addition of individual-difference reports should have explained additional variance. Instead, mediated expression models—whereby individual-difference reports operate as distal constructs that influence romantic interest through target-

specific constructs—may prove more robust than the direct influence and perceiver $\times$ target moderation models.

Third, baseline romantic interest proved to be more predictable than later romantic interest from individual differences and target-specific variables also reported at baseline. Interestingly, final-report romantic interest was more difficult to predict than in established relationship contexts (Joel et al., 2020), a finding we did not anticipate. It is plausible that most of these potential partnerships did not have a strong dyadic foundation (e.g., no sustained reciprocal interest yet), and so the target-specific constructs that we assessed might prove relatively ephemeral—rapidly shifting for the better or worse as these relationships evolve.

Fourth and finally, the models were unable to predict the extent to which romantic interest increased vs. decreased over the subsequent waves. It might seem obviously true that baseline measures could not predict slopes over time, but published studies commonly report such effects in established relationship contexts (e.g., Impett et al., 2008; McNulty et al., 2013; Murray et al., 2011; Valentine et al., 2020), and they follow from theories positing that incompatibilities are latent early in relationships and primarily reveal themselves with time (Felmlee, 1995). Future research will need to examine why the current findings revealed a different conclusion, and it is possible that we did not assess enough time points for most potential partners to reliably detect change.

Machine learning can illuminate which outcomes are predictable and which sets of measures are useful in making those predictions. But traditional multilevel modeling approaches can provide additional insights into the nature of the associations between successful predictors and a given outcome while appropriately accounting for the nested structure of the dataset. In addition, even though the findings for hypothesis 2 suggested that individual-difference reports

were unlikely to moderate the effects of target-specific reports on romantic interest, it would be sensible to directly test influential moderation hypotheses of this form. Although the meta-theoretical perceiver $\times$ target moderation account of compatibility can take a wide variety of forms, our particular measures put us in a strong position to test one of these theories especially precisely: ideal partner preference-matching. Thus, we preregistered a second stage to our analysis plan (after conducting the preregistered analyses reported above) that specifically set out to (a) plot the effects of specific meaningful predictors, and (b) test theories of ideal partner preference-matching.

Stage 2

The form of perceiver $\times$ target compatibility that has received the most consistent research attention over the past two decades is ideal partner preference-matching (Eastwick et al., 2019a; Fletcher et al., 1999; in press). Ideal partner preference-matching refers to the hypothesis that people who profess a strong ideal for a particular attribute in a partner (e.g., the individual-difference report “My ideal partner is attractive”) should be especially likely to positively evaluate partners who possess the attribute (e.g., the target-specific report “_____ is attractive”). Ideal-partner preference matching is a paradigmatic illustration of the meta-theoretical perceiver $\times$ target account of compatibility (i.e., perceivers like x will fit with targets like y), and it further presumes that participants themselves can articulate (as conveyed by their stated ideals) the sort of partner with whom they will fit.

There are (at least) two strong analytic techniques available for testing this hypothesis (Eastwick et al., 2019a). The first is the pattern metric, which predicts romantic interest from the Fisher z -transformed within-person correlation between (a) all available ideal partner preference measures (in this case, ideals for 14 traits), and (b) the participant’s perception of the partner on

those same (14) traits. This approach addresses whether people are especially likely to experience romantic interest for partners who possess traits that match their overall pattern of ideals. Critically, participants' ratings on ideals and traits include some amount of general positivity, and the psychometric solution to this "normative desirability confound" requires that the researcher mean-center all items before calculating the within-person correlation (i.e., the *corrected pattern metric*; Rogers, Wood, & Furr, 2018; Wood & Furr, 2016). The second is the *level metric*, which predicts romantic interest one trait at a time from each Ideal $\times$ Trait interaction (controlling for the main effect of the ideal and the trait). This approach addresses whether people with strong ideals for a particular trait are especially likely to experience romantic interest in partners to the extent that those partners possess that trait. Our stage 2 analysis plan included preregistered tests of both of the corrected pattern metric and level metric approaches.

Method

We used the same dataset described in Stage 1 (i.e., participants, procedure, and materials).

Analysis plan stage 2: Specific predictors. We used multilevel modeling to depict (one-at-a-time) each of the meaningful predictors that was retained at the interpretation step of VSURF in stage 1. We preregistered that we would focus on the interpretation (i.e., moderate) selection step, as it seemed like a balanced decision criterion that would yield an informative set of predictors, most of which would have made meaningful (rather than tiny) contributions. In Figure 5, 8 of the 12 interpretation step analyses were significantly different from zero; in these 8 analyses, 30 different predictors (11 individual-difference reports, 19 target-specific reports)

were retained in the model at least once (see Appendices A and B). We used multilevel modeling to conduct the following analysis on each of these 30 predictors:

$$\text{romantic interest} = \beta_0 + \beta_1 \text{predictor} + \beta_2 \text{time} + \beta_3 \text{time}^2 + \beta_4 \text{predictor} \times \text{time} + \beta_5 \text{predictor} \times \text{time}^2 + u_{\text{participant}} + u_{\text{partner}} + \varepsilon \quad (1)$$

The $u_{\text{participant}}$ term is the random effect associated with the participant (intercept), the u_{partner} term is the random effect associated with the potential partner, nested within participant (intercept), and ε is the residual error that remains. We included the time^2 terms because the descriptive plots revealed that romantic interest tended to decline quickly and then asymptote (Figure 2); it is possible that some predictors had an effect on final-report romantic interest because they affected the bend of this curve. For all analyses using equation 1, time was scored such that $\text{time} = 0$ corresponded to the wave that the potential partner entered the dataset, and so (β_1) corresponds to the main effect of a given predictor when the participant reported on the potential partner for the first time. All predictors were standardized; romantic interest was left on its original 1-7 scale for graphical clarity. The parallel results for the dating subset are contained in the Supplemental materials.

We also used equation 1 to depict the individual-difference predictors that were retained at the interpretation VSURF step in the analyses that were limited to only the 58 “common” individual difference variables, as labeled in Appendix A and described in the “Removing rare individual difference measures” section in the Supplemental Materials. Six of the eight interpretation step analyses were significantly different from zero, and in these analyses, 16 different individual-difference constructs were retained in the model at least once.

Finally, we conducted analyses examining ideal partner preference-matching using (a) 14 ideal-partner preference items reported on the in-lab questionnaire (e.g., physical attractiveness, dependable, exciting, optimistic) and (b) the 14 corresponding partner-trait items reported at the

first wave the potential partner entered the database. Using equation 1, we conducted both the (a) corrected pattern metric (1 analysis) and (b) level metric (14 analyses) tests as described in Eastwick et al. (2019a). Specifically, for the corrected pattern metric analysis, “predictor” was a Fisher-z scored version of the within-person correlation between the 14 ideal ratings and the 14 partner-trait ratings after sample-mean centering all 28 items. For the level metric analysis, “predictor” was the Ideal $\times$ Trait interaction (after sample-standardizing the ideal and trait); the main effects of ideal and trait were also included in this analysis (as well as the Ideal $\times$ Time, Ideal $\times$ Time², Trait $\times$ Time, and Trait $\times$ Time² terms).

Results

Successful predictors in equation 1: Preregistered analyses. The 30 predictors that were retained in every statistically significant machine learning analysis (at the interpret VSURF step) are presented in Figure 6 (the 11 individual-difference predictors) and Figure 7 (the 19 target-specific predictors). Individual difference variables had five opportunities to serve as predictors (twice by themselves and three times in combination with target-specific variables), and target-specific variables had six opportunities to serve as predictors (three times by themselves and three times in combination with individual difference variables). Most predictors were retained in just one or two analyses, although the model retained the target-specific variable Partner: Attractive as a predictor all six times. Full results of all 30 regressions are presented in Supplemental Materials.

The panels within each figure are sorted by the (absolute value of) the β_I effect size. For example, of the 11 individual-difference reports (Figure 6), sociosexuality (attitudes) exhibited the largest main effect on romantic interest ($\beta_I = .18$), whereas the ideal preference for a level-headed partner had the smallest main effect ($\beta_I = .00$). The 11 individual-difference predictors varied in the extent to which they exhibited main effects (β_I), slope effects (β_d), or curvilinear

effects (β_5), but all effects tended to be modest. Of the 19 target-specific reports (Figure 7), perceiving the potential partner to be attractive had the largest main effect ($\beta_I = .57$), whereas the desirability of alternatives had the smallest main effect ($\beta_I = .08$). The majority of these predictors exhibited significant main effects (β_I) on romantic interest.

Table 2 presents multilevel regression betas (target nested within participant, sorted by the absolute value of β within romantic interest DV type) that correspond to each machine learning analysis in which the predictor was retained. These analyses were conducted not on the full three-level dataset (as in Equation 1 and depicted in Figures 7 and 8) but rather on the two-level dataset with $N = 1,065$ rows used in the machine learning analysis (see Footnote 3). In other words, these analyses precisely show the association of a predictor with the exact romantic interest DV (out of four) for which the predictor was selected. Most—albeit not all—predictors were significantly different from zero; effect sizes generally tended to be in the small-to-medium range. Predictors with smaller betas might have been retained because they tended to overlap little with other predictors (and hence accounted for unique variance when competing with other variables in the machine learning analyses), or perhaps because they exerted their effects through nonintuitive nonlinear effects and interactions among other predictors *in their batch*. For example, perhaps “Partner: Dominant” was retained in the initial romantic interest analysis because it overlaps only modestly with the other target-specific predictors, or perhaps participants experience initial romantic interest for potential partners they perceive as dominant primarily when they also reported high values of one or more of the various attachment features items.

Figure 6: Successful Individual-Difference Predictors (Full Dataset)

Note: Equation 1 results for the 11 individual-difference predictors that contributed to the significant machine learning models in stage 1 (Figure 5). Predictors are sorted in the order of the magnitude of the β_I (wave = 1) effect size.

Figure 7: Successful Target-Specific Predictors (Full Dataset)

Note: Equation 1 results for the 19 target-specific predictors that contributed to the significant machine learning models in stage 1 (Figure 5). Predictors are sorted in the order of the magnitude of the β_1 (wave = 1) effect size.

Table 2: Basic Associations (with Romantic Interest) for Predictors Retained in the Machine Learning Models

Predictor	IV Type	<i>Initial-Report</i> β	<i>Peak</i> β	<i>Final-report</i> β	<i>Change</i> β
Partner: Attractive	Target	.42***	.40***	.19***	
Proximity Seeking	Target	.31***	.27***		
Perceived Interest	Target	.28***	.22***	.18***	
Separation Distress	Target	.27***	.22***		
Mixed Signals	Target	.24***			
Partner: Exciting	Target	.23***			
Secure Base	Target	.22***			
Prevention Facilitation	Target	.20***	.18***		
Self-Disclosure	Target	.18***	.19***		
Relative Power	Target	-.18***	-.16***		
Trust	Target	.16***	.15***		
Sociosexuality (Attitudes)	Individual	.14**			
Desirable Alternatives	Target	.11***	.06		
Partner: Confident	Target	.10**	.09**		
Sexual Contact	Target	.09**			
Values: Hedonism	Individual	.07			
Partner R'ship Status	Target	.010* (η^2)		.008* (η^2)	
Self: Ambitious	Individual	.04	.05		
Partner: Dominant	Target	.04			
Ideal Friend: Optimistic	Individual	-.02			
Ideal Partner: Level-Headed	Individual	.00	.01		
Partner: Realistic	Target		.17***		
Investments	Target		.14***		
Romantic Standards	Individual		.04		
Liberal	Individual		.03		
Growth Beliefs	Individual		-.03		
Values: Achievement	Individual		.01		
Values: Compassion	Individual			-.08*	
Behav. Activation (Reward)	Individual			-.08*	
Partner-Disclosure	Target			.06	

Note: Multilevel regression β s (with target nested within participant) predicting romantic interest across four forms of the DV (initial-report, peak, final-report, and change). IV Type = “Individual” refers to constructs about the participant him/herself; IV Type = “Target” references to constructs reported by the participant about the potential partner. Predictor β s are included in the table only when the predictor (a) was retained by the random forest models at the VSURF interpret step in Stage 1 for that particular DV and (b) the random forest model accounted for variance that was significantly greater than zero. Effect sizes for the categorical variable “Partner R’ship Status” are partial eta-squared values (calculated from the F value).

Successful predictors in equation 1: Common constructs only. We also conducted a set of machine learning analyses in stage 1 with a reduced set of 58 individual-difference constructs that are especially common in the close relationships literature according to Joel et al. (2020; see Supplemental Materials). The 16 individual-differences that were retained in one of the statistically significant machine learning analyses (at the interpret VSURF step) are presented in Figure 8. A few noteworthy individual differences exerted main effects in these analyses that did not emerge in Figure 6. For example, participants reported greater romantic interest (across the full trajectory) to the extent that they had higher ideals for an attractive partner, which coincides with classic perspectives suggesting that ideals exert positive main effects on romantic evaluations in established relationships ($r = .20-.40$; Murray et al., 1996a). Also, men reported more romantic interest than women, which is consistent with evolutionary perspectives suggesting that men tend to be more eager than women when initiating sexual relationships (Buss & Schmitt, 1993). Few other significant effects emerged, however.

Figure 8: Successful Individual-Difference Predictors (Common Constructs Only)

Note: Equation 1 results for the 16 individual-difference predictors that contributed to the significant machine learning models in the analyses reported in the section “Removing rare individual difference measures” in stage 1. Predictors are sorted in the order of the magnitude of the β_1 (wave = 1) effect size.

Ideal Partner Preference-Matching Analyses (Preregistered).

Corrected pattern metric. The corrected pattern metric assesses how well a potential partner's attributes (as assessed when the partner first entered the dataset) matches a given participant's ideal partner preferences across all 14 partner-preference items (see Table 3) after subtracting normative desirability (Wood & Furr, 2016). The corrected pattern metric exhibited no main effect (β_1), slope effect (β_4), or curvilinear effect (β_5); that is, ideal matching had no discernable effect on participants' romantic interest in potential partners (Figure 9). Also, if we simply eliminate all the terms involving Time and Time² from the analysis, the overall corrected pattern metric effect (i.e., at the average time point in the sample) is $\beta = -.02$, $t(6099) = -0.38$, $p = .704$.

Level metric. Table 3 presents the results of all 14 level metric tests, sorted (from left to right) by the strength of the main effect of the trait. That is, attractiveness had the strongest predictive effect on participants' romantic interest ($B = .49$; approximately half a romantic interest-scale point with every *SD* of attractiveness), whereas passiveness had the weakest effect ($B = .03$). These traits effects can be conceptualized as the strength of the functional (i.e., revealed) preference for the trait in the full sample of participants (Ledgerwood et al., 2018); how strongly does a given trait predict participants' romantic interest judgments, on average? All traits exhibited significant positive predictive effects except for dominance and passiveness.

The Ideal $\times$ Trait interactions test the predictive validity of ideal partner preference-matching: That is, does a trait predict romantic interest more strongly for people who ideally say they want the trait? There were zero (out of 14) significant Ideal $\times$ Trait interactions (average $\beta_1 = .02$ in Table 3), revealing no evidence that participants who expressed strong (vs. weak) ideals for a given attribute were especially likely to express romantic interest in potential partners who

possessed the attribute. For slope effects, 2 of 14 level metric effects were significant and positive and 2 of 14 were significant and negative; average $\beta_4 = .001$. For curvilinear effects, 2 of 14 level metric effects were significant and positive and 1 of 14 was significant and negative; average $\beta_5 = .001$. In summary, ideal partner preference-matching effects were extremely small and typically no different from zero, and the significant effects that did emerge did not seem to be systematically positive vs. negative in direction.

Figure 9: Ideal Partner Preference-Matching Over Time (Corrected Pattern Metric)

Regression term	<i>B</i>	<i>t</i>
Intercept β_0	5.03	77.13***
Time β_2	-0.46	-26.29***
Time ² β_3	0.03	14.08***
Pattern metric β_1	-0.03	-0.60
Pattern metric $\times$ Time β_4	0.01	0.62
Pattern metric $\times$ Time² β_5	0.00	-0.31

Note: Bolded rows are the focal pattern metric tests. β s refer to terms in equation 1.

Table 3: Level Metric Tests of Ideal Partner Preference-Matching

Regression term	Attractive		Exciting		Realistic		Creative		Ambitious		Supportive		Confident	
	<i>B</i>	<i>t</i>	<i>B</i>	<i>t</i>	<i>B</i>	<i>t</i>	<i>B</i>	<i>t</i>	<i>B</i>	<i>t</i>	<i>B</i>	<i>t</i>	<i>B</i>	<i>t</i>
Intercept β_0	5.04	83.69***	5.04	78.88***	5.04	76.92***	5.06	77.82***	5.04	79.57***	5.06	80.32***	5.03	77.24***
Ideal	0.20	3.17**	0.05	0.78	-0.01	-0.17	-0.10	-1.43	-0.02	-0.26	-0.11	-1.67	-0.10	-1.53
Time β_2	-0.47	-26.50***	-0.46	-25.79***	-0.46	-25.60***	-0.46	-24.95***	-0.46	-25.60***	-0.47	-26.43***	-0.44	-24.41***
Ideal $\times$ Time	-0.04	-2.26*	0.01	0.57	0.01	0.39	0.05	2.57*	-0.07	-4.03	-0.02	-0.99	0.01	0.62
Time ² β_3	0.03	14.34***	0.03	13.47***	0.03	13.32***	0.03	13.05***	0.03	13.44***	0.03	14.36***	0.03	12.49***
Ideal $\times$ Time ²	0.00	2.15*	0.00	-0.83	0.00	-0.36	0.00	-1.80	0.00	2.02	0.00	-0.50	0.00	-0.86
Trait	0.49	10.27***	0.29	5.76***	0.20	3.95***	0.20	3.65***	0.18	3.56***	0.16	3.14**	0.15	3.02**
Trait $\times$ Time	-0.02	-1.20	-0.05	-2.87**	0.01	0.58	0.02	0.85	0.01	0.75	0.00	-0.25	-0.03	-1.86
Trait $\times$ Time ²	0.00	-1.02	0.00	1.54	0.00	-1.36	0.00	-0.91	0.00	-0.57	0.00	0.03	0.00	0.71
Ideal $\times$ Trait β_1	0.00	0.08	-0.01	-0.14	0.01	0.17	-0.04	-0.86	0.02	0.51	0.02	0.49	0.07	1.31
Ideal $\times$ Trait $\times$ Time β_4	0.02	1.39	0.00	-0.02	0.00	-0.14	0.00	-0.21	0.00	-0.12	0.04	2.54*	-0.07	-3.95***
Ideal $\times$ Trait $\times$ Time² β_5	0.00	-0.55	0.00	1.40	0.00	1.54	0.00	0.82	0.00	0.86	0.00	-2.54*	0.01	3.80***

Regression term	Level-headed		Optimistic		Patient		Spontaneous		Dependable		Dominant		Passive	
	<i>B</i>	<i>t</i>	<i>B</i>	<i>t</i>	<i>B</i>	<i>t</i>	<i>B</i>	<i>t</i>	<i>B</i>	<i>t</i>	<i>B</i>	<i>t</i>	<i>B</i>	<i>t</i>
Intercept β_0	5.06	78.06***	5.04	77.48***	5.03	78.85***	5.04	77.62***	5.04	79.67***	5.04	77.12***	5.04	77.81***
Ideal	-0.02	-0.29	-0.08	-1.31	-0.13	-1.95	0.00	-0.02	-0.07	-1.19	-0.04	-0.59	-0.14	-2.11
Time β_2	-0.46	-25.58***	-0.47	-25.84***	-0.46	-25.85***	-0.46	-25.57***	-0.47	-26.08***	-0.46	-25.26***	-0.46	-25.53***
Ideal $\times$ Time	-0.03	-1.80	-0.01	-0.36	0.01	0.61	-0.01	-0.41	-0.01	-0.39	-0.05	-2.44	-0.01	-0.36
Time ² β_3	0.03	13.62***	0.03	13.74***	0.03	13.79***	0.03	13.32***	0.03	13.88***	0.03	13.76***	0.03	13.59***
Ideal $\times$ Time ²	0.00	0.58	0.00	-0.07	0.00	-0.47	0.00	0.62	0.00	-0.37	0.00	2.20*	0.00	0.59
Trait	0.14	2.69**	0.13	2.63**	0.13	2.54*	0.12	2.40*	0.11	2.27*	0.09	1.62	0.03	0.66
Trait $\times$ Time	0.01	0.39	-0.01	-0.49	0.01	0.77	-0.01	-0.54	0.03	1.75	0.00	-0.21	0.02	1.25
Trait $\times$ Time ²	0.00	-1.07	0.00	0.06	0.00	-0.90	0.00	0.07	0.00	-1.94	0.00	0.10	0.00	-0.63
Ideal $\times$ Trait β_1	-0.01	-0.17	0.03	0.68	0.01	0.26	0.02	0.42	0.03	0.57	0.05	1.14	0.04	0.88
Ideal $\times$ Trait $\times$ Time β_4	0.00	0.07	0.02	0.88	0.03	1.75	-0.05	-3.12**	0.04	2.24*	0.00	-0.22	0.00	-0.23
Ideal $\times$ Trait $\times$ Time² β_5	0.00	0.42	0.00	-0.45	0.00	-1.01	0.01	3.45**	0.00	-1.65	0.00	-0.78	0.00	0.12

Note: “Trait” refers to the participants’ perception of the trait in the potential partner. Bolded rows are the focal level metric tests. Columns are sorted in order of decreasing strength of the trait effect. β s refer to terms in equation 1 (other rows are control variables).

Additional Ideal Partner Preference Analyses (Exploratory). In this section, we report four additional analytic approaches that some prior studies have used to garner evidence for ideal partner preference-matching.

Warmth/trustworthiness and vitality/attractiveness constructs. When participants report their ideal partner preferences for various attributes, their ratings often factor into one of three broader attribute constructs: warmth/trustworthiness, vitality/attractiveness, and status/resources (Fletcher et al., 1999). The traits that we chose to assess in this study were not directly inspired by this tripartite framework; nevertheless, four of the traits we included (i.e., supportive, dependable, level-headed, and realistic) load onto the warmth/trustworthiness factor as identified by Fletcher et al. (1999, Table 1), and six of the traits (i.e., attractive, exciting, ambitious/driven, confident, spontaneous, dominant) load onto the vitality/attractiveness factor. None of the traits that we assessed load onto the Fletcher et al. (1999) status/resources factor.

We reconducted the corrected pattern metric and level metric analyses reported above using only these 10 items rather than the full set of 14 items. The corrected pattern metric again exhibited no main effect, slope effect, or curvilinear effect (Figure 10), and if we simply eliminate all the terms involving Time and Time² from the analysis, the overall corrected pattern metric effect is $\beta = .00$, $t(6095) = 0.07$, $p = .944$.

Table 4 presents the results of the level metric tests on the warmth/trustworthiness and vitality/attractiveness factors. Both traits exerted positive main effects, and the effect size associated with vitality/attractiveness was approximately 1.5 times as strong as warmth/trustworthiness (i.e., $B = .32$ vs. $.20$). Critically, neither of the Ideal $\times$ Trait interactions were significant. For vitality/attractiveness, the slope and curvilinear effects went in opposite directions such that, as time passed, ideal partner-preference matching on vitality/attractiveness

initially had a negative effect on romantic interest (i.e., the negative β_4 term, which is the opposite of the predicted direction), and it then eventually reverses (i.e., the positive β_5 term). Existing theory provides little guidance for interpreting this pattern.

Nevertheless, we should stress that we did not have any status/resources traits in the current study, and Fletcher et al. (in press) found support for the level metric in established relationships on this (and only this) factor. So it is certainly plausible that status/resources traits would have revealed support for ideal partner preference matching, had we assessed them.

Functional-summarized preference correlations. We also conducted the “functional-summarized preference correlation” variant of the level metric analysis used in some prior studies (also called a stated-revealed preference correlation; Brumbaugh & Wood, 2013; Eastwick & Smith, 2018; Wood & Brumbaugh, 2009). This analysis first requires that the researcher calculates a within-person slope (i.e., a personal regression β) that captures the within-person association (calculated across targets) between a given attribute and romantic interest for each participant; these slopes represent each participant’s *functional preference* for a given attribute (i.e., the extent to which the attribute inspired romantic interest for the participant across all targets; Ledgerwood et al., 2018). Then, we calculated the simple (between-persons) correlation of these functional preference values with the ideal partner preference for that attribute as reported on the intake questionnaire (i.e., also called a *summarized preference*; Ledgerwood et al., 2018). Summarized-functional preference correlations in prior work have tended to be moderately sized in contexts where participants rate photographs (e.g., $r = \sim .20$; Brumbaugh & Wood, 2013; Wood & Brumbaugh, 2009) and near-zero when participants rate initial attraction partners ($r = \sim .03$; Eastwick & Finkel, 2008b). The present analysis is the first assessment of functional-summarized preference correlations beyond initial attraction.

Table 5 presents the summarized-functional preference associations for the current study. The correlations ranged from $r = -.08$ to $.09$, with an average $r = .02$; none was significantly different from zero. Thus, similar to prior studies examining initial attraction contexts, there was little evidence that summarized preferences (i.e., the extent to which participants said that they ideally preferred the attribute on the intake questionnaire) were associated with functional preferences (i.e., the extent to which participants experienced strong romantic interest in response to a given attribute in a set of potential partners).

Scholars occasionally draw inferences about ideal partner preference matching by examining whether sex differences in summarized preferences match sex differences in functional preferences (Eastwick & Finkel, 2008b; Li et al., 2013). In other words, given that men say they care about attractiveness more than women (i.e., summarized preferences), does attractiveness actually predict men's romantic interest more strongly than women's romantic interest (i.e., functional preferences)? With respect to summarized preferences: Of the 14 ideal partner preference items, men gave significantly higher ratings than women to attractiveness, $t(206) = 2.81, p = .005, d = .39$, and women gave higher ratings than men to supportive, $t(206) = -5.25, p < .001, d = .74$; ambitious/driven, $t(206) = -4.85, p < .001, d = .68$; dominant, $t(206) = -4.34, p < .001, d = .62$; dependable, $t(206) = -3.60, p < .001, d = .50$; and confident, $t(206) = -2.52, p = .012, d = .35$. However, with respect to functional preferences: Men and women did not differ in their functional preferences (i.e., personal regression β s) for any of these 6 traits, all $ps > .315, ds < .15$. (Indeed, men and women did not significantly differ in their functional preference for any of the 14 traits.)

Raw pattern metric. The *raw pattern metric* is similar to the corrected pattern metric but does not entail mean-centering each item. This approach was used commonly in past research

(Fletcher et al., 1999, 2000), including by members of the current research team (e.g., Eastwick et al., 2011). However, psychometric scholars (Rogers et al., 2018; Wood & Furr, 2016) note that this approach leads to inflated effect size estimates because of the influence of the normative desirability confound; raw pattern metric scores may predict evaluative outcomes not due to the degree of match between ideals and a partner's traits but because such similarity metrics are inflated by the average desirability of the items used in their calculation. Thus, the raw pattern metric may be linked to positively valenced outcomes (e.g., romantic interest) simply due to shared valence alone (i.e., people like targets with positive traits) rather than any fit with ideals. Nevertheless, we present results for the raw pattern metric here (Table 6) to be comprehensive and to offer a contrast with the corrected pattern metric reported above (cf. Fletcher et al., in press). As expected, the β_1 estimates in this analysis are much stronger (in the predicted positive direction) than for the corrected pattern metric. In other words, the raw pattern metric may be more likely to reveal a positive estimate than the corrected pattern metric; failing to subtract normative desirability may inflate the association of ideal partner preference-matching with romantic evaluations.

Ideal-trait correlations. This final alternative approach omits the dependent measure (i.e., romantic interest) entirely and simply presents the correlations between the participant's ideals and the participant's perception of the partner's traits (i.e., *ideal-trait correlations*). Sometimes, scholars conduct these analyses on samples where participants describe the traits of established relationship partners and presume that a positive correlation indicates that participants selected into these relationships because the partner matched the participant's ideals (e.g., Conroy-Beam & Buss, 2016; Gerlach et al., 2019). However, this presumption is not valid: Myriad additional processes will produce positive ideal-trait correlations even in the absence of

participants having (at some previous time) selected the partner because the partner matched their ideals (e.g., “perceiver effects” such that people who profess an ideal for particular trait also “see” that trait in their social milieu; Eastwick et al., 2019a). Nevertheless, we present these estimates here to be comprehensive.

In the current dataset, all ideal-trait correlations were positive (Table 7), and the betas were medium in size ($\beta = .21$ on average). Recall that we failed to document ideal partner preference-matching effects in the preregistered analyses above, and recall that a very small number of these relationships had become established, mutually exclusive partnerships. Yet we replicate the positive ideal-trait correlations found in other studies (e.g., Conroy-Beam & Buss, 2016; Gerlach et al., 2019). Thus, it does not seem that there is a need to posit that such positive correlations result from a process whereby participants positively evaluate and/or select romantic partners who match their ideals. Instead, these correlations seem likely to emerge from other psychological processes (e.g., “perceiver effects”) that are not matching effects Eastwick et al., 2019a).

Figure 10: Ideal Partner Preference-Matching Over Time (Corrected Pattern Metric, Ten Fletcher et al., 1999, items only)

Regression term	<i>B</i>	<i>t</i>
Intercept β_0	5.03	77.22***
Time β_2	-0.46	-26.29***
Time ² β_3	0.03	14.07***
Pattern metric β_1	0.00	0.08
Pattern metric $\times$ Time β_4	-0.00	-0.16
Pattern metric $\times$ Time² β_5	0.00	0.32

Note: Bolded rows are the focal pattern metric tests. β s refer to terms in equation 1.

Table 4: Level Metric Tests of Ideal Partner Preference-Matching on the Fletcher et al. (1999) Constructs

Regression Term	Warmth/ Trustworthiness		Vitality/ Attractiveness	
	<i>B</i>	<i>t</i>	<i>B</i>	<i>t</i>
Intercept β_0	5.03	77.84***	5.02	77.12***
Ideal	-0.09	-1.32	-0.01	-0.16
Time β_2	-0.47	-25.74***	-0.45	-24.93***
Ideal $\times$ Time	-0.01	-0.72	-0.05	-2.88**
Time ² β_3	0.03	13.51***	0.03	12.76***
Ideal $\times$ Time ²	0.00	-0.24	0.00	2.02*
Trait	0.20	4.01***	0.32	6.30***
Trait $\times$ Time	0.01	0.61	-0.02	-1.12
Trait $\times$ Time ²	0.00	-1.20	0.00	0.11
Ideal $\times$ Trait β_1	0.03	0.60	0.00	0.11
Ideal $\times$ Trait $\times$ Time β_4	0.02	1.41	-0.03	-2.16*
Ideal $\times$ Trait $\times$ Time² β_5	0.00	-0.06	0.01	2.96**

Note: “Trait” refers to the participants’ perception of the trait in the potential partner. Bolded rows are the focal level metric tests. β s refer to terms in equation 1 (other rows are control variables).

Table 5: Functional-Summarized Preference Correlations

Attribute	<i>r</i>
Spontaneous	-.084
Creative	-.066
Confident	-.038
Level-headed	-.037
Exciting	-.022
Realistic	.022
Dominant	.023
Optimistic	.027
Attractive	.050
Supportive	.051
Patient	.052
Passive	.056
Ambitious	.084
Dependable	.087
Average <i>r</i>	.015

Note: *N*s range from 174-193, depending on the analysis. *N*s are lower than the total sample 208 because functional preferences cannot be calculated for participants who provide the same trait rating to all targets. Attributes are sorted by the (average) size of the correlation.

Table 6: Ideal Partner Preference-Matching (Raw Pattern Metric)

Regression term	<i>B</i>	<i>t</i>
Intercept β_0	5.04	77.26***
Time β_2	-0.46	-26.15***
Time ² β_3	0.03	14.07***
Pattern metric β_1	0.10	2.05*
Pattern metric $\times$ Time β_4	0.01	0.37
Pattern metric $\times$ Time² β_5	0.00	-1.06

Note: Bolded rows are the focal pattern metric tests. β s refer to terms in equation 1.

Table 7: Ideal-Trait Correlations

Attribute	β
Creative	.29***
Dominant	.28***
Level-headed	.23***
Attractive	.22***
Passive	.22***
Realistic	.22***
Ambitious	.21***
Confident	.21***
Optimistic	.20***
Exciting	.19***
Spontaneous	.18***
Patient	.17***
Supportive	.15***
Dependable	.13**

Note: Attributes are sorted by the (average) size of the ideal-trait standardized beta (β).

Discussion

Stage 2 of our analysis plan used a common multilevel modeling approach to the study of early relationship development over time. First, we analyzed and plotted (one at a time) all of the predictors that were retained (at least once) by our machine learning models in stage 1. For individual-difference predictors, having unrestricted sociosexual attitudes, wanting an ideal partner who is attractive, and being male exhibited the strongest predictive effect on romantic interest; the others had more modest effects. For the target-specific predictors, several of the predictors were substantial, such as perceiving the potential partner (at study entry) to have positive qualities (e.g., attractive, exciting) and other variables associated with the activation of the normative attachment system (e.g., proximity seeking, separation distress, secure base; Tancredy & Fraley, 2006). People also reported more romantic interest when they felt the potential partner was interested in them and also when they received mixed signals from the partner, which is consistent with Tennov's (1979) classic perspective that romantic infatuation is often inspired by a blend of hope (i.e., "I think they are into me") and uncertainty (i.e., "I get mixed signals about whether they are into me").

Findings for hypothesis 2 in the machine learning component of the study (i.e., stage 1) suggested that individual-difference reports were unlikely to moderate target-specific reports. We tested this possibility more directly by examining one popular hypothesis of this form: ideal partner preference-matching. The two clearest analytic techniques (i.e., the corrected pattern metric, the level metric) revealed no evidence for ideal partner preference-matching; participants were no more or less likely to report romantic interest in potential partners who matched vs. mismatched their ideals, in either the full sample (presented here) or the dating subsample (see the Supplemental Materials). Importantly, the raw pattern metric did reveal positive effects,

which suggests that prior studies using this approach (e.g., Eastwick et al., 2011) might have found evidence for ideal partner preference-matching because of the normative desirability confound—a statistical artifact (Wood & Furr, 2016). Ideal-trait correlations were strong and positive, which supports the suggestion that these correlations are caused by processes other than ideal partner preference matching (e.g., perceiver effects; Rau et al., in press). In general, our failure to find support for ideal partner preference-matching is consistent with the machine learning findings from stage 1 (and from Großmann et al., 2019 and Joel et al., 2020):

Moderation effects of individual-difference reports (i.e., perceiver $\times$ target accounts of compatibility) may be very small when used to predict romantic evaluations. Critically, however, we did not assess status/resources traits in this study, and there is some evidence that ideal partner preference-matching effects are especially likely to emerge for those traits in particular (Fletcher et al., in press). If it turns out that ideal partner preference-matching effects emerge robustly for the status/resources dimension but not the other dimensions (or other perceiver $\times$ target accounts of compatibility), explanations for such a pattern would require significant new theory development.

General Discussion

This study examined early relationship development longitudinally—one of the first studies of its kind. An exceptional feature of the dataset is that a participant’s relationship with a given potential partner did not ever need to “turn into something” to be included. Rather, the participant merely had to experience a modicum of romantic interest in the partner at some point during a 7-month period. Thus, this design provides a window into the nature of single individuals’ rising and falling romantic pursuits over time, and it captured both the (small) set of potential partners that ultimately became dating relationships and the (large) set that fizzled out.

Core Findings

These analyses provide insights into the types of constructs and processes that are more or less influential in early relationship development. Individual differences (e.g., sociosexuality attitudes) collectively explained a modest amount of the variance in people's initial-report and peak romantic interest, although target-specific reports (e.g., perceptions of positive qualities, attachment features) explained a greater amount (H1). Perceiver $\times$ target moderation accounts of compatibility generally performed poorly, both in the aggregate (H2) and in the specific tests of ideal partner-preference matching that we conducted in stage 2. Also, predictors of final-report romantic interest were uncommon (H3), and predictors of change in romantic interest were nearly nonexistent (H4).

The basic descriptive data help illuminate some key base rates with respect to early relationship development. At the person level, relationship formation was a common experience, albeit far from ubiquitous. Specifically, 38% of participants ended up dating at least one person casually or seriously over the 7-month period. These values seem consistent with Campbell et al. (2016) and Gerlach et al. (2019)—two of the few other prospective studies of singles—who reported that 39% and 34% (respectively) of participants formed a relationship over a 5-month period. In contrast, relationship formation at the relationship level was far less common: In the current study, only 11% of the potential partners would eventually become casual or serious dating partners. These values are compatible with those in Machia et al. (2020), who reported that 15% of friends-with-benefits relationships transitioned to a romantic relationship over the course of a year. These low percentages would likely drop even further if we had managed to track relationships from the moment two people met: The likelihood that a person will ultimately form a relationship with *any* of the 10-12 strangers they meet at a speed-dating event is

approximately 5%, which amounts to $< 1\%$ per stranger (Asendorpf et al., 2011; Eastwick, 2019). It will take considerably more intensive tracking efforts to understand what these survival curves look like over the full time course of early-relationship development.

Prior work has suggested that the normative trajectory of romantic interest over an entire relationship resembles an arc that rises and falls (Eastwick et al., 2018, 2019b). Intriguingly, the spaghetti plots in Figure 3 (i.e., the potential partners that never became relationships) do not resemble arcs on average—they start in the moderate range and typically decline from that point. There are several possible explanations for this pattern. One possibility is that rising and falling arcs describe dating and sexual relationships that survive long enough for something mutual to happen, whereas most “one-way” romantic interests flicker and disappear. A second possibility is that this survey design was too coarse to capture the rise of the arc: That is, perhaps romantic interest rose over the course of an initial conversation or two and had already peaked for most participants when the survey link arrived in their inbox weeks later. A third possibility is that the design of the study unintentionally encouraged participants to wait until they were especially confident that someone had strong romantic potential before nominating him/her, and thus the downward slide reflects inevitable regression to the mean. To differentiate among these possibilities, we would need to recruit potential partners from an initial encounter, regardless of initial interest level, and then follow them intensively over the coming days, weeks, and months. Future studies should be designed with these considerations in mind.

Finally, the current data speak to the nature of the hookup culture on college campuses (Garcia et al., 2012; Wade, 2017)—or at least on one college campus. On the one hand, the current data indicate that the circle of partners with whom participants had sexual contact is wider than (and also subsumes) the circle they casually or seriously dated; these students seem

more inclined to have sexual contact than to use the “dating” label. On the other hand, sexual contact was a positive predictor of romantic interest (albeit a small one), which suggests that hooking up might serve as a gateway to a more intimate relationship, on average. Future longitudinal research on hookups should be sure to track information on the specific partners with whom participants are hooking up. Otherwise, numbers can be spun into something quite dramatic (our 208 participants hooked up 1,400 times!) when in fact they reflect something a bit more mundane (participants had only $M = 1.5$ hookup partners over a period of 7 months, which means they tended to hook up with the same person multiple times).

Theoretical Implications

Most of the variables assessed in the current study were derived from existing theories and models of close relationships. In terms of individual differences, sociosexuality attitudes (e.g., “sex without love is okay”) exerted a moderately positive main effect on romantic interest, which potentially explains why people higher in sociosexuality eventually acquire more casual *and committed* romantic relationships—they may simply be more amorous in early relationship contexts (Eastwick et al., 2019b; Penke & Asendorpf, 2008). Also, the substantial main effect of gender lends support to evolutionary models of sex differences in romantic eagerness (Buss & Schmitt, 1993; Fletcher et al., 2014), and the main effect of the ideal preference for an attractive partner supports models that posit a motivational function for high ideals (i.e., the projection process documented by Murray et al., 1996a). Many other individual differences that commonly exert robust effects in established relationships (e.g., attachment avoidance, self-esteem, implicit theories; see Figures 7 and 9) seemed to exert small or nonexistent direct effects here; this is at least preliminary evidence that the individual-differences components of these theories do not generalize well to early relationship development.

Among the target-specific variables that tended to emerge, those that assessed dyadic communication processes (e.g., perceived interest, mixed signals, self-disclosure) generally tended to reveal robust effects, as anticipated by many classic models of relationship formation (Altman & Taylor, 1973; Knapp, 1978; Tennov, 1979). Also, several of the normative components of attachment theory performed extremely well (e.g., proximity seeking, separation distress, secure base), which suggests that the activation of the attachment system is a promising early sign in many fledging relationships (Eastwick & Finkel, 2008a; Heffernan et al., 2012). Target-specific perceptions of positive traits performed well, especially the traits that fit within the vitality/attractiveness construct (e.g., attractive, exciting), which is theorized to be central to relationship initiation (Fletcher et al., 2014). Nevertheless, perceptions of traits did not emerge as often as the more dyad-centered constructs on the whole.

The tests of hypothesis 2 were a central theoretical contribution of the current study. These tests revealed that individual differences explained little (if any) variance in the machine learning models above and beyond target-specific predictors. This finding is consistent with an underlying process in which target-specific predictors mediate the effects of individual differences, not unlike the classic conceptualization of “complete mediation” whereby the effect of the distal predictor is reduced to zero by the inclusion of the mediator (Baron & Kenny, 1986). In fact, the findings for hypothesis 2 make the novel conceptual assertion that there may be many undiscovered mediators that explain why gender and sociosexuality (i.e., two of the stronger individual differences that emerged) predict romantic interest; prior research has documented few target-specific variables that mediate the downstream effects of these constructs (cf. Conley et al., 2011). However, the hypothesis 2 effects are not consistent with a process where individual differences exert direct effects or moderate the effects of target-specific predictors on

romantic evaluations.⁶ Along with three other machine learning studies (Großmann et al., 2019, and Joel et al., 2017; 2020), there is now accumulating evidence that perceiver $\times$ target accounts of compatibility are unlikely to successfully explain the prominence of relationship effects in romantic evaluations (Eastwick & Hunt, 2014; Kenny, 2019).

These machine learning studies thus serve a crucial role in the service of theory development, even though machine learning itself works through an atheoretical process of testing variables at random until an optimal solution emerges. Mate Evaluation Theory (MET) is one theory that has been constructed (in part) from prior machine learning efforts (Eastwick et al., 2020). MET seeks to explain how it can simultaneously be true that (a) relationship effects constitute the largest percentage of variance in romantic evaluations (Kenny, 2019), and (b) relationship effects largely cannot be explained by appealing to perceiver $\times$ target interactions. MET explains these seemingly incompatible pieces of evidence by positing not one but two conceptually distinct sources of relationship effects. The first source (called the “feature lens”) refers to individual differences in the way certain perceivers evaluate targets based on the targets’ stable features (e.g., traits). This source includes any account suggesting that “certain people evaluate certain other people positively” and encompasses all forms of the meta-theoretical perceiver $\times$ target account of compatibility (e.g., ideal preference-matching, similarity-matching, mate-value matching; Chopik & Lucas, 2019; Van Scheppingen et al., 2019; Sparks et al., 2020; Tidwell et al., 2013; Watson et al., 2004). The second source (called

⁶ The current article tested effects on romantic interest (i.e., a romantic evaluation) as the dependent measure. We also examined *commitment* as a secondary evaluative dependent measure in the machine learning analyses, and all four hypotheses were again supported; see the Supplemental Materials. But it is certainly possible that some individual-difference $\times$ target-specific construct interactions robustly predict outcomes *other* than romantic evaluations. If true, the same mediational logic would apply. In other words, the current data suggest that the perceiver $\times$ target account of compatibility does not predict romantic evaluations especially well, but future research should test whether the perceiver $\times$ target account predicts other (less evaluative) judgments, which themselves exert downstream effects on romantic evaluations (i.e., mediated moderation).

the “target-specific lens”) refers to history, narrative, “microculture,” idioms, rituals, and other forms of personal knowledge that are bound to one and only one relationship (Bell et al., 1987; Dunleavy & Booth-Butterfield, 2009; Finkel, 2020; Garcia-Rada et al., 2018; Harris et al., 2014; Rossignac-Milon & Higgins, 2018; Rossignac-Milon et al., 2020; Weigel & Murray, 2000). This source captures effects that are not generalizable to other similar perceivers and targets, including events and disclosures that partners experience with each other that are not available to other perceivers. In other words, Lawrence might evaluate Issa uniquely positively not because she matches his ideals or because they have similar interests (i.e., feature lens), but instead because of the way she supported his career aspirations at a critical point in his life or because he enjoys how she counters his teasing with her own (i.e., target-specific lens).

This approach suggests that the reason that compatibility effects are difficult to predict is because the information that determines relationship effects varies idiosyncratically not simply from person to person, but also from relationship to relationship. That is, compatibility primarily emerges as a consequence of the narrative history and idioms that are created within a particular relationship that does not generalize to other relationships (Bell et al., 1987; Garcia-Rada et al., 2018; Harris et al., 2014; Rossignac-Milon & Higgins, 2018). This perspective generates the prediction that accounting for relationship effects will require that scholars tailor items in a way that incorporates the relationship’s own narrative structure (Adler et al., 2017; Bühler & Dunlop, 2019; Sparks et al., 2020). For example, it may be the case that Lawrence feels uniquely positive about Issa because of the way they tease each other—and he would feel less positive if that dynamic changed—but that particular standard would not apply to his past or future relationships. Future work that better allows participants to define for themselves what events or patterns make a given relationships uniquely positive or negative may be critical for predicting

compatibility effects, especially if the classic perceiver $\times$ target approach continues to reveal extremely small effect sizes..

Strengths and Limitations

This article provides an intensive look at the romantic lives of young single people as they considered different potential romantic partners. No previous studies have incorporated into the study of early relationship development repeated longitudinal measurements of multiple targets, and so the trajectories that we documented here fill a crucial gap in the close relationships literature (Eastwick et al., 2019b). Furthermore, we incorporated both machine learning approaches and traditional multilevel models in an attempt to balance concerns about overfitting (Yarkoni & Westfall, 2017) against the utility of presenting familiar growth curve models accounting for the nested structure of our data (Singer & Willet, 2003) that are most directly comparable to the existing literature. We preregistered our analysis plans in both stage 1 and stage 2 to establish *a priori* what we believed to be the most informative approach to addressing our primary research questions. Finally, this study illustrates how the study of singles (Pepping et al., 2018) can incorporate target-specific variables and constructs in their research; participants do not need to be in one exclusive romantic relationship to report on different romantic targets (for a polyamory example, see Moors et al., 2019).

This study also has a number of limitations that can be addressed by future research. First, as noted above, we did not capture participants' romantic interest from the moment they met the potential partners. Doing so will be a very resource-intensive undertaking—perhaps requiring a consortium of scholars—especially if it proves generalizable that (a) only 40% of a sample of singles starts a new dating relationship in a ~6-month period (as we found here), and

(b) the odds of relationship formation with a stranger at the target-specific level are 1% or less (Asendorpf et al., 2011).⁷

Second, we did not have access to objective measures of the nature of the interaction between the participant and the potential partner. Such constructs may have performed well, especially given that the interaction-focused (but participant-reported) measures were often retained by the machine learning models.

Third, we did not have access to the potential partners' self-reported individual differences. These measures would have provided a cleaner comparison between the perceiver $\times$ target account of compatibility tested here—in which all variables were filtered through the participant's own mind—and the one tested in Joel et al. (2020) that also incorporated such partner-reports. Furthermore, it is interesting to consider that partner-reports of individual differences account for a very small amount of variance (5% or less) in prior machine learning work on established relationships (Großmann et al., 2019; Joel et al., 2020), yet they account for much more variance in speed-dating contexts (e.g., 20-25%; Joel et al., 2017); it remains unclear which context is more comparable with early relationship development.⁸

Fourth, our participants were all from a single college campus embedded within a WEIRD culture (Heinrich et al., 2010). These findings may not generalize to cultures that are

⁷ A back-of-the-envelope calculation captures the magnitude of this challenge: If $N = 5000$ single participants enroll in a study, $N = 2000$ will have dated at least one partner 6 months later. If each of those $N = 2000$ diligently reported on 5 strangers over time (the average number of targets in the current study, yielding $N = 10,000$ target strangers), and they dated 1% of those strangers, the usable sample would only be $N = 100$.

⁸ We did, however, have access to one informant-rating about the potential partners: *physical attractiveness* as rated by third-party coders who viewed photographs of the potential partners that were uploaded by the participants (see Supplemental materials for details). The effect of coder-rated attractiveness on romantic interest was very small overall ($\beta = .03$) and not significant. This analysis suggests that the current context (i.e., early relationship development) is more akin to a close relationships context (in which the effect of coder-rated attractiveness on romantic evaluations is also very small: $r = \sim .05$; Eastwick et al., 2014) rather than an initial attraction context (in which the effect of coder-rated attractiveness is quite large: $r = \sim .50$ (Back et al., 2011).

more restrictive of sexuality or relational mobility (Kito et al., 2017) or cultures with high levels of parent involvement (Gui, 2017).

Fifth, we used the random forests machine learning approach, which is an approach that trains each component of the model on 2/3 of the available dataset, then tests it on the remaining 1/3 of the dataset. That is, each tree is evaluated on its ability to predict the outcome variable in a subsample of data that were not used to fit that tree. Although such resampling approaches help to avoid statistical overfitting issues (Yarkoni & Westfall, 2017), they do not speak to the generalizability of the findings in a way that collecting a new dataset would, particularly if that new study had different sample properties. The current study is but one dataset with one particular set of measures, and extensions to new datasets with new measures would be valuable.

Sixth and finally, we were only in a strong position to directly test one out of several possible perceiver $\times$ target accounts of compatibility (i.e., ideal partner-preference matching for traits). Other studies should directly test perceiver $\times$ target effects on the particular variables that are supposed to be especially central to similarity-attraction (e.g., attitudes, health behaviors; Bahns et al., 2017) and to mate-value (e.g., popularity, sociality; Fisher et al., 2008).

Conclusion

The data reported in this article suggest that early relationship development is a turbulent and volatile period in which different potential partners migrate in and out of people's lives. Over the 7-month period of this study, all participants reported on multiple potential partners, and many would ultimately go on to form sexual or dating relationships—at least temporarily. Our machine learning approach revealed that a wide variety of target-specific and individual-difference variables helped to explain why romantic interest was higher for some of these potential partners than others. Also, we used both macro (i.e., the machine learning “stacking

variables” strategy) and micro (i.e., the level and corrected pattern metric tests) approaches to test perceiver $\times$ target accounts of compatibility. Our lack of support for these accounts reinforces the need for scholars to develop and test new explanations for the prominence of compatibility in human attraction that goes beyond fit between different stable features of perceivers and targets. These endeavors will be critical in explaining why some relationships form—and why some of them eventually thrive—whereas many others do not.

Context

This project arose at the intersection of two threads of research. First, although speed-dating studies were very useful at illuminating initial attraction (Eastwick & Finkel, 2008b), it had become clear by the early 2010s that speed-dating designs were not well suited for the study of sexual contact or dating relationship initiation. After all, the base rate of these events among speed-dating matches proved to be very low (see Footnote 7). To overcome this challenge, Drs. Molden, Finkel, and Carswell designed and conducted the current study to capture participants' real-life rising and falling romantic interests, and they succeeded in capturing sexual contact and dating relationship formation longitudinally for the first time (to our knowledge). Second, Dr. Joel (with Dr. Eastwick as co-pilot) had recently spearheaded a major machine learning effort examining 43 datasets of established couples (Joel et al., 2020). Once this prior project had been completed, they extended their analytic approach to this dataset. They first tested whether their prior findings replicated in the current dataset (see analysis plan [here](#)), and they then supplemented those analyses with the many additional descriptive and theoretically-driven tests presented above.

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Appendix A: Individual-difference Report Variables (164) Used in Machine Learning Analyses

Construct	Example item	# of items	Citation (for established scales)	Retained by machine learning?	
				Full (of 5)	Dating (of 4)
Age [†]	How old are you?	1		0	0
Agreeableness [†]	I sympathize with others' feelings.	4	Donnellan et al., 2006	0	0
Approach goals	In relationships, I generally try to enhance the bonding and intimacy in my romantic relationship.	4	Impett et al., 2008	0	1
Assessment	I often critique work done by myself or others.	12	Kruglanski et al., 2000	0	0
Attachment anxiety [†]	I worry about being abandoned.	18	Brennan et al., 1998	0	0
Attachment avoidance [†]	I prefer not to show a partner how I feel deep down.	18	Brennan et al., 1998	0	1
Attractive resistance	If an attractive person (of my preferred sex) approached me sexually, it would be hard to resist, no matter how well I knew him or her.	1	Bailey et al., 1994	0	0
Avoidance goals	In relationships, I generally try to avoid getting embarrassed, betrayed, or hurt by my romantic partner.	4	Impett et al., 2008	0	0
Behavioral activation (drive)	I go out of my way to get things I want.	4	Carver & White, 1994	0	0
Behavioral activation (fun)	I am always willing to try something new if I think it will be fun.	4	Carver & White, 1994	0	0
Behavioral activation (reward)	When I am doing well at something, I love to keep at it.	5	Carver & White, 1994	1	0
Behavioral inhibition	I feel pretty worried or upset when I think or know somebody is angry with me.	7	Carver & White, 1994	0	0
Capitalization	I usually respond enthusiastically when loved-ones tell me about something good that has happened to them.	2	Gable et al., 2004	0	0
Casual sex approval (family)	My family would disapprove of me having casual sex.	1		0	0
Casual sex approval (friends)	My friends would disapprove of me having casual sex.	1		0	0
Cheating	If I could maintain a long-term relationship with one partner while having sexual relations outside of my relationship, I would do so.	1	Landolt et al., 1995	0	0
Collective self-construal	When I am in a group, it often feels to me like that group is an important part of who I am.	2	Cross et al., 2000	0	0
Conscientiousness [†]	I get chores done right away.	4	Donnellan et al., 2006	0	0
Control over passion	No matter how hard they try, people can't really change the sexual	4		0	0

	attraction/desire or passion they feel toward someone.				
Depression [†]	I did not feel like eating; my appetite was poor.	20	Radloff, 1977	0	0
Desperation	I sometimes feel as though I would date anyone who is interested in me.	2		0	0
Destiny beliefs [†]	Potential relationship partners are either compatible or they are not.	11	Knee, 1998	0	0
Education (father) [†]	What is the highest education level achieved by your father? [some high school...graduate degree]	1		0	0
Education (mother) [†]	What is the highest education level achieved by your mother? [some high school...graduate degree]	1		0	0
Extraversion [†]	I am the life of the party.	4	Donnellan et al., 2006	0	1
Forgiveness	I tend to forgive quickly when someone hurts my feelings.	3	Brown, 2003	0	1
Friend value	I am a desirable friend.	4		0	0
Friendship comfort	In general, I am comfortable expressing my interest forming a friendship with someone.	1		0	0
Friendship initiation	I usually initiate a friendship with someone rather than wait for that person to initiate.	1		0	0
Friendship standards	I am very picky about my choice of friends.	1		0	0
Gender [†]	What is your gender? [male, female]	1		0	0
Gender identity	I have many interests (e.g., hobbies, possible careers) which are not stereotypic of my gender.	1		0	0
Growth beliefs [†]	The ideal relationship develops gradually over time.	11	Knee, 1998	1	0
Health (overall) [†]	In general, would you say your health is [poor...excellent]	1		0	0
Health (symptoms) [†]	Migraine headache	33	Cohen & Hoberman, 1983	0	0
Height	What is your height?	1		0	0
Ideal friend: ambitious	Ambitious / Driven	1		0	0
Ideal friend: attractive	Physically attractive	1		0	0
Ideal friend: confident	Confident	1		0	0
Ideal friend: creative	Creative	1		0	0
Ideal friend: dependable	Dependable	1		0	0
Ideal friend: dominant	Dominant	1		0	0
Ideal friend: exciting	Exciting	1		0	0
Ideal friend: level-headed	Level-headed	1		0	0
Ideal friend: optimistic	Optimistic	1		1	0
Ideal friend: passive	Passive	1		0	0
Ideal friend: Patient	Patient	1		0	0

Ideal friend: realistic	Realistic	1		0	0
Ideal friend: spontaneous	Spontaneous	1		0	0
Ideal friend: supportive	Supportive	1		0	0
Ideal partner: ambitious [†]	Ambitious / Driven	1		0	0
Ideal partner: attractive [†]	Physically attractive	1		0	0
Ideal partner: confident [†]	Confident	1		0	0
Ideal partner: creative [†]	Creative	1		0	0
Ideal partner: dependable [†]	Dependable	1		0	0
Ideal partner: dominant [†]	Dominant	1		0	0
Ideal partner: exciting [†]	Exciting	1		0	0
Ideal partner: level-headed [†]	Level-headed	1		2	0
Ideal partner: optimistic [†]	Optimistic	1		0	0
Ideal partner: passive [†]	Passive	1		0	1
Ideal partner: patient [†]	Patient	1		0	0
Ideal partner: realistic [†]	Realistic	1		0	0
Ideal partner: spontaneous [†]	Spontaneous	1		0	0
Ideal partner: supportive [†]	Supportive	1		0	0
Impression management	I am a completely rational person.	10	Paulhus, 1984	0	0
Income (household) [†]	What is the approximate total income of the household in which you were primarily raised?	1		0	0
Independence	My personal identity, independent of others, is very important to me.	12	Singelis, 1994	0	1
Interdependence	I have respect for the authority figures with whom I interact.	12	Singelis, 1994	0	0
Liberal [†]	I endorse many aspects of liberal political ideology.	2	Eastwick et al., 2009	1	0
Limerence	When I am romantically interested in someone, I often ruminate upon every word and gesture from our interactions.	4	Feeney & Noller, 1990	0	0
Locomotion	I enjoy actively doing things, more than just watching and observing.	12	Kruglanski et al., 2000	0	1
Loneliness	I lack companionship.	3	Hughes et al., 2004	0	0
Long-term preference	I prefer a long term relationship with one partner.	1	Landolt et al., 1995	0	0
Mate value	I am a desirable dating partner.	5	Landolt et al., 1995	0	0
Naps	During the past month, how often have you taken naps during the day? [never...3+ times a week]	1		0	0
Narcissism	I see myself as a good leader.	8	Ames et al., 2006	0	0
Need to belong	I want other people to accept me.	10	Leary et al., 2013	0	2
Neuroticism [†]	I have frequent mood swings.	4	Donnellan et al., 2006	0	0

Openness [†]	I have a vivid imagination.	4	Donnellan et al., 2006	0	0
Parental divorce [†]	Are your parents divorced? [yes, no]	1		0	0
Passion theories [†]	If you lose sexual attraction for your partner, you will never recover it.	10	Carswell & Finkel, 2018	0	0
PDA	It's fine with me if others see me be physically affectionate towards romantic partners.	4		0	0
Power	I can get people to listen to what I say.	15	Anderson et al., 2012	0	0
Prevention focus	Growing up, I typically obeyed rules and regulations that were established by my parents.	5	Higgins et al., 2001	0	0
Promotion focus	I have often accomplished things that got me "psyched" to work even harder.	6	Higgins et al., 2001	0	0
Reciprocity (friend)	I tend to want to be friends with people whom I think want to be friends with me.	2		0	0
Reciprocity (romantic)	I tend to be romantically interested in people who like me back.	4		0	0
Rejection sensitivity (concern)	How concerned or anxious would you be over whether or not your friend would do this favor?	8	Downey & Feldman, 1996	0	0
Rejection sensitivity (expectations)	I would expect that my parents would he/she would willingly do this favor for me.	8	Downey & Feldman, 1996	0	1
Relational self-construal	When I feel very close to someone, it often feels to me like that person is an important part of who I am.	2	Cross et al., 2000	0	2
Romantic comfort	In general, I am comfortable expressing my romantic interest to someone I am interested in.	1		0	0
Romantic initiation	I usually initiate a dating or romantic relationship with someone rather than wait for that person to initiate.	1		0	0
Romantic standards	I am very picky about my choice of romantic partners.	1		1	0
R'ship goals: casual dates	Finding someone to date casually [yes, no]	1		0	0
R'ship goals: casual friend	Developing new casual friendships [yes, no]	1		0	0
R'ship goals: close friend	Developing new close friendships [yes, no]	1		0	0
R'ship goals: serious	Finding a serious romantic relationship [yes, no]	1		0	0
R'ship goals: short-term	Finding short-term romantic relationships (e.g., one-night sexual encounters or brief affairs) [yes, no]	1		0	0
R'ships long-term	In considering possible romantic partners, I typically think about their "long-term" potential.	1		0	0
R'ships serious	My romantic relationships are nearly always committed and serious.	1		0	0
Self-concept clarity	In general, I have a clear sense of who I am and what I am.	12	Campbell et al., 1996	0	0

Self-esteem [†]	I feel that I am a person of worth, at least on an equal basis with others.	10	Rosenberg, 1965	0	0
Self: ambitious [†]	Ambitious / Driven	1		2	0
Self: attractive [†]	Physically attractive	1		0	0
Self: confident [†]	Confident	1		0	0
Self: creative [†]	Creative	1		0	1
Self: dependable [†]	Dependable	1		0	0
Self: dominant [†]	Dominant	1		0	0
Self: exciting [†]	Exciting	1		0	0
Self: level-headed [†]	Level-headed	1		0	0
Self: optimistic [†]	Optimistic	1		0	0
Self: passive [†]	Passive	1		0	0
Self: patient [†]	Patient	1		0	0
Self: realistic [†]	Realistic	1		0	0
Self: spontaneous [†]	Spontaneous	1		0	0
Self: supportive [†]	Supportive	1		0	0
Self-control	I am good at resisting temptation.	13	Tangney et al., 2004	0	0
Self-respect	I have a lot of respect for myself.	3	Kumashiro et al., 2002	0	0
Sex drive	I have a strong sex drive.	2		0	0
Sexual orientation	I am exclusively attracted to members of the opposite sex.	1	Eastwick et al., 2011	0	0
Sleep quality	During the past month, would you rate your overall sleeping quality as [very bad...very good]	1		0	0
Social anxiety [†]	I find myself worrying that I won't know what to say in social situations.	19	Mattick & Clarke, 1998	0	0
Social desirability	I never regret my decisions.	10	Paulhus, 1984	0	0
Sociosexuality (attitudes)	Sex without love is okay.	3	Penke & Asendorpf, 2008	1	0
Sociosexuality (behaviors)	With how many different partners have you had sex (sexual intercourse) within the last 12 months?	3	Penke & Asendorpf, 2008	0	1
Sociosexuality (desire)	How often do you have fantasies about having sex with someone with whom you do NOT have a committed romantic relationship? [never...several times per week]	3	Penke & Asendorpf, 2008	0	0
Staying awake	During the past month, how often have you had trouble staying awake while driving, eating meals, etc. [never...3+ times a week]	1		0	0
Stereotype awareness (general)	People generally do not expect women to do well in Math and Science courses.	1		0	0
Stereotype awareness	My professors think that women will do not well in Math and Science	1		0	0

(specific)	courses.				
Stereotype endorsement	I do not expect women to do well in Math and Science courses.	1		0	0
Subjective well-being [†]	In most ways, my life is close to ideal.	5	Diener et al., 1985	0	0
Success expectations: casual dates	Finding someone to date casually	1		0	0
Success expectations: casual friend	Developing new casual friendships	1		0	0
Success expectations: close friend	Developing new close friendships	1		0	0
Success expectations: serious	Finding a serious romantic relationship	1		0	0
Success expectations: short-term	Finding short-term romantic relationships (e.g., one-night sexual encounters or brief affairs)	1		0	0
Values: achievement	Competence and success	1	Schwartz & Bilsky, 1987	1	0
Values: authority	Respect for authority	1	Schwartz & Bilsky, 1987	0	0
Values: avoid hurting partners	I go to great lengths to avoid hurting romantic partners.	1		0	0
Values: benevolence	Enhancing the welfare of those close to me	1	Schwartz & Bilsky, 1987	0	0
Values: casual sex	It is against my values to have casual sex.	1		0	0
Values: compassion	Compassion	1	Schwartz & Bilsky, 1987	1	0
Values: conformity	Meeting social expectations	1	Schwartz & Bilsky, 1987	0	0
Values: fairness	Fairness	1	Schwartz & Bilsky, 1987	0	2
Values: hedonism	Pleasure and self-gratification	1	Schwartz & Bilsky, 1987	1	0
Values: love	Love	1	Schwartz & Bilsky, 1987	0	0
Values: power	Status and prestige	1	Schwartz & Bilsky, 1987	0	0
Values: purity	Purity	1	Schwartz & Bilsky, 1987	0	0
Values: relationships	Relationships/Friendships	1	Schwartz & Bilsky, 1987	0	0
Values: religion [†]	Religion/Spirituality	1	Schwartz & Bilsky, 1987	0	0
Values: security	Stability and harmony	1	Schwartz & Bilsky, 1987	0	0
Values: self-direction	Independence	1	Schwartz & Bilsky, 1987	0	0
Values: stimulation	Novelty and excitement	1	Schwartz & Bilsky, 1987	0	0
Values: tradition	Respect for tradition	1	Schwartz & Bilsky, 1987	0	0
Values: universalism	Understanding and tolerance of others	1	Schwartz & Bilsky, 1987	0	0
Values: wealth	Wealth	1	Schwartz & Bilsky, 1987	0	0
Variety preference	I would prefer to have a variety of sexual partners.	1	Landolt et al., 1995	0	0

Weight	What is your weight (in pounds)?	1		0	0
Well being (autonomy) [†]	I have confidence in my opinions, even if they are contrary to the general consensus.	3	Ryff & Keyes, 1995	0	0
Well being (growth) [†]	I think it is important to have new experiences that challenge how you think about yourself and the world.	3	Ryff & Keyes, 1995	0	0
Well being (mastery) [†]	In general, I feel I am in charge of the situation in which I live.	3	Ryff & Keyes, 1995	0	0
Well being (purpose) [†]	Some people wander aimlessly through life, but I am not one of them.	3	Ryff & Keyes, 1995	0	0
Well being (relationships) [†]	People would describe me as a giving person, willing to share my time with others.	3	Ryff & Keyes, 1995	0	0
Well being (self-acceptance) [†]	When I look at the story of my life, I am pleased with how things have turned out.	3	Ryff & Keyes, 1995	0	0

Note: Response options other than numerical rating scales are presented after the example items in brackets. † = a common individual-difference measure that was retained in the “Common Constructs only” analyses in Figure 8 (58 items total).

Appendix B: Target-Specific Variables (30) Used in Machine Learning Analyses

Construct	Example item	# of items	Citation (for established scales)	Cross-sectional r with DV	Retained by machine learning?	
					Full (of 6)	Dating (of 6)
Desirable alternatives	The alternatives to my current relationship with this person are desirable.	1	Rusbult et al., 1998	.03	2	0
Investments	I've put a lot into my relationship with this person that would be lost if our relationship ended (time, effort, shared friends, and so forth).	1	Rusbult et al., 1998	.31***	1	2
Mixed signals	I am often confused by mixed romantic signals I receive from this person	2		.24***	1	0
Partner r'ship status	Is this person currently in a romantic relationship (with someone other than yourself)? [partnered, "I don't know," single]	1		.010 (η^2)	1	0
Partner: ambitious	I think this person is ambitious/driven	1		.19**	0	0
Partner: attractive	I think this person is physically attractive	2		.51***	6	1
Partner: confident	I think this person is confident	1		.08	2	0
Partner: creative	I think this person is creative	1		.20**	0	0
Partner: dependable	I think this person is dependable	1		.17*	0	2
Partner: dominant	I think this person is dominant	1		-.04	1	0
Partner: exciting	I think this person is exciting	1		.32***	1	0
Partner: level-headed	I think this person is level-headed	1		.19**	0	1
Partner: optimistic	I think this person is optimistic	1		.22**	0	0
Partner: passive	I think this person is passive	1		.03	0	1
Partner: patient	I think this person is patient	1		.18**	0	0
Partner: realistic	I think this person is realistic	1		.21**	1	0
Partner: spontaneous	I think this person is spontaneous	1		.07	0	0
Partner: supportive	I think this person is supportive	1		.16*	0	0
Partner-disclosure	This person feels comfortable opening up to me.	1		.23**	1	0
Perceived interest	This person is romantically interested in me.	1		.32***	3	0
Prevention facilitation	This person helps me become the person I feel it is my duty and responsibility to be.	1	Molden et al., 2009	.21**	2	1

Promotion facilitation	This person helps me become the person I ideally aspire to be.	1	Molden et al., 2009	.20**	0	0
Proximity seeking	It is important to me to see or talk with this person regularly.	1	Tancredy & Fraley, 2006	.39***	2	3
Relative power	Who has more power in this relationship? [him/her...me]	1		-.11	3	1
Safe haven	This person is the first person that I would turn to if I had a problem.	1	Tancredy & Fraley, 2006	.32***	0	0
Secure base	If I achieved something good, this person is the person that I would tell first.	1	Tancredy & Fraley, 2006	.28***	1	1
Self-disclosure	I feel comfortable opening up to this person.	1		.29***	2	1
Separation distress	When I am away from this person, I feel down.	1	Tancredy & Fraley, 2006	.28***	2	1
Sexual contact	Have you engaged in any romantic physical contact (kissing or other sexual activities) with this person? [no,yes]	1	Eastwick & Finkel, 2008b	.17*	1	0
Trust	I trust this person.	1		.23**	3	2

Note: The item for Partner: attractive was actually assessed twice (in two different sections of the questionnaire); for the machine learning analyses, both items were averaged together, and for the ideal partner preference-matching analyses, we used only the item that appeared in the same portion of the questionnaire as the other 13 trait items. Response options other than numerical rating scales are presented after the example items in brackets. Cross sectional r values were calculated on the very first target that participants reported on ($N = 208$) at the very first wave.