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A Worldwide Test of the Predictive Validity of Ideal Partner Preference Matching

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Ideal partner preferences (i.e., ratings of the desirability of attributes like attractiveness or intelligence) are the source of numerous foundational findings in the interdisciplinary literature on human mating. Recently, research on the predictive validity of ideal partner preference matching (i.e., Do people positively evaluate partners who match vs. mismatch their ideals?) has become mired in several problems. First, articles exhibit discrepant analytic and reporting practices. Second, different findings emerge across laboratories worldwide, perhaps because they sample different relationship contexts and/or populations. This registered report—partnered with the Psychological Science Accelerator—uses a highly powered design ($N = 10{,}358$) across 43 countries and 22 languages to estimate preference-matching effect sizes. The most rigorous tests revealed significant preference-matching effects in the whole sample and for partnered and single participants separately. The "corrected pattern metric" that collapses across 35 traits revealed a zero-order effect of $\beta = .19$ and an effect of $\beta = .11$ when included alongside a normative preference-matching metric. Specific traits in the "level metric" (interaction) tests revealed very small (average $\beta = .04$) effects. Effect sizes were similar for partnered participants who reported ideals before entering a relationship, and there was no consistent evidence that individual differences moderated any effects. Comparisons between stated and revealed preferences shed light on gender differences and similarities: For attractiveness, men's and (especially) women's stated preferences underestimated revealed preferences (i.e., they thought attractiveness was less important than it actually was). For earning potential, men's stated preferences underestimated—and women's stated preferences overestimated—revealed preferences. Implications for the literature on human mating are discussed.

Keywords: attraction, close relationships, human mating, ideals, matching hypothesis

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continued

The study of human mating is vast and interdisciplinary, spanning fields as diverse as economics (Hitsch et al., 2010), evolutionary psychology (Buss & Schmitt, 2019), family studies (Boxer et al., 2015), sociology (Lewis, 2016), and social/personality psychology (Fletcher et al., 2019). Despite the considerable depth and breadth of these fields, they share in common a key construct: *ideal partner preferences*. Ideal partner preferences are the attributes (e.g., attractiveness, intelligence, sense of humor) that people say they desire in a romantic partner, and, for 80 years, scholars have been using this construct as the foundation for a variety of theories and

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continued

models that explain how humans pursue and maintain mating relationships (Buss, 1989; Eagly & Wood, 1999; Fletcher et al., 1999; Hill, 1945; see Eastwick, Luchies, et al., 2014, for a review).

For many decades, scholars made the straightforward assumption that ideal partner preferences affected how positively people feel about their romantic partners—which is itself a key predictor of health and mortality (Robles et al., 2014). However, only in the last 25 years have researchers begun to empirically examine the preference-matching question: Does a person positively evaluate a given romantic partner to the extent that the partner's attributes match the person's ideals? This matching hypothesis is the core novel prediction offered by the Ideal Standards Model—an influential model in the close-relationship tradition (Fletcher et al., 1999, 2000; Simpson et al., 2001)—and this hypothesis emerges in evolutionary psychological models as well (Buss, 1989; Conroy-Beam & Buss, 2016; Li & Meltzer, 2015; Shackelford & Buss, 1997; Sugiyama, 2005). Indeed, it is challenging to articulate what the ancestral, functional consequences of ideal partner preferences would be unless the match between preferences and a partner's attributes had some meaningful association with romantic evaluations.

Does the empirical evidence support this matching hypothesis? In brief, the evidence is murky, and it has actually become murkier rather than clearer over time. Today, researchers can cite empirical articles supporting or refuting any point they wish to make about this matching hypothesis. This state of affairs is unfortunate because precise effect size estimates for the matching hypothesis will have

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generative and theory-building implications no matter what they turn out to be. If the match between ideals and a partner's traits predicts romantic evaluations with (at least) modest effect sizes, then scholars should be able to assess participants' ideals and match them with new, compatible partners or determine whether their current relationships are likely to encounter difficulties. However, if these effect sizes are small or near-zero, then explanations for the role of compatibility in human mating will need to become grounded in alternative theories that do not rely on attribute matching (e.g., the way two people coconstruct their expectations, shared reality, or relationship narrative; Berscheid & Ammazzalorso, 2001; Eastwick, Finkel, & Joel, 2023; Rossignac-Milon & Higgins, 2018). Inspired by other large collaborative replication efforts (Coles et al., 2022; Vohs et al., 2021), the current project aims to gather the *strongest possible evaluation* of the predictive validity of ideal partner preferences—perhaps the most interdisciplinary and theoretically central construct in research on human mating.

Ongoing Challenge 1: Lack of Standard Analytic Practices

One reason that the predictive-validity evidence to date remains murky is differing analytic and reporting practices. There are many ways that the matching hypothesis has been operationalized—some more rigorous than others. Specifically, researchers have tested the predictive validity of ideal partner preferences in four primary ways: ideal-trait correlations, the raw pattern metric, the corrected pattern metric, and the level metric. Our own systematic review yielded 35 published studies (Supplemental Table S1) that have reported data that (a) examine participants' evaluations of a person they have met face-to-face (i.e., from speed-dating partners to established romantic partners) and (b) bear on at least one of these four approaches. The four approaches are illustrated with a mock data set in Supplemental Table S2.

First, scholars sometimes report *ideal-trait correlations*: For a particular trait, the researcher calculates the association between participants' ideals and the partners' traits (Example 1a in Supplemental Table S2) in a sample that presumably involved some prior selection event (e.g., the partners are people whom the participants selected as a romantic partner). In other words, do people with a stronger preference for a trait end up with partners who are higher on the trait? However, the selection event is not used as a measured variable (i.e., there are no "unselected" partners)—so it cannot serve as a dependent measure—and no evaluative outcomes, such as attraction or relationship satisfaction, are collected (Conroy-Beam & Buss, 2016; Gerlach et al., 2019). Thus, these correlations are not rigorous tests of the matching hypothesis, as there are many alternative explanations for any such correlation (Eastwick, Finkel, & Simpson, 2019; Fletcher et al., 2020). Indeed, the canonical articles using this approach (e.g., Fletcher et al., 1999; Murray et al., 1996) generally presumed that these correlations reflected a motivated reasoning process (e.g., people are motivated to believe that their current partner possesses the traits that they ideally want) rather than ideal partner preference matching. These correlations are included in the analysis plan because they are available as a matter of course when conducting the more rigorous tests described next.

A second *pattern metric (raw)* approach uses the within-person correlation between (a) each participant's ideals and (b) a target partner's traits (usually rated by participants themselves) across *all* available traits. Researchers subject this correlation to a Fisher z transformation and then use it to predict an evaluative outcome (e.g., relationship satisfaction; Example 1b in Supplemental Table S2). This approach typically reveals moderately sized associations ($r = .20$–$.40$) with relationship satisfaction, which is consistent with the ideal partner preference-matching hypothesis. However, as methodologists have compellingly described (Rogers et al., 2018; Wood & Furr, 2016), this approach has a major shortcoming: The predictive power of the raw pattern metric is confounded with the normative desirability of the ideal traits and target partner traits that are used to calculate the within-person correlation. In other words, the raw pattern metric approach may have garnered support for the ideal partner preference-matching hypothesis because people tend to report positive evaluative outcomes when they think their partner has positive traits; thus, this approach does not uniquely test whether the *match* between ideals and partner traits has predictive effects. Approaches using Euclidean distance metrics share this shortcoming (e.g., Conroy-Beam et al., 2016; see Rogers et al., 2018).

A third *pattern metric (corrected)* approach follows Wood and Furr's (2016) recommendation to mean center each ideal rating and partner trait rating (a and b in the paragraph above) prior to the calculation of the within-person correlation; just as with the raw pattern metric, this correlation can then be z scored and used to predict an evaluative outcome (Example 1c in Supplemental Table S2). This procedure removes the normative desirability confound and permits a clean test of the ideal partner preference-matching hypothesis, and published effect sizes range from near zero to $r \sim .25$ (Eastwick, Finkel, & Simpson, 2019; Fletcher et al., 2020; Lam et al., 2016).

A fourth-*level metric* approach refers to the statistical interaction between the participant's ideal and the partner's trait (i.e., The Ideal × Trait Term) when predicting an evaluative outcome (controlling for the main effects of the ideal and trait; example 1d in Supplemental Table S2). For example, assume there is a positive association of (a) perceiving a partner to be funny with (b) attraction to that partner. The level metric tests whether this association is stronger (i.e., more positive) among participants who have high (rather than low) ideals for a funny partner—as if participants with high ideals are "weighing" the trait more positively in their evaluative judgments. This approach is designed to be implemented one trait at a time, which is critical when testing theories positing that ideals for specific attributes have functional outcomes (e.g., the hypothesis that heterosexual women have a stronger preference for *financial success* in a partner because they have historically needed to differentiate strong from weak providers more so than heterosexual men; Buss, 1989; Eastwick & Finkel, 2008; Eastwick, Luchies, et al., 2014; Li et al., 2013; Pérusse, 1993). Significant effects emerge sporadically using this approach (e.g., Fletcher et al., 2020; Valentine et al., 2020), but high-powered level metric tests across multiple attributes are uncommon.

Critically, few articles report more than one of the four approaches (see Supplemental Table S1), and researchers who draw conclusions from the weaker approaches (i.e., ideal–trait correlations, the raw pattern metric) are more likely to conclude support for the matching hypothesis than are researchers who use the stronger approaches (i.e., the corrected pattern metric, the level metric). This registered report addressed the challenge of discrepant reporting practices by bringing together a diverse team of researchers who all committed to a preregistered analysis plan with all four analytic strategies described above.

Ongoing Challenge 2: Differences Between Established Relationships and Initial Attraction

A second reason that the state of the matching hypothesis is uncertain is that ideal partner preference-matching effects may depend on relationship context. The matching hypothesis has historically received support when participants evaluated a current romantic partner, as suggested by studies of established relationships (e.g., Fletcher et al., 1999, 2000, 2020; Zentner, 2005). However, the hypothesis has not commonly been supported when participants evaluated a partner with whom they were not romantically involved, as suggested by studies of initial attraction (e.g., Eastwick & Finkel, 2008; Selterman & Gideon, 2022; Wu et al., 2018). Moreover, direct comparisons of effect sizes for established relationship versus initial attraction partners remain elusive, as studies conducted in these two contexts typically differ from each other in innumerable ways.

To address context as a potentially critical moderator, the current project collected data on both established relationship and initial attraction partners using a method (adapted from Eastwick, Finkel, & Eagly, 2011, and Sparks et al., 2020) that enables a clean comparison between these two contexts. Specifically, participants who were in an established relationship completed scales about their current romantic partner, and participants who were single completed the *identical scales* about the partner with whom they would most desire to have a romantic relationship. By using the same items and procedure in both relationship contexts, the two effect sizes can be compared with each other more straightforwardly than in prior studies.

Researchers have speculated that a difference between initial attraction and established relationship contexts could emerge because the ideal standards model primarily applies to long-term partnerships and/or because participants only draw from their (abstract) ideal partner preferences once the relationship itself becomes an abstract entity with a hypothetical future (Eastwick, Luchies, et al., 2014; Meltzer et al., 2014). Nevertheless, there are two reasons for such a difference that would be grounded in motivated perceptional processes rather than the ideal standards model per se. First, people may adjust their *perceptions of their partner's traits* to match their ideals (Murray et al., 1996), perhaps especially if they are happy in their current relationship. This interpretation is always plausible whenever participants provide their own ratings of a partner's traits—the most common method in this literature by far.[1] To examine this possibility, we also assessed each partner's level of formal education (e.g., high school, college degree)—a more objective measure that should be less subject to motivated reinterpretation than typical trait ratings of the partner. To the extent that preference-matching effects are a function of motivated perception of the partner's traits, the effect size for the level metric should be smaller for the level of the partner's education.

Second, people may adjust their *ideals* to match their perceptions of their partner's traits (Gerlach et al., 2019; Neff & Karney, 2003), perhaps especially if they are happy in their current relationship. One way to address this alternative explanation is to collect participants' ideals before the relationship forms in the first place (Eastwick, Finkel, & Eagly, 2011). To examine the possibility that people use their prerelationship ideals when evaluating an ongoing relationship, we also recruited an additional sample via Cloud Research. These participants reported their ideals when single, and then, after they started a new romantic relationship (several months later), they completed measures about their current romantic partner. To the extent that preference-matching effects are a function of the motivated shifting of one's own ideals, the effect sizes in this "newly partnered" sample should be smaller.

The Current Research

This collaborative effort produced the largest cross-national data set of participants' evaluations and judgments about preferred-gender targets they know personally (e.g., romantic partners, friends, acquaintances). The specific research questions (RQs) in the Primary Planned Analyses section are outlined in Table 1. RQs 1–4 rely on traditional null hypothesis significance testing; nevertheless, interpretations will focus primarily on effect size estimates vis-à-vis Cohen's (1992) small, medium, and large conventions. Effect sizes for the level metric (i.e., statistical interactions) will be interpreted as fractions of the attribute main effects. In tutorials of interaction statistical power (Baranger et al., 2023; Giner-Sorolla, 2018), a "knockout" interaction (i.e., interaction effect size β = main effect size β) is akin to a medium-sized effect, and a "50% attention" interaction (i.e., interaction effect size β = 50% of main effect size β) is akin to a small effect. All four RQs were evaluated with all four analytic approaches described above.

Method

This study mimics the design of an influential, initial test of the predictive validity of ideal partner preference matching (Fletcher et al., 1999, Study 6). Specifically, participants (a) provided their ideals on a variety of traits, (b) rated their current romantic partner on those same traits, and finally (c) reported an evaluation of their current partner as the outcome dependent measure. This procedure remains the gold standard in this research space, but it was updated in three ways: (1) participants who were single were not excluded from participating but were instead given the chance to evaluate the person with whom they most desire to have a romantic relationship (as in Eastwick, Finkel, & Eagly, 2011, Study 3); (2) participants also evaluated three additional targets—peers of their preferred gender (as in Sparks et al., 2020)—to enable additional analytic tests (elaborated below); and (3) participants rated a larger set of traits (not just the traits highlighted in Fletcher et al., 1999, but also the Big Five personality traits; Goldberg, 1993).

Ethics

Each research group ensured that they had approval from their institution's Ethics Committee or institutional review board to

[1] To illustrate, 30 of the 35 studies in Supplemental Table S1, or 86%, used this approach, whereas 23% asked partners to self-report their own traits, and 20% used some "objective" measure of the trait (these numbers add to more than 100% because some studies employed multiple approaches). The current study is primarily designed to establish robust effect size estimates for the (most common) participant-perception approach, which could then inform power analyses for future investigations of the other two (considerably more intensive, but usually less well-powered) approaches.

Table 1
Design Table: Primary Planned Analyses (Research Questions and Hypotheses)

Research question	Hypothesis	*N*
1. What is the (overall) effect size of ideal partner preference matching?	a. Ideal-trait correlations (rs) are greater than zero. b. The raw pattern metric (*r*) is greater than zero. c. The corrected pattern metric (*r*) is greater than zero. d. Level metric tests (interaction βs) are greater than zero.	10,358 (full sample)
2. What is the effect size of ideal partner preference matching in initial attraction contexts?	a. Ideal-trait correlations (rs) are greater than zero. b. The raw pattern metric (*r*) is greater than zero. c. The corrected pattern metric (*r*) is greater than zero. d. Level metric tests (interaction βs) are greater than zero.	4,152 (subsample)
3. What is the effect size of ideal partner preference matching in established relationship contexts?	a. Ideal-trait correlations (rs) are greater than zero. b. The raw pattern metric (*r*) is greater than zero. c. The corrected pattern metric (*r*) is greater than zero. d. Level metric tests (interaction βs) are greater than zero.	5,544 (subsample)
4. Does the effect size of ideal partner preference matching depend on initial attraction versus established relationship context?	a. Ideal-trait correlations (rs) are larger when reporting on current partners than desired partners. b. The raw pattern metric (*r*) is larger when reporting on current partners than desired partners. c. The corrected pattern metric (*r*) is larger when reporting on current partners than desired partners. d. Level metric tests (interaction βs) are larger when reporting on current partners than desired partners.	4,152 versus 5,544 (two subsamples)

Note. All (a) ideal-trait correlations and (d) level metric tests involve 35 separate tests, one for each attribute in Tables 2 and 3. In these cases, we used a Holm–Bonferroni correction (Holm, 1979) to control the family-wise Type I error rate, and we discuss possible power implications in the A Priori Power Analysis Plan section in the Supplemental Materials.

conduct the study; that the study was covered by the approved University of California, Davis IRB (exempt protocol 1898056-1 “The Preference-Matching Project”); or that the study was exempt (see the Supplemental Materials for details).

Participants

Our final sample consisted of N = 10,358 participants (after planned exclusions; see the Data Processing section for details) from 60 samples and 43 different countries (Supplemental Table S3 and Figure 1). Some of the 60 samples assessed only student (undergraduate and graduate) participants (k = 22 samples), some assessed only community participants (k = 8), and some assessed a blend of student and community participants (k = 30). Students typically received course credit, and community members were compensated in a manner determined appropriate for their local context (e.g., cash, electronic payments, gift cards, raffles, and some were not directly compensated).

Participants were M = 28.5 years old (SD = 11.7; we assumed that values less than 10 or greater than 100 were typos). In terms of gender, N = 6,833 (66.0%) were women, N = 3,394 (32.8%) were men, N = 127 (1.2%) preferred to self-describe their gender, and N = 4 provided no response. In terms of sexual orientation, N = 8,366 (80.7%) were straight/heterosexual, N = 1,217 (11.7%) were bisexual, N = 361 (3.5%) preferred to self-describe, N = 202 (2.0%) were gay, N = 162 (1.6%) were lesbian, and N = 50 (0.5%) either skipped this question or this question was intentionally omitted because queer identities were punishable in that context. In terms of education, N = 89 (0.9%) reported less than high school, N = 3,601 (34.8%) reported high school, N = 2,559 (24.7%) reported some college, N = 2,556 (24.7%) reported 4-year degree, N = 1,370 (13.2%) reported master’s degree, N = 182 (1.7%) reported doctorate or professional degree, and N = 1 provided no response.

Procedure

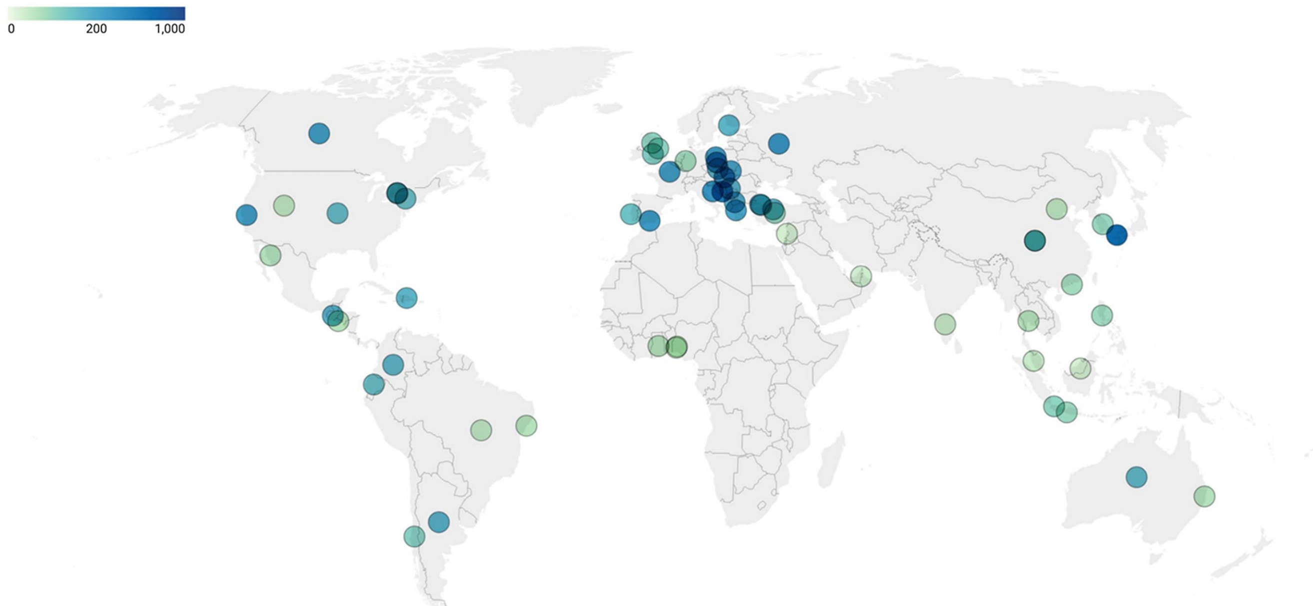
The entire study consisted of a survey that could be completed on an electronic device. Data collection began on February 1, 2023 (after the Stage 1 registered report was approved), and closed on November 10, 2023.

After providing consent and clicking a ReCAPTCHA button (to prevent bots from accessing the survey), participants completed two blocks of measures (in a counterbalanced order). In the first block, they rated the desirability of 35 ideal partner preference attributes (as well as their ideal for a “high level of education,” to be used in a separate analysis), and they completed a brief set of demographic items and individual-difference measures.

The second block consisted of a set of items about specific partners. Using a procedure implemented successfully by Sparks et al. (2020, Study 2), participants were asked to provide the first name and last initial of four individuals whom they know personally.[2] They were instructed to choose individuals of their romantically preferred gender who are not related to them, who are around the same age as them (i.e., peers), and whom they have met in person. Participants who were in a romantic relationship were instructed to list their current romantic partner as the first of the four individuals; participants who were single were asked to list “the person with whom you would most desire to have a romantic relationship” (Eastwick, Finkel, & Eagly, 2011, Study 3) as the

[2] This potentially identifying information was removed and replaced with numerical codes prior to the public posting of the data set.

Figure 1
Sixty Samples Included in the Preference-Matching Project



Note. Locations indicate the university where the data were collected or—in the cases of online community samples—the center of the relevant country. Map created with Datawrapper (Lorenz et al., 2012). See the online article for the color version of this figure.

first of the four individuals. Third, they rated the first of the four targets (i.e., the current partner or most desired partner) on the same set of 35 attributes. Fourth, they rated the first of the four targets on the romantic evaluation dependent measure. The third and fourth steps were counterbalanced. Fifth, they repeated the third and fourth steps (randomly counterbalanced for each target) for each of the remaining three targets (presented in a random order). The first target was completed prior to the remaining three peer targets because the preregistered analysis plan focused on these targets in particular.

Data, analysis code, codebook, and preregistration (i.e., the Stage 1 article) are available at https://osf.io/b29vu/?view_only=35a15592f8b04cdfb9ab32f45c73f3c6.

Materials

Translation

For surveys in languages other than English, participating laboratories translated the original English materials into the target language (see Supplemental Table S3). All laboratories first used the translate feature in Qualtrics (which uses Google translate) to generate the initial translation, edited as necessary, and then had an independent researcher who was fluent in the target language read it over for comprehensibility. Then, consistent with translation best practices (Benet-Martinez, 2007), one or more (different) researchers who were fluent in English and the target language back-translated, compared the back-translation against the original, and resolved discrepancies. Researchers at different universities who were administering surveys in the same language collaborated to ensure that their surveys were as similar as possible. In total, the surveys were administered in 22 different languages (see Supplemental Table S3 for details).

Ideal Partner Preferences

Participants rated 35 attributes (Supplemental Table S4) in an ideal romantic partner on a scale ranging from 1 (*not at all desirable*) to 11 (*highly desirable*). Scale derivation work by Fletcher et al. (1999) produced a popular measure of three factors: warmth/trustworthiness, vitality/attractiveness, and status/resources. We included five items assessing warmth/trustworthiness, five items assessing vitality/attractiveness, and four items assessing status/resources from this measure. We also included ten moderately-to-highly desirable traits that emerged in a more recent article using a similar scale-derivation procedure (Sparks et al., 2020), the Ten-Item Personality Inventory (i.e., a measure of the Big Five personality traits; Gosling et al., 2003), and one trait with potentially crucial cross-cultural relevance (*smells good*; Roberts et al., 2020). The full collection of 35 attributes contained a mix of attributes that typically range from low to high levels of (self-reported) desirability in an ideal partner.

In addition, participants rated the extent to which “a high level of education is desirable” in their ideal romantic partner on a 1 (*not at all desirable*) to 11 (*highly desirable*) scale.

Partner Attributes

Participants rated how the 35 attributes characterized each target on a scale from 1 (*not at all characteristic*) to 11 (*highly characteristic*). They also indicated the highest level of education that the partner had completed from a set of six options ranging from low to high (e.g., less than high school, high school, some college, 4-year degree, master's degree, doctorate, or professional degree). The wording of these categories was adapted to each countries' educational context where needed; all adaptations contained six categories in ascending order. We decided a priori to treat this item separately from the other 35 attributes because it is distinct on both a conceptual level (i.e., it is not really a psychological trait but rather an objective fact about a person) and a measurement level.

Romantic Evaluation (Dependent Measure)

Participants reported their *romantic evaluation* of each of their four nominated targets on six items ("I am romantically interested in _____," "_____ is the only person I want to be romantically involved with," "_____ is very much my ideal romantic partner," "It is important to me to see or talk with _______ regularly," "_______ is the first person that I would turn to if I had a problem," and "If I achieved something good, _______ is the person that I would tell first") on a 1 (*strongly disagree*) to 11 (*strongly agree*) scale (see Supplemental Table S5). Importantly, this measure was designed to be equally applicable to relationships with peers and with romantic partners (see the Supplemental Material for scale-derivation details). Reliabilities were α = .92, ω = .92 on the full sample; α = .91, ω = .91 on the partnered sample; and α = .85, ω = .85 on the single sample.

Individual-Difference Measures and Demographic Information

Participants completed additional items including a 16-item measure of individualism/collectivism (e.g., "I'd rather depend on myself than others," "Parents and children must stay together as much as possible"; Triandis & Gelfand, 1998), a 12-item measure of relational mobility (e.g., "They [the people around you] have many chances to get to know other people," "It is easy for them to meet new people"; Thomson et al., 2018), and an item assessing relationship status (i.e., *yes* vs. *no* to "I am currently in a committed, romantic relationship").

Participants also indicated the nature of their relationship with each of the four targets using the following (mutually exclusive) categories: spouse or fiancé, boyfriend/girlfriend/committed romantic partner, casual romantic/sexual partner, friend, colleague or coworker, acquaintance, and stranger. Additional individual differences and demographic information (beyond those referenced in the article) are described in the Supplemental Materials.

Attention Checks

In addition to the ReCAPTCHA button, there were two additional "directed query" attention checks (Abbey & Meloy, 2017). First, after the consent form, participants saw an item that lists the names of the seven continents and instructions that read: "If you are reading this query, please select 'Other' and type the word 'nonsense' in the blank to assure the researchers that you are reading the instructions." Because some participants typed in a nonsense word into the blank space, we decided (before running any analyses) to use all participants who selected "Other" and typed something in the space. Second, for the first target only, the romantic evaluation items contained an additional item that stated: "Please select '3' for this item to show that you are paying attention."

Relationship Formation Hypothesis

As described above, one possible explanation for the stronger support for ideal partner preference matching in established close relationship (vs. initial attraction) contexts is that people may be motivated to change their ideals to match their current partner's attributes (Gerlach et al., 2019; Neff & Karney, 2003). To test this possibility, we collected a separate sample of N = 1,585 participants (i.e., online workers from the "Cloud Research Approved List" on MTurk; Hauser et al., 2023) who completed two surveys at two points in time, about 3.5 months apart (M = 104 days, SD = 12, range = 77–124). The sample consists of (a) participants who were in a relationship with the same partner at both time points (N = 709), (b) participants who were single at both time points (N = 687), and (c) participants who were single at the first time point and in a relationship with a new partner at the second time point (N = 189).

The recruitment plan and demographics for this sample are described in detail in the Relationship Formation Hypothesis section of the Supplemental Materials; we preregistered that these participants would be analyzed separately from the main analyses that correspond to the Supplemental Table S3 worldwide sample, given the procedural differences and the fact that these participants were all from the United States.

These participants completed a subset of the measures reported above. Specifically, at time 1, they reported their ideal partner preferences and demographics in a 3-min survey (for $1), and then at time 2, they completed the partner attribute and dependent measure items in a 10-min survey (for $5). They completed the relationship status item on both surveys, but the surveys did not include the additional individual differences and the three additional targets (i.e., these participants only completed items about the current partner or most desired partner).

Data Processing

Once again, our final international sample consisted of N = 10,358 participants. Not included in this value are the participants who were excluded from analyses because they (a) "straight-lined" (i.e., gave the same numerical response to) either the 35 ideal partner preference items or the 35 attribute ratings (N = 194), (b) failed to pass both attention checks (N = 2,600), or (c) failed to reach the debriefing screen (N = 6,932; most of these participants stopped responding a short way into the survey).

Participants were included in the N = 10,358 total and the overall analysis (i.e., RQ [1]) but excluded from the relationship status subgroup analyses if they (a) indicated that they were "single" but then categorized the first target they nominated as "spouse or fiancé" or "boyfriend/girlfriend/committed romantic partner" or (b) indicated that they were "in a relationship" but then categorized the first target they nominated as anything other than "spouse or fiancé" or "boyfriend/girlfriend/committed romantic partner." A total of N = 662 were included in the overall sample but excluded from the relationship status subgroup analyses for these reasons, which yielded N = 5,544 participants in the "partnered" category (with an average relationship length of M = 6.3 years, SD = 8.8, assuming the N = 12 values above

1,000 months were typos) and $N = 4{,}152$ participants in the "single" category for analyses.

We did not anticipate, nor did we have, a high proportion of missing/incomplete data (less than 1% for all variables). Nevertheless, we also used predictive means matching using the mice package for R (van Buuren & Groothuis-Oudshoorn, 2011) to investigate the possible consequences of missingness in a separate set of sensitivity analyses for Tables 2 and 3 (see Supplemental Materials).

Results

Primary Planned Analyses

As preregistered, these analyses pertained only to the first target that participants evaluated. All analyses were conducted as multilevel models that accounted for the nesting of participant within the $k = 60$ samples (see Tables 2 and 3 notes). Specifically, we included random intercept (u_0) and slope (u_1) terms in each analysis, and the random

Table 2
Ideal-Trait Correlations (Analysis Plan 1a Through 4a)

	Ideal-trait correlation			
Attribute	Overall	Partnered	Single	*t* for comparison
1. Attractive (V/A)	.29***	.28***	.31***	2.44
2. Intelligent	.35***	.38***	.31***	−4.69***
3. Humorous	.39***	.40***	.37***	−3.96***
4. Considerate (W/T)	.31***	.30***	.30***	−1.04
5. Honest	.30***	.33***	.25***	−5.19***
6. Understanding (W/T)	.31***	.31***	.29***	−1.19
7. Ambitious	.41***	.45***	.38***	−6.19***
8. Sporty and athletic	.39***	.41***	.36***	−3.24**
9. Fun	.37***	.35***	.39***	−0.63
10. Sensitive (W/T)	.36***	.36***	.36***	−1.79
11. A good lover (V/A)	.34***	.33***	.32***	−4.24***
12. Nice body (V/A)	.29***	.27***	.32***	2.69
13. Confident	.34***	.34***	.32***	−2.85
14. Sexy (V/A)	.36***	.34***	.41***	1.91
15. Financially secure (S/R)	.24***	.25***	.25***	−0.62
16. Supportive (W/T)	.31***	.31***	.28***	−2.22
17. Dresses well (S/R)	.33***	.34***	.31***	−2.78
18. A good listener (W/T)	.28***	.26***	.29***	−2.50
19. Loyal	.27***	.33***	.20***	−8.43***
20. Successful (S/R)	.29***	.30***	.28***	−3.61***
21. Adventurous (V/A)	.38***	.39***	.38***	−4.09***
22. Good job (S/R)	.28***	.30***	.27***	−2.22
23. Religious	.57***	.63***	.53***	−8.97***
24. Patient	.26***	.28***	.26***	−1.94
25. Extraverted, enthusiastic (Ext.)	.37***	.41***	.34***	−4.52***
26. Critical, quarrelsome (Agr.)	.39***	.39***	.42***	−0.10
27. Dependable, self-disciplined (Con.)	.31***	.33***	.29***	−3.61***
28. Anxious, easily upset (Emo.)	.27***	.28***	.27***	−0.83
29. Open to new experiences, complex (Opn.)	.36***	.37***	.34***	−3.15**
30. Reserved, quiet (Ext.)	.35***	.39***	.31***	−4.31***
31. Sympathetic, warm (Agr.)	.32***	.32***	.32***	−1.51
32. Disorganized, careless (Con.)	.25***	.24***	.26***	−0.29
33. Calm, emotionally stable (Emo.)	.27***	.29***	.25***	−3.82***
34. Conventional, uncreative (Opn.)	.34***	.35***	.32***	−3.09**
35. Smells good	.38***	.34***	.42***	−0.32
W/T average	.41***	.40***	.39***	−2.95**
V/A average	.40***	.37***	.43***	−0.74
S/R average	.34***	.34***	.34***	−1.95
Ext. average	.36***	.42***	.31***	−5.76***
Agr. average	.37***	.36***	.38***	0.68
Con. average	.29***	.29***	.29***	−1.94
Emo. average	.27***	.27***	.26***	−1.79
Opn. average	.36***	.37***	.36***	−3.53***

Note. In the Big Five averages, Items 26, 28, 30, 32, and 34 were reverse scored. Values are the regression estimated βs (β_1s) from the following equation: Partner attribute = $\beta_0 + \beta_1\text{Ideal} + u_0 + u_1\text{Ideal} + \varepsilon$. The random slope ($u_1$) for the sample is omitted when models do not converge. *t* for comparison refers to the β_3 estimate in the following model, which tests the difference between the partnered and single columns: Partner attribute = $\beta_0 + \beta_1\text{Ideal} + \beta_2\text{RelStatus} + \beta_3\text{Ideal} \times \text{RelStatus} + u_0 + u_1\text{Ideal} + \varepsilon$. Values with asterisks are omitted for estimates that fail a Holm–Bonferroni test (Holm, 1979) within each column of 35 traits. V/A = vitality/attractiveness; W/T = warmth/trustworthiness; S/R = status/resources; Ext. = extraversion; Agr. = agreeableness; Con. = conscientiousness; Emo. = emotional stability; Opn. = openness to experience; RelStatus = relationship status.
** $p < .01$. *** $p < .001$.

Table 3

Effect Sizes for Tests of Ideal Partner Preference Matching (Analysis Plan 2b–4b, 2c–4c, 2d–4d)

Analysis	Overall	Partnered	Single	*t* for comparison
Pattern metric				
Raw	.37***	.38***	.32***	3.06**
Corrected	.19***	.17***	.19***	3.27**
Level metric				
1. Attractive (V/A)	.02**	.00	.05***	3.14**
2. Intelligent	.03***	.00	.03	3.46***
3. Humorous	.04***	.01	.06***	4.30***
4. Considerate (W/T)	.00	−.04***	.04***	5.79***
5. Honest	.02	−.01	.02	2.72
6. Understanding (W/T)	.02	−.01	.04***	4.72***
7. Ambitious	.07***	.05***	.08***	3.69***
8. Sporty and athletic	.07***	.06***	.08***	2.41
9. Fun	.02	−.03**	.05***	6.45***
10. Sensitive (W/T)	.06***	.07***	.06***	0.80
11. A good lover (V/A)	.04***	.02	.06***	1.72
12. Nice body (V/A)	.02	.01	.06***	3.66***
13. Confident	.04***	.01	.04***	3.70***
14. Sexy (V/A)	.02**	.02	.04***	2.74
15. Financially secure (S/R)	.04***	.04***	.06***	2.51
16. Supportive (W/T)	.01	−.01	.02	3.59***
17. Dresses well (S/R)	.03***	.03	.04***	2.14
18. A good listener (W/T)	.01	−.02	.05***	5.62***
19. Loyal	.03***	.03**	.02	0.46
20. Successful (S/R)	.05***	.03	.06***	3.97***
21. Adventurous (V/A)	.05***	.07***	.07***	3.36***
22. Good job (S/R)	.05***	.05***	.06***	2.16
23. Religious	.13***	.10***	.07***	−0.21
24. Patient	.01	−.02	.04	4.01***
25. Extraverted, enthusiastic (Ext.)	.07***	.09***	.03	−1.63
26. Critical, quarrelsome (Agr.)	.08***	.10***	.08***	1.36
27. Dependable, self-disciplined (Con.)	.03***	−.01	.06***	5.27***
28. Anxious, easily upset (Emo.)	.07***	.05***	.08***	3.25**
29. Open to new experiences, complex (Opn.)	.05***	.05***	.06***	3.78***
30. Reserved, quiet (Ext.)	.09***	.09***	.07***	0.28
31. Sympathetic, warm (Agr.)	.02	−.01	.04	4.38***
32. Disorganized, careless (Con.)	.04***	.05***	.05***	1.73
33. Calm, emotionally stable (Emo.)	.03***	.02	.04***	2.10
34. Conventional, uncreative (Opn.)	.07***	.09***	.05***	−0.04
35. Smells good	.01	.03	.02	1.06
W/T average	.00	−.03***	.02	4.50***
V/A average	.01	−.02*	.05***	5.30***
S/R average	.03***	.03**	.07***	4.30***
Ext. average	.07***	.08***	.04**	−1.43
Agr. average	.03**	.04***	.05***	1.22
Con. average	.03**	.01	.06***	4.73***
Emo. average	.05***	.01	.07***	3.82***
Opn. average	.05***	.05***	.05**	2.41*

Note. In the Big Five averages, Items 26, 28, 30, 32, and 34 were reverse scored. Values for pattern metric (raw) and pattern metric (corrected) are the regression estimated β (β_1) from the following equation: Romantic evaluation = $\beta_0 + \beta_1$PatternMetric + u_0 + u_1PatternMetric + ε. Values for the level metric are the Ideal × Trait interaction estimated βs (β_3s) from the following equation: Romantic evaluation = $\beta_0 + \beta_1$Ideal + β_2PartnerAttribute + β_3Ideal × PartnerAttribute + u_0 + u_1PartnerAttribute + ε. In all cases, the random slope (u_1) for the sample is omitted when models do not converge. "*t* for comparison" for the pattern metric tests refers to the β_3 estimate in the following model: Romantic evaluation = $\beta_0 + \beta_1$PatternMetric + β_2RelStatus + β_3PatternMetric × RelStatus + u_0 + u_1PatternMetric + ε. "*t* for comparison" for the level metric tests refers to the β_7 estimate in the following model: Romantic evaluation = $\beta_0 + \beta_1$Ideal + β_2PartnerAttribute + β_3Ideal × PartnerAttribute + β_4RelStatus + β_5Ideal × RelStatus + β_6PartnerAttribute × RelStatus + β_7Ideal × PartnerAttribute × RelStatus + u_0 + u_1PartnerAttribute + ε. Values with asterisks are omitted for estimates that fail a Holm–Bonferroni test (Holm, 1979) within each column of 35 traits. V/A = vitality/attractiveness; W/T = warmth/trustworthiness; S/R = status/resources. Ext. = Extraversion; Agr. = Agreeableness; Con. = Conscientiousness; Emo. = Emotional Stability; Opn. = Openness to Experience; RelStatus = relationship status.

* $p < .05$. ** $p < .01$. *** $p < .001$.

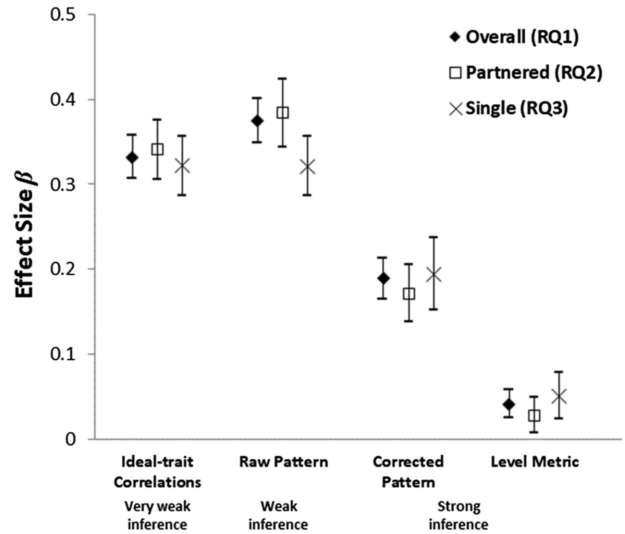
slope (u_1) for the sample was omitted when a given analysis did not converge. Overall, these random terms were fairly modest in magnitude: For the overall sample analyses reported in Table 2, random intercept (u_0) terms accounted for 2.3% of the variance on average (i.e., 2.3% of the residual variance in the trait dependent measure was attributable to the sample), and random slope (u_1) terms accounted for 0.3% of the variance. For the overall sample analyses reported in Table 3, random intercept (u_0) terms accounted for 3.4% of the variance on average, and random slope (u_1) terms accounted for 0.6% of the variance. In other words, the trait means (i.e., the DV in Table 2) and romantic evaluation DV (i.e., the DV in Table 3) showed some minor differences (about 3%) across samples. However, the association of ideals with traits (i.e., the associations in Table 2) and the association of traits with romantic evaluations (i.e., the associations in Table 3) differed very little (less than 1%) across samples.[3] All variables were standardized ($M = 0$, $SD = 1$) for each analysis.

As described above (and in Supplemental Table S2), *ideal-trait correlations* refer to the between-persons association of the ideal rating and the partner attribute rating for a given attribute. One association is calculated for each attribute, and the dependent measure is not used in this calculation (Table 2). The pattern metric (raw) is the association between (a) a *Fisher z* scored version of the within-person correlation between the 35 ideal ratings and the 35 partner-attribute ratings and (b) the romantic evaluation measure. The pattern metric (corrected) is the association between (a) a *Fisher z* scored version of the within-person correlation between the 35 ideal ratings and the 35 partner-attribute ratings after sample-mean centering all 70 items and (b) the romantic evaluation measure. The *level metric* is The Ideal × Attribute interaction predicting the romantic evaluation measure, controlling for the main effect of ideal and attribute (Table 3).

Given that we are assessing three constructs from Fletcher et al. (1999) and all five of the Big Five constructs (see Table 2), the ideal-trait correlations and level metric tests were conducted not only at the item level but also at the construct level for the three constructs of Fletcher et al. (1999; i.e., warmth/trustworthiness, vitality/attractiveness, and status/resources) and the Big Five (i.e., extraversion, agreeableness, conscientiousness, emotional stability, and openness to experience). The pattern metric analyses were calculated on the full set of 35 attributes because such profile correlations require many items to assess reliably (Wood & Furr, 2016).

Given that the corrected pattern metric and the level metric provide the strongest tests of the ideal partner preference-matching hypothesis, our interpretations of the findings rely primarily on these effect sizes. We provide the ideal-trait correlations and raw pattern metric effect sizes for completeness and transparency. Importantly, the ideal-trait correlations and level metric analyses in Tables 2 and 3 require 35 statistical tests, one for each attribute. Therefore, we implemented a Holm–Bonferroni correction (Holm, 1979) for all instances where we conducted 35 statistical tests, and we only conclude support for attributes that pass this significance threshold (i.e., .05/35 = .0014 = α for the lowest p value of the 35; .05/34 = .0015 = α for the second lowest p value of the 35; .05/33 = .0015 = α for the third lowest p value). In all tables, the attributes are listed in the order that participants spontaneously nominated them in the classic article by Fletcher et al. (1999; see Supplemental Table S4). A summary of the central findings is depicted in Figure 2.

Figure 2
Results for Research Questions 1–3



Note. Values for ideal-trait correlations and level metrics are averaged across the 35 traits. Bars depict upper and lower 95% confidence intervals. RQ = research question.

Weak Inference Tests

As anticipated, ideal-trait correlations (Table 2) were positive and significant across the board ($\beta_1 = .33$ across the 35 traits on average): Participants who had high ideals for a trait tended to report that the target possessed higher amounts of that trait. These correlations trended higher for partnered ($\beta_1 = .34$ on average) than single ($\beta_1 = .32$ on average) participants, and 16 out of 35 of the partnered versus single comparisons passed the Bonferroni–Holm correction. Nevertheless, these partnered versus single differences tended to be very small.

Moreover, as expected, the raw pattern metric (i.e., the within-person correlation between the 35 ideals and traits) predicted romantic interest strongly, with effect sizes in the medium-to-large range ($\beta_1 = .37$ in the full sample; see Table 3). As with the ideal-trait correlations, this association was slightly stronger for partnered ($\beta_1 = .38$) than single ($\beta_1 = .32$) participants.

In a nonpreregistered analysis, we additionally examined whether a measure of Euclidean distance (i.e., the square root of the sum of the squared differences between ideals and traits; Rogers et al., 2018) predicted the romantic evaluation DV when used in place of the raw pattern metric. Results showed that this measure performed similarly: Larger Euclidean distances negatively predicted positive evaluations in the full sample ($\beta_1 = -.31$, $p < .001$) and for both partnered ($\beta_1 = -.31$, $p < .001$) and single ($\beta_1 = -.29$, $p < .001$) participants.

Strong Inference Tests

The corrected pattern metric successfully predicted the romantic evaluation ($\beta_1 = .19$ in the full sample; see Table 3). In other words,

[3] We calculated these percentage variance values using the r2mlm package in R (Shaw et al., 2023).

a pure measure of preference matching across 35 different traits predicted the evaluative dependent measure with a small-to-medium effect size. The association was actually larger in the single ($\beta_1 = .19$) than the partnered ($\beta_1 = .17$) subsample, but the difference was quite small.[4]

The level metric results were more modest, although many were significantly different from zero (Table 3). As with the corrected pattern metric, these effects tended to be larger for single than partnered participants, although, again, such differences were very small. Intriguingly, level metric interaction effects tended to be larger for traits that are not as commonly assessed in this research space, like religiosity and extraversion. The level metric interaction effects were quite small for traits that are normatively very desirable and commonly studied, like warmth/trustworthiness and vitality/attractiveness traits.

Overall, the level metric effect sizes illustrate why such interactions have been hard to detect in prior studies: The average interaction $\beta_3 = .04$ is a 15% attenuation interaction given the average $\beta_2 = .27$. To put the effect size challenges in context, we used the Shiny App InteractionPoweR (Baranger et al., 2023; Finsaas et al., 2021) and the average values across all the 35 level metric tests: $\beta_1 = .02$, $\beta_2 = .27$, $\beta_3 = .04$ (see equation in note of Table 3), and the average ideal-trait correlation $\beta = .33$ from Table 2. Using these values, achieving 80% power to detect an interaction effect of $\beta_3 = .04$ would require $N = 4{,}475$ participants.[5] (The largest level metric effect—religiosity—would still require $N = 470$ to achieve 80% power.) In summary, the current data suggest that level metric effects do exist, but such interactions will require substantial, if not enormous, resources to detect.

Level of Education Level Metric Analysis

It was also possible to test the level metric interaction for level of education using the same multilevel analyses described in the Table 3 note (Romantic evaluation = $\beta_0 + \beta_1$Ideal + β_2PartnerAttribute + β_3Ideal × PartnerAttribute + u_0 + u_1PartnerAttribute + ε) using the ideal "level of education" item and the partner's actual level of education (coded on a 6-point continuous scale). We calculated this estimate for the overall sample, single participants, and partnered participants, and we also tested the difference between single and partnered participants. For the overall sample, this interaction was $\beta_3 = .06$, $t(1991.84) = 6.33$, $p < .001$. For single participants, this interaction was $\beta_3 = .03$, $t(1421.33) = 1.95$, $p = .051$; for partnered participants, this interaction was $\beta_3 = .03$, $t(5522.28) = 2.70$, $p = .007$, and the difference between single and partnered participants was not significant, $t(9020.83) = 0.50$, $p = .618$.

Relationship Formation Hypothesis

This hypothesis pertains to the separate sample of CloudResearch participants who completed the surveys at two time points, about 3.5 months apart. We conducted the raw pattern metric, corrected pattern metric, and level metric analyses on these three samples (see Table 4). Some of the findings echoed the Table 3 results for the full international sample. For example, for both the steadily partnered and the newly partnered sample, the raw pattern metric was considerably larger than the corrected pattern metric (especially in the steadily partnered sample), but the corrected pattern metric was still significant and of a meaningful effect size ($\beta = .24$). Estimates for the steadily partnered and newly partnered sample were similar, suggesting that both sets of participants maintained their ideals over the intervening months and drew from them when evaluating their partners, regardless of whether or not they were dating that partner when they reported their ideals at Time 1. Intriguingly, for the single participants, the corrected pattern metric was essentially zero: Unlike the participants in the international single sample in Table 3, ideal partner preference matching seemed to have no bearing on the evaluations of these single participants—a finding we revisit in the Discussion section. Once again, level metric findings were erratic and small on average (the smaller sample size here yielded a larger range of negative and positive values, relative to Table 3); preferences for religiosity and extraversion perhaps deserve additional study going forward nonetheless.

With respect to level of education, for the steadily partnered sample, the level metric interaction was $\beta_3 = .05$, $t(705) = 1.46$, $p = .144$; for steadily single participants, this interaction was $\beta_3 = .03$, $t(683) = 0.77$, $p = .444$; and for newly partnered participants, this interaction was $\beta_3 = .05$, $t(185) = 0.71$, $p = .480$. The difference between these three samples was not significant, $F(2, 1573) = 0.12$, $p = .890$.

Exploratory Descriptive Analyses

Table 5 presents descriptive analyses of the average preferences of participants in the data set, both stated (i.e., rated ideals) and revealed (i.e., the association between the attribute and the evaluative dependent measure; Wood & Brumbaugh, 2009). Colloquially speaking, the ideal partner preference ratings (i.e., the means for each attribute) capture the extent to which people generally *say* that each attribute is important in an ideal partner, whereas the revealed preferences (i.e., the slopes for each attribute predicting the dependent variable [DV]) capture the extent to which each attribute *actually predicts* people's romantic evaluations of partners.[6] This table also includes the rank ordering of both sets of 35 preferences.

On the whole, stated and revealed preferences aligned in terms of ranking, although some intriguing differences did emerge. For example, the attributes "confident," "a good listener," "patient," and "calm, emotionally stable" ranked considerably more highly as stated preferences than as revealed preferences. In contrast, the attributes "attractive," "a good lover," "nice body," "sexy," and "smells good" ranked considerably more highly as revealed preferences than as stated preferences. In fact, "a good lover" was the no. 1 largest revealed preference but actually ranked 12th in terms of stated preferences (we also conducted separate analyses on the

[4] Some perspectives (e.g., Biesanz, 2010; Fletcher et al., 2020; Wood et al., 2019) add a measure of normative matching alongside "distinctiveness" metrics like these. Using this approach, effect sizes are about half as large as those reported here, but still significant; see the Normative Preference Matching section.

[5] The power to detect a standardized interaction effect β is very close to the power to detect a correlation of size β, with two caveats: (1) Larger main effects of the two interacting variables (in this case, ideals and attribute perceptions) increase power, and (2) a larger correlation between the two main effects can increase or decrease power, depending on the size of the main effects (Baranger et al., 2023). These mitigating forces are not especially large in these analyses, and so the N required to achieve 80% power to detect $\beta_3 = .04$ (4,475) is only slightly smaller than the N required to achieve 80% power to detect $r = .04$ (4,900).

[6] This analysis applies at the level of the entire data set on the primary target only; we calculate a related form of revealed preference (which we call a "functional preference"; Ledgerwood et al., 2018) that makes use of all four targets in a later section.

Table 4
Relationship Formation Hypothesis

Analysis	Steadily partnered	Steadily single	Newly partnered	F for comparison
Pattern metric				
Raw	.50***	.18***	.39***	20.86***
Corrected	.24***	.01	.24***	10.78***
Level metric				
1. Attractive (V/A)	.00	.02	.07	0.56
2. Intelligent	−.05	−.03	.08	1.93
3. Humorous	.03	.02	.14***	3.44
4. Considerate (W/T)	.02	−.03	−.09	1.28
5. Honest	−.06	−.02	.08	1.75
6. Understanding (W/T)	.00	−.02	−.07	0.43
7. Ambitious	.12***	.02	.16	3.68
8. Sporty and athletic	.06	.05	.10	0.28
9. Fun	−.03	−.01	.08	0.95
10. Sensitive (W/T)	.03	−.01	.06	0.53
11. A good lover (V/A)	−.07	−.03	.07	2.43
12. Nice body (V/A)	−.04	.01	.06	1.12
13. Confident	.03	.07	.15	1.16
14. Sexy (V/A)	.04	−.01	.01	0.67
15. Financially secure (S/R)	.10	−.02	.19	5.33
16. Supportive (W/T)	.06	−.04	.04	2.80
17. Dresses well (S/R)	.03	.02	.26***	6.54
18. A good listener (W/T)	−.01	−.08	.02	1.77
19. Loyal	−.01	−.05	.01	0.72
20. Successful (S/R)	.03	−.03	.18	3.62
21. Adventurous (V/A)	.10	.02	.21**	3.87
22. Good job (S/R)	.14***	.02	.15	4.03
23. Religious	.24***	−.01	.37***	13.51***
24. Patient	.09	.01	−.07	2.96
25. Extraverted, enthusiastic (Ext.)	.09	−.01	.08	2.14
26. Critical, quarrelsome (Agr.)	.15***	.05	.10	2.25
27. Dependable, self-disciplined (Con.)	.05	−.03	.19**	4.94
28. Anxious, easily upset (Emo.)	.06	.02	.05	0.36
29. Open to new experiences, complex (Opn.)	.01	.09	.13	2.18
30. Reserved, quiet (Ext.)	.14***	.02	.16	4.12
31. Sympathetic, warm (Agr.)	.07	.04	−.06	1.69
32. Disorganized, careless (Con.)	.01	−.01	.02	0.16
33. Calm, emotionally stable (Emo.)	.10	.02	.07	1.34
34. Conventional, uncreative (Opn.)	.03	.04	−.04	0.66
35. Smells good	.03	−.04	.10	2.50
W/T average	−.04	−.05	−.05	0.06
V/A average	−.06	.00	.04	1.55
S/R average	.07*	.00	.23***	4.54*
Ext. average	.13***	.03	.07	2.42
Agr. average	.10**	.08*	−.03	1.41
Con. average	.05	−.04	.11	2.58
Emo. average	.08*	.00	.07	1.36
Opn. average	−.03	.07	.00	2.24

Note. In the Big Five averages, Items 26, 28, 30, 32, and 34 were reverse scored. Note that in these analyses, there is no within-sample dependency. Values for pattern metric (raw) and pattern metric (corrected) are the regression estimated βs (β_1) from the following equation: Romantic evaluation = $\beta_0 + \beta_1$PatternMetric + ε. Values for the level metric are the Ideal × Trait interaction estimated βs (β_3s) from the following equation: Romantic evaluation = $\beta_0 + \beta_1$Ideal + β_2PartnerAttribute + β_3Ideal × PartnerAttribute + ε. RelStatus is a three-level categorical variable, so "F for comparison" for the pattern metric tests refers to the omnibus test of the two β_3 estimates in the following model: Romantic evaluation = $\beta_0 + \beta_1$PatternMetric + β_2RelStatus + β_3PatternMetric × RelStatus + ε. "F for comparison" for the level metric tests refers to the omnibus test of the two β_7 estimates in the following model: Romantic evaluation = $\beta_0 + \beta_1$Ideal + β_2PartnerAttribute + β_3Ideal × PartnerAttribute + β_4RelStatus + β_5Ideal × RelStatus + β_6PartnerAttribute × RelStatus + β_7Ideal × PartnerAttribute × RelStatus + ε. Values with asterisks are omitted for estimates that fail a Holm–Bonferroni test (Holm, 1979) within each column of 35 traits. V/A = vitality/attractiveness; W/T = warmth/trustworthiness; S/R = status/resources. Ext. = extraversion; Agr. = agreeableness; Con. = conscientiousness; Emo. = emotional stability; Opn. = openness to experience; RelStatus = relationship status.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

partnered and single subsamples, revealing identical conclusions; see Supplemental Tables S10 and S11).

Table 5 also calculates gender differences in the preference for attractiveness (i.e., the average of the items "attractive," "nice body," and "sexy") and earning potential (i.e., the average of the items "ambitious," "financially secure," and "good job"). Some theoretical perspectives anticipate that men will place greater weight on attractiveness, and women will place greater weight on earning potential (Buss, 1989). These gender differences indeed emerged when participants reported their stated preferences. Nevertheless, consistent with past meta-analytic work (Eastwick, Luchies, et al., 2014; Eastwick, Neff, et al., 2014) and the very small-level metric analyses documented in Table 3, these gender differences did not emerge in participants' revealed preferences.

We can also use the Table 5 ranking approach to illuminate *why* a gender difference incongruity emerges between stated and revealed preferences. Men's stated preferences tended to underestimate the value they actually placed on "attractive," "nice body," and "sexy" by about six ranks (out of 35; 1 = highest ranked, 35 = lowest ranked) on average (see Supplemental Table S12). That is, their stated preferences for these three traits ranked 9, 18, and 17, respectively, but their revealed preferences for these three traits ranked 7, 13, and 6. However, women underestimated the value they placed on these three traits by a full 13 ranks (out of 35): Their stated preferences for these three traits ranked 18, 28, and 23, respectively, but their revealed preferences for these three traits ranked 8, 17, and 5 (i.e., about the same as men). As for "ambitious," "financially secure," and "good job," men's stated preferences underestimated their value by about four ranks: Their stated preferences for these three traits ranked 25, 25 (tied), and 27, respectively, but their revealed preferences for these three traits ranked 22, 24, and 20. In contrast, women's stated preferences *over*estimated their value by about four ranks: Their stated preferences for these three traits ranked 22, 17, and 18, respectively, but their revealed preferences for these three traits ranked 24, 25, and 21 (i.e., again, about the same as men). In summary, both men's and women's stated preferences appeared to underestimate the weight they place on attractiveness, but this underestimation effect was more pronounced for women than for men. In contrast, men's stated preferences slightly underestimated the weight they placed on earning potential, and women's stated preferences slightly overestimated the weight they placed on earning potential.

Secondary Planned Analyses

Normative Preference Matching

A difference between the effect sizes associated with the raw pattern metric and the corrected pattern metric implies—but does not directly test—the idea that participants positively evaluate partners to the extent that they perceive those partners to have consensually desirable traits (Fletcher et al., 2020). The direct test of this idea entails calculating a normative pattern metric: the association between (a) a Fisher *z*-scored version of the within-person correlation between the *sample average of* the 35 ideal ratings (not the participant's own rating) and (the participants' own ratings of) the 35 partner-attribute ratings and (b) the romantic evaluation measure.

Using the multilevel analyses described in the Table 3 note, we calculated this estimate for the overall sample, single participants, and partnered participants, and we also tested the difference between single and partnered participants. For the overall sample, this effect was $\beta_1 = .37$, $t(39.35) = 29.38$, $p < .001$. For single participants, this effect was $\beta_1 = .32$, $t(33.68) = 18.14$, $p < .001$; for partnered participants, this effect was $\beta_1 = .39$, $t(56.99) = 19.84$, $p < .001$; and the difference between single and partnered participants was significant, $t(6765.48) = 2.17$, $p = .030$. These effect sizes suggest that, when participants perceived that partners had normatively "ideal" traits, they evaluated those partners very positively, regardless of their own idiosyncratic ideal partner preferences.

In some research areas that examine analogous forms of multivariate matching (e.g., Biesanz, 2010; Fletcher et al., 2020; Wood et al., 2019), it is common practice to predict a dependent measure from both the normative and distinctive metrics simultaneously. Similarly, we can predict the romantic evaluation DV using the following equation (Equation 1):

$$\begin{aligned}\text{Romantic evaluation} = \beta_0 &+ \beta_1\text{NormativePatternMetric} \\ &+ \beta_2\text{CorrectedPatternMetric} + u_0 \\ &+ u_1\text{NormativePatternMetric} \\ &+ u_2\text{CorrectedPatternMetric} + \varepsilon. \qquad (1)\end{aligned}$$

Using this approach, the normative preference-matching effects closely approximate the effect sizes when included in the equation alone: in the full sample, $\beta_1 = .34$, $t(37.85) = 26.59$, $p < .001$; in the single subsample, $\beta_1 = .29$, $t(32.15) = 15.76$, $p < .001$; and in the partnered subsample $\beta_1 = .37$, $t(59.33) = 20.21$, $p < .001$. However, the corrected pattern metric effect sizes were approximately half the size of what they were when included in the equation alone: in the full sample, $\beta_2 = .11$, $t(31.42) = 10.71$, $p < .001$; in the single subsample, $\beta_2 = .13$, $t(41.70) = 6.69$, $p < .001$; and in the partnered subsample, $\beta_2 = .09$, $t(47.09) = 5.66$, $p < .001$. In other words, idiosyncratic preference matching offers a small ($\beta = .09$–$.13$), yet significant, boost above and beyond normative preference matching, and normative preference matching is approximately three times as large.

Individual-Difference Moderation

It is plausible that ideal partner preference-matching effects vary across studies in the existing literature due to individual differences across participant populations. A study by Lam et al. (2016) pointed to the intriguing possibility that there are important cross-cultural factors at play. In this reasonably large ($N = 472$) study, these scholars found that the corrected pattern metric had a significant predictive association with relationship evaluations in Taiwan ($r = .22$), but not in the United States ($r = .05$), and the difference between these two correlations was significant. Reasons for a Taiwan–United States difference remain somewhat speculative, but one relevant distinction between these two cultures is relational mobility—that is, the ability to meet new people and select into (and out of) relationships on the basis of personal desires (Kito et al., 2017; Thomson et al., 2018; Yuki & Schug, 2012). Americans, by virtue of their higher relational mobility, might be more likely than Taiwanese to "try out" relationships that mismatch their ideals, perhaps especially if they presume that they could later end the relationship with minimal consequences. Then, if people are motivated on average to feel positively about their partners after investing time and energy into the relationship

Table 5
Descriptive Statistics for Stated and Revealed Preferences

Attribute	Stated preference *N*	*M*	*SD*	Rank	Revealed preference β	Rank
1. Attractive	10,343	8.86	1.89	16	.42***	8
2. Intelligent	10,348	9.39	1.65	9	.38***	12
3. Humorous	10,345	9.34	1.78	11	.36***	13
4. Considerate	10,343	9.59	1.60	7	.40***	10
5. Honest	10,347	10.08	1.38	2	.43***	5
6. Understanding	10,346	9.84	1.46	4	.42***	7
7. Ambitious	10,344	8.13	2.34	24	.22***	24
8. Sporty and athletic	10,347	7.16	2.43	29	.10***	29
9. Fun	10,351	9.43	1.66	8	.38***	11
10. Sensitive	10,340	8.10	2.35	25	.28***	19
11. A good lover	10,338	9.26	1.99	12	.56***	1
12. Nice body	10,348	8.02	2.15	26	.32***	16
13. Confident	10,347	8.77	1.87	17	.18***	26
14. Sexy	10,342	8.39	2.20	19	.42***	6
15. Financially secure	10,342	8.38	2.19	20	.20***	25
16. Supportive	10,346	9.92	1.52	3	.49***	3
17. Dresses well	10,344	8.19	2.18	23	.24***	22
18. A good listener	10,346	9.69	1.60	5	.35***	14
19. Loyal	10,345	10.10	1.53	1	.51***	2
20. Successful	10,344	8.22	2.22	22	.29***	17
21. Adventurous	10,338	7.89	2.36	27	.16***	27
22. Good job	10,342	8.30	2.17	21	.24***	21
23. Religious	10,340	4.83	3.33	31	.04**	31
24. Patient	10,342	9.35	1.70	10	.29***	18
25. Extraverted, enthusiastic	10,343	7.70	2.19	28	.13***	28
26. Critical, quarrelsome	10,339	3.41	2.65	33	−.04**	33
27. Dependable, self-disciplined	10,348	9.26	1.81	12	.33***	15
28. Anxious, easily upset	10,341	3.10	2.24	34	.02	32
29. Open to new experiences, complex	10,346	8.64	2.10	18	.23***	23
30. Reserved, quiet	10,338	5.53	2.66	30	.07***	30
31. Sympathetic, warm	10,345	9.61	1.59	6	.40***	9
32. Disorganized, careless	10,340	2.80	2.17	35	−.05***	34
33. Calm, emotionally stable	10,344	9.26	1.75	12	.26***	20
34. Conventional, uncreative	10,343	4.02	2.56	32	−.07***	35
35. Smells good	10,346	9.10	1.98	15	.45***	4
W/T average	10,356	9.43	1.29		.48***	
V/A average	10,353	8.48	1.56		.50***	
S/R average	10,353	8.27	1.81		.31***	
Ext. average	10,344	7.08	1.78		.04**	
Agr. average	10,348	9.10	1.61		.25***	
Con. average	10,348	9.23	1.56		.21***	
Emo. average	10,347	9.08	1.56		.14***	
Opn. average	10,350	8.31	1.75		.19***	

Attribute	*N*	Stated preference *M*	*SD*	Gender diff. *t*	*d*	Revealed preference β	Gender diff. *t*	*q*
Attractiveness composite								
Heterosexual men	2,935	8.73	1.70	13.10***	0.22	.46***	0.19	0.02
Heterosexual women	5,408	8.35	1.80			.45***		
Earning potential composite								
Heterosexual men	2,933	7.50	1.85	27.51***	0.71	.27***	0.78	0.00
Heterosexual women	5,410	8.74	1.63			.28***		

Note. Effect sizes *d* and *q* are coded such that positive effect sizes are in the predicted direction. Gender differences were only calculated for participants who identified as a man or a woman and who selected the option "straight/heterosexual" for their sexuality. Stated preferences are means. Revealed preferences are β_1 terms in the equation: Romantic evaluation = $\beta_0 + \beta_1$PartnerAttribute + u_0 + u_1PartnerAttribute + ε. In all cases, the random slope (u_1) for the sample is omitted when models do not converge. W/T = warmth/trustworthiness; V/A = vitality/attractiveness; S/R = status/resources. Ext. = extraversion; Agr. = agreeableness; Con. = conscientiousness; Emo. = emotional stability; Opn. = openness to experience; Diff. = difference.
** $p < .01$. *** $p < .001$.

(Joel & MacDonald, 2021), high relational mobility populations may include a larger proportion of people with ideal-mismatching partners who nevertheless report high satisfaction. A second potentially relevant distinction is individualism–collectivism (Triandis & Gelfand, 1998), as individuals in collectivistic cultures may be especially likely to adopt the ideal partner preferences of their parents (Locke et al., 2020). If the attributes of one's romantic partner implicate family members in collectivistic societies, this fact may motivate collectivistic (but not individualistic) individuals to remain attuned to the extent to which the partner mismatches their ideals.

To test whether relational mobility (i.e., the average of the 12 items; Thomson et al., 2018), individualism (i.e., either the four-item horizontal individualism or four-item vertical individualism subscales; Triandis & Gelfand, 1998), or collectivism (i.e., either the four-item horizontal collectivism or four-item vertical collectivism subscales; Triandis & Gelfand, 1998) affects ideal partner preference matching, we examined whether these five individual-difference measures moderated all the analyses reported in Table 3 that pertained to RQs 1–3 (i.e., effect sizes associated with the overall sample, single participants, and partnered participants). Again, we used Bonferroni–Holm correlations for each set of 35 tests. Table 6 uses "+" signs to indicate positive, significant interaction terms (i.e., ideal preference matching is stronger among participants who are *higher* in relational mobility/individualism/collectivism) and "–" signs to indicate negative significant interaction terms (i.e., ideal preference matching is stronger among participants who are *lower* in relational mobility/individualism/collectivism). The predicted direction of moderation is depicted in a row at the top of Table 6. Reliabilities for relational mobility were $\alpha = .82$ ($\omega = .81$) on the full sample, $\alpha = .82$ ($\omega = .81$) on the partnered sample, and $\alpha = .82$ ($\omega = .80$) on the single sample; reliabilities for horizontal individualism were $\alpha = .71$ ($\omega = .72$) on the full sample, $\alpha = .69$ ($\omega = .70$) on the partnered sample, and $\alpha = .73$ ($\omega = .74$) on the single sample; reliabilities for vertical individualism were $\alpha = .67$ ($\omega = .68$) on the full sample, $\alpha = .67$ ($\omega = .67$) on the partnered sample, and $\alpha = .69$ ($\omega = .69$) on the single sample; reliabilities for horizontal collectivism were $\alpha = .74$ ($\omega = .74$) on the full sample, $\alpha = .74$ ($\omega = .74$) on the partnered sample, and $\alpha = .73$ ($\omega = .73$) on the single sample; and reliabilities for vertical collectivism were $\alpha = .69$ ($\omega = .72$) on the full sample, $\alpha = .68$ ($\omega = .71$) on the partnered sample, and $\alpha = .69$ ($\omega = .72$) on the single sample.

Very few of these interactions were statistically significant. Moreover, in the full table, 21 interactions were in the predicted direction of moderation (i.e., no shading in Table 6), and 23 interactions were in the opposite of the predicted direction (i.e., gray shading). For example, when interactions emerged for the corrected pattern metric, they tended to be positive interactions (eight out of nine times), regardless of whether the prior literature anticipated that these interactions would be negative (relational mobility, individualism) or positive (collectivism). Given the ambiguity of these results and related concerns about moderation with measured variables (Rohrer et al., 2022), we hesitate before interpreting them any more deeply.

Functional Preferences

Given that participants rated four total targets in the primary sample, it was possible to calculate each participant's *functional preference* for each attribute (Ledgerwood et al., 2018). A functional preference (also called a "driver of liking"; Lawless & Heymann, 2010) is the strength with which an attribute (e.g., attractiveness) predicts *a given person's romantic evaluations* across a series of targets—how much the attribute "matters" for a given participant. In this case, each participant's functional preference can be measured as the association of an attribute with the dependent measure across the four targets. Functional preferences in this context are very similar to the revealed preferences described above. The distinction is that a functional preference (typically) refers to a preference that has been measured separately for each participant, and this requires that the participant rates multiple targets. The descriptive analyses in Table 5 only used the first (primary) target that participants evaluated.

A new approach by Rights and Sterba (2019) permits the calculation of the extent to which these functional preferences exhibit stable individual differences across targets. Specifically, the *R* package *r2mlm* (Shaw et al., 2023) provides the percentage of variance accounted for by the random-effects component (i.e., "slope variation" or $R_t^{2(v)}$) for a particular attribute as a fraction of the total variance.[7]

We calculated these values for all 35 attributes, the three constructs of Fletcher et al. (1999), all Big Five traits, and the two pattern metric analyses (Table 6). The $R_t^{2(v)}$ variance estimates for the 35 attributes, the three constructs of Fletcher et al. (1999), and all Big Five constructs essentially denote the extent to which there are stable individual differences in the tendency for some people to exhibit stronger functional preferences than other people for a given attribute (Eastwick, Finkel, & Joel, 2023).

These values tended to be larger than zero, but they were fairly modest: The average of the 35 traits was $R_t^{2(v)} = 3.1\%$, and no trait exceeded 5%. In other words, individual differences in the way that participants weigh a given trait accounts for about 3% of the variance in romantic evaluations. We also calculated the $R_t^{2(v)}$ variance estimates for the two pattern metric analyses; these values denote the extent to which there are stable individual differences in the tendency to desire a partner who matches (vs. mismatches) one's ideals across all attributes. For example, the results for the corrected pattern metric indicated that individual differences in the way that people weigh the match between ideals and traits across all traits account for about 7% of the variance in romantic evaluations.

Discussion

Central Takeaways

This is the first report from the Preference-Matching Project: the largest examination of ideal partner preference matching to date (N = 10,358 participants). In brief, ideal partner preference matching predicted romantic evaluations—when collapsing across a large array of traits. That is, the effect size for the corrected pattern metric was modest but meaningful ($\beta = .19$), and it did not differ appreciably between the partnered ($\beta = .17$) and single ($\beta = .19$) subsamples. Normative desirability proved to be an important consideration, too: Participants who perceived that partners matched the normative (i.e., sample-wide) ideal partner strongly desired

[7] Unlike the analyses above, this analysis ignores nesting within sample, and we conduct the analysis on a data set that contains four rows per participant (one for each target). Now, the random slope effect captures variability across participants (not samples) in the extent to which the attribute predicts the dependent measure.

Table 6
Secondary Planned Analyses

	Overall					Partnered					Single					
		Ind.		Col.			Ind.		Col.			Ind.		Col.		
Analysis	R	H	V	H	V	R	H	V	H	V	R	H	V	H	V	Functional preference
Predicted direction of moderation	−	−	−	+	+	−	−	−	+	+	−	−	−	+	+	
Pattern metric																
Raw			−	−	−	−	−	−	−	−		+		+		2.61%
Corrected	+	+		+			+		+	−	+	+		+		6.87%
Level metric																
1. Attractive (V/A)									+							1.21%
2. Intelligent																0.53%
3. Humorous																2.02%
4. Considerate (W/T)							+									1.47%
5. Honest							+									0.98%
6. Understanding (W/T)																2.04%
7. Ambitious																4.87%
8. Sporty and athletic																4.53%
9. Fun							+									1.68%
10. Sensitive (W/T)																4.15%
11. A good lover (V/A)																4.12%
12. Nice body (V/A)						+										3.82%
13. Confident							+									3.51%
14. Sexy (V/A)				+					+							3.68%
15. Financially secure (S/R)																4.11%
16. Supportive (W/T)																1.34%
17. Dresses well (S/R)																3.32%
18. A good listener (W/T)																2.29%
19. Loyal																1.49%
20. Successful (S/R)																2.71%
21. Adventurous (V/A)																4.75%
22. Good job (S/R)																4.13%
23. Religious						−	−		−							4.77%
24. Patient																4.59%
25. Extraverted, enthusiastic (Ext.)						−										4.98%
26. Critical, quarrelsome (Agr.)																3.60%
27. Dependable, self-disciplined (Con.)																1.67%
28. Anxious, easily upset (Emo.)																4.94%
29. Open to new experiences, complex (Opn.)																3.96%
30. Reserved, quiet (Ext.)																3.51%
31. Sympathetic, warm (Agr.)																2.36%
32. Disorganized, careless (Con.)																3.75%
33. Calm, emotionally stable (Emo.)																3.11%
34. Conventional, uncreative (Opn.)																2.97%
35. Smells good																3.02%
W/T average	−					−										2.13%
V/A average	+			+		+	+		+					+		2.01%
S/R average																3.36%
Ext. average																2.91%
Agr. average														+		2.10%
Con. average		+														2.61%
Emo. average	+					+										4.01%
Opn. average						−										2.75%

Note. In the Big Five averages, Items 26, 28, 30, 32, and 34 were reverse scored. Individual-difference moderation values for pattern metric (raw) and pattern metric (corrected) derive from the interaction β (β_3) from the following equation: Romantic evaluation = β_0 + β_1PatternMetric + β_2IndividualDifference + β_3 PatternMetric × IndividualDifference + u_0 + u_1PatternMetric + ε. Values for the level metric derive from the interaction βs (β_7s) from the following equation: Romantic evaluation = β_0 + β_1Ideal + β_2PartnerAttribute + β_3Ideal × PartnerAttribute + β_4IndividualDifference + β_5Ideal × IndividualDifference + β_6PartnerAttribute × IndividualDifference + β_7Ideal × PartnerAttribute × IndividualDifference + u_0 + u_1PartnerAttribute + ε. In all cases, the random slope (u_1) for the sample is omitted when models do not converge. The "+" indicates significant positive moderation; the "–" indicates significant negative moderation; the predicted pattern of moderation is depicted in the first five rows. The "+" and "–" signs were omitted for estimates that failed a Holm–Bonferroni test (Holm, 1979) within each column of 35 traits. Shaded "+" and "–" signs are in the opposite of the predicted direction. Functional preferences refer to the $R_t^{2(v)}$ variance estimate from Rights and Sterba (2019) that captures the percentage of variance (out of 100%) accounted for by individual differences in the association of the attribute/pattern metric with the romantic evaluation dependent measure. R = relational mobility moderation; Ind. = Individualism moderation (H = horizontal, V = vertical); Col. = collectivism moderation (H = horizontal, V = vertical); V/A = vitality/attractiveness; W/T = warmth/trustworthiness; S/R = status/resources. Ext. = extraversion; Agr. = agreeableness; Con. = conscientiousness; Emo. = emotional Stability; Opn. = openness to experience.

those partners (β = .37). When included together (as recommended by Biesanz, 2010; Fletcher et al., 2020), normative preference matching remained strong (β = .34), while the corrected pattern metric was cut to a small (but still significant) effect size (β = .11). Approaches like the raw pattern metric and Euclidean distance revealed medium-to-large effects, likely because they blend normative and distinctive matching together into a single measurement mixture (Rogers et al., 2018; Wood & Furr, 2016).

The level metric (i.e., Ideal × Trait interaction) tests were also highly informative. These effects were quite small on average (β = .04), which may be why they have rarely been significant in prior studies (β = .04 would require a sample size of $N = 4{,}475$ to detect with 80% power; no prior study was even close to achieving such a large sample size; see Supplemental Table S1). Notably, the level metric tests for the commonly studied, highly desirable attributes in this literature (e.g., traits in the warmth/trustworthiness and vitality/attractiveness categories) did not even differ from zero in the full sample (β = .00–01). Alternatively, traits that are rarely studied in this literature and that received moderate ideal ratings on average showed much larger level metric effects, like extraversion (β = .07) and religious (β = .13). It appears that the predictive validity of specific traits is more likely to be detectable for traits that land in a middling range of desirability (i.e., what could be called "horizontal" attributes; Hitsch et al., 2010) rather than traits that are highly normatively desirable (i.e., "vertical" attributes).

In two cases, expected moderation effects failed to emerge. First, we did not find much evidence that certain people or certain populations were especially likely to rely on their ideals. Our preregistered tests of potentially relevant individual differences (Table 6) revealed no interpretable pattern. Indeed, the multilevel modeling approach of Rights and Sterba (2019) suggested that the slope random effects corresponding to the sample (u_1) in Table 3 explained less than 1% of the variance. In other words, the average association between an attribute and the romantic evaluation dependent measure tended not to vary reliably depending on which of the 60 samples generated it. Slightly larger (but still modest) amounts of variability emerged for (a) the tendency for some people to desire particular traits more than others across four different partners (3.1%; Table 6), (b) the tendency for mean levels of the traits to vary across samples (2.3%; cultures vary in the extent to which participants view partners as "humorous" or "ambitious"), and (c) the tendency for mean levels of the dependent measure to vary across samples (3.4%; cultures vary in the extent to which participants are happy in their relationships). These latter three types of effects might be more promising candidates for tests of moderation.

Second, for the most part, effect sizes in the partnered and single samples were similar. Many scholars (including several in the project coordinator group of the current project) once believed that ideal partner preference matching was more likely to predict outcomes in established relationships rather than initial attraction contexts (Eastwick, Luchies, et al., 2014). It is possible that the earlier literature suggested this pattern because studies of ongoing relationships classically gravitated toward the uncorrected pattern metric (which reveals medium-to-large effects; Fletcher et al., 1999, 2000), whereas initial attraction studies were inspired by perspectives on gender differences for specific traits in isolation (e.g., attractiveness, earning potential) and therefore tended to rely on level metric tests (which reveal very small effects; Eastwick & Finkel, 2008).

Nevertheless, one curious data point remains: Why did the single participants in the relationship formation subsample show no effects whatsoever? These participants first reported their ideals in isolation while they were single. Then, about 3.5 months later, these (still single) participants completed the rest of the procedure. The corrected pattern and level metric tests suggested that these participants were not drawing from their previously reported ideals at all (Table 4). And yet, this separation of 3.5 months seemed to matter very little for participants who were partnered at both time points, or participants who were single at Time 1 and partnered at Time 2. There are perhaps two ways of explaining these data. First, perhaps the people who were single at both time points had several rejection experiences in the interim, and their ideals changed more than the single participants who had the acceptance experience of becoming partnered during this time frame (Charlot et al., 2019). Second, perhaps single people who are very attracted to a particular partner are motivated to interpret the partner's traits in line with their ideals, but only if they have recently been reminded of their ideals. Researchers in this area should keep a keen eye on whether single participants are reporting their ideals and measures about a potential partner at the same or a different moment in time (e.g., most speed-dating studies ask participants to report their ideals on an intake form, and then participants evaluate potential partners several days later). This seemingly incidental methodological feature may matter a great deal for reasons that are not yet clear.

Finally, we presented a new approach that allows researchers to explore the distinction between stated preferences (i.e., preferences for traits as rated on scales) and revealed preferences (i.e., preferences as captured by the strength of the association between the trait and the DV). When the 35 attributes were ranked in the whole sample, it was possible to document cases where stated preference judgments (relatively) overestimated revealed preference judgments: Participants actually liked attributes like "confident," "a good listener," "patient," and "calm, emotionally stable" less than they thought they did. In other cases, participants' stated preferences were underestimates, as in the case of "attractive," "a good lover," "nice body," "sexy," and "smells good." This approach was also able to illuminate why gender differences emerge for stated (but not revealed) preferences for attractiveness and earning potential attributes (Table 5). Specifically, for attractiveness, both men's and women's stated preferences underestimated their revealed preferences, but women's tendency to underestimate proved far stronger than men's. For earning potential, a "mirror image" pattern emerged such that men's stated preferences underestimated their revealed preferences, but women's stated preferences overestimated their revealed preferences. Moving forward, this approach could be used to examine other hypotheses about accuracy and bias using various measures of preferences.

Strengths and Limitations

This study has a number of strengths. Our partnership with the Psychological Science Accelerator (Moshontz et al., 2018) meant that the data were collected across 43 countries using a questionnaire that had been translated (and back-translated) into 22 different languages. Critically, our highly powered design meant that the estimates of effect sizes throughout this article are far more precise than is typical in most studies in this research area. Moreover, this article was approved as a registered report, which meant that the design and analytic approach were reviewed before the data were collected.

This study also makes several important theoretical contributions. The pattern of effect sizes suggests that studies are far more likely to find empirical support to the extent that they focus on matching across many variables simultaneously rather than single attributes in isolation (e.g., gender differences in specific attributes, Eastwick & Finkel, 2008; a "top 3 most important" attributes approach, Sparks et al., 2020). Furthermore, the fact that effect sizes tended to be about three times larger for normative matching rather than the corrected pattern metric sheds new light on the intuitive idea that "people know what they want in a partner." Yes, people's stated preferences capture the attributes that are *generally* desirable in partners, but a given person's *distinctive* preferences only modestly (but still significantly) capture the attributes that they find especially desirable. These estimates also help clarify theories about the origin and nature of relationship variance (i.e., compatibility), as they represent one of the strongest attempts to use attribute matching to explain why people are more likely to experience attraction and romantic contentment with some partners rather than others. The current data suggest that the corrected pattern metric across 35 traits may be able to explain 2%–4% of relationship variance. But of course, social relations model approaches suggest that romantic evaluative measures are mostly (i.e., >50%) comprised of relationship variance (Kenny, 2019). The lion's share of human romantic compatibility remains unaccounted for, and we may have to stretch beyond attribute-matching concepts like similarity and preference matching to explain it (Eastwick, Finkel, & Joel, 2023).

This study also has some limitations. This study only used measured variables, and experimental approaches will be required to understand the causal consequences of ideals (Eastwick, & Ledgerwood, 2019; Rohrer et al., 2022). Furthermore, the participants' partners did not actually take part in this study, and effect sizes will likely decline across the board if the partner's (rather than the participant's) reports of the partner's traits are used instead (Hromatko et al., 2015). If one conservatively estimated that the zero-order corrected pattern metric would decline to (say) $r = .10$, a sample size of $N = 779$ participants would be necessary to achieve 80% power—a challenging but not impossible task. Moreover, the 35 attributes that we assessed here are certainly not exhaustive, and our results suggest the wisdom of testing the predictive validity of other traits that (a) receive middling (i.e., not especially high) normative desirability ratings or (b) are prioritized in some cultures more than others. Finally, even though we sampled participants from all over the world, most of them had at least a high school level of education, and many of them likely live in situations where they have substantial freedom of choice over who they could select as a romantic partner. Future research would need to examine how mate evaluations take place in contexts where people themselves have limited input over whom they are expected to court or marry.

Conclusion

The present study partnered with the Psychological Science Accelerator to test the predictive validity of ideal partner preferences across 43 different countries. Results revealed that ideals did indeed have predictive power, although results were highly dependent on whether preference matching was conceptualized as a normative match (βs ranging from .30 to .40), an idiosyncratic or distinctive match (βs .10–.20), or as the level of specific traits (average $\beta = .04$). These data—especially given the size and breadth of the data set—should be able to provide effect size benchmarks for future studies of human mate preferences, regardless of whether researchers are interested in stated preferences, revealed preferences, or preference-matching effects.

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