

An Introduction to the Cohabitation Index

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Abstract

Academics have repeatedly challenged the online-dating industry for both its methodology and opaqueness, a critique scholars hope will highlight the ineffectiveness of coeval matching algorithms to predict long-term compatibility. Recent publications, however, have also proposed a number of statistically relevant factors that portend relationship stability, several of which emerge directly from the notion of shared-space (i.e., “domestic”) compatibility. We build upon the academic edifice of cohabitation (dis)similarity to create a new matching algorithm: the Cohabitation Index (US 63/109,054). Developed from the extensive academic literature on social-exchange theory and the psychosocial model of the perceived-ideal partner, the Cohabitation Index (CI) offers a powerful metric that quantifies long-term relationship stability while enjoying support from both peer-reviewed scholarship and robust statistical results.

Keywords

Algorithms — Matching — Cohabitation

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1. Motivation

We wish to answer the question many online-dating users likely ask themselves when creating their profiles: *What is the probability that two matched members of a dating site will have a successful long-term relationship?* Unfortunately, the sheer number of variables involved in both interpersonal dynamics and the vagaries of human agency makes this question impossible to answer. Many of the critical metrics known to presage relationship instability and dissolution cannot possibly be evaluated through the impersonal prism of matching algorithms and database filters (e.g., deescalating conflict [9], cooperation [19], neuroticism [8], etc.). Despite this ineluctable limitation, however, online-dating sites claim their “proprietary algorithms” identify and exploit those variables that adumbrate relationship success—all while academics continue to publish research suggesting these algorithms hold little, if any, predictive value.

1.1 Criticism

General objections to the prescience of matching algorithms fall into two principal categories: methodology and func-

tion. Finkel, et al. [8], for instance, criticize both industry studies for ignoring randomized experiments and dating sites for eschewing cross-validation techniques by failing to test independent samples; they further recognize that similarity measures across multiple dimensions do not account for canceling effects, while common-response questions often inflate compatibility scores. The objection to function involves the uncertainty of precision. Not only is it impossible to gauge predictive efficacy when proprietary “black box” algorithms are unavailable for inspection, but even ostensibly promising results can be hopelessly misleading. For example, an algorithm that *blindly* predicts marital stability for a random 100-couple sample will likely enjoy a 93% success rate if that sample is taken from a population with a 7% divorce rate ([8]: 40). It should be easy to imagine how a superior algorithm with even modest predictive powers might produce a poorer result when applied to the same cohort.

But even if we assume the similarity (or complementarity) approach of matching algorithms can predict compatibility under limited conditions, how do we know which dimensions will yield predictive results? Demographic data provide a documented and reliable guide to compatibility, but those filters are predictably too coarse-grained to be useful. Personality typing is nearly ubiquitous (e.g., eHarmony, Perfect Match, etc.), but academics criticize its effectiveness (e.g., [5], [8], etc.). The remaining variables often used in matching algorithms (e.g., interests, political affiliation, entertainment preferences, etc.), what Davidson et al. [4] characterize as “horizontal attributes,” hold even less import. In fact, a longitudinal study of 231 couples by Hill, Rubin, and Peplau found that “couple similarity...did not differentiate between the intact and breakup groups very strongly” ([18]: 95), a 44-year-old result that still finds modern statistical support. Though simi-

larity measures might be the only game in town—and they do presage a certain level of *initial* attraction in strictly controlled environments—their effect on relationship satisfaction has not shown to be “significantly different from zero” ([8]: 46). This is not a surprising result when one considers the number of factors matching algorithms are expected to predict (Figure 1).

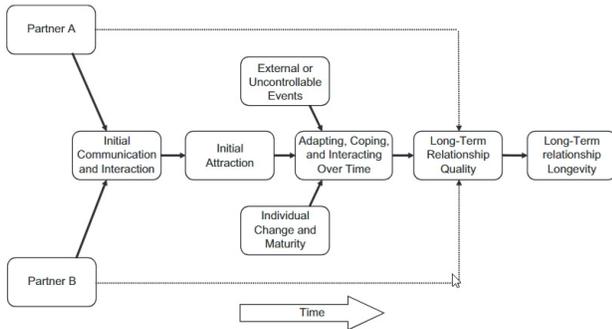


Figure 1. Relationship trajectory (Finkel et al., 2012)

1.2 A New Approach

Other variables, however, do seem amenable to matching techniques. Recent research suggests modelers can approximate long-term compatibility by privileging metrics that promote relationship *stability*, including intimacy and shared history (e.g., [23], [25], etc.). Hiekel et al. [11] even go so far as to stipulate that “intimacy is the key dimension predicting union stability” [abstract]. This is fortunate, for we argue a significant portion of relationship stability is an outgrowth of cohabitation success. And though we cannot *prove* a correlation exists between positive cohabitation and union stability, it seems unlikely a stable and satisfying relationship can survive within a framework of domestic incompatibility.

Modern research strongly supports this view. Rosenfeld et al. [20], for example, argue that premarital cohabitation, in particular, lowers the rate of divorce and provides the “practical experience” required to teach couples “how to adapt to each other” [abstract]. Bree [1] proposes that failure to meet cohabiting expectations “can lead to disappointment, frustration, and...hostility” (2). Vanover [25] is even more explicit, claiming cohabitation success is “significantly associated with marital stability” (11), and in a study of divorced couples, he reports 34% of respondents cited “not getting enough attention” as the reason for divorce (10). Finally, of the “eight characteristics” of a successful marriage proposed by Srivastava [23], three relate directly to cohabitation: (1) assumption of permanence, (2) intimacy/enjoyment, and (3) cherished history. Assuming these studies accurately assess the importance of shared-space compatibility, they also project a connection between (and among) cohabitation, intimacy, and stability—where any break in the chain subverts the entire relationship. Without intimacy and shared memories, there will likely be instability; without the promise and safety of shared space, the potential for intimacy is strained and stability is

threatened. In every case, cohabitation compatibility clears the path toward relationship success.

But why should we privilege cohabitation success as a necessary (if insufficient) condition for stability in romantic relationships? There are two reasons. First, premarital cohabitation, which is now often viewed as a “trial run” preceding a marriage commitment, has become increasingly common within coeval society—soaring, as Kuperberg [12] concludes, to a 900% increase in the last 50 years. Mernitz [15] reports *two of every three* young adults in the U.S. engage in cohabiting prior to marriage, and Sassler and Lichter [22] claim roughly 75% of U.S. adults in their early 30’s have cohabited *at least once*. Second, there are real risks to getting it wrong. Busby et al. [2] find that “positive lessons learned in previous relationship experiences are...overwhelmed by negative carry-over” [abstract]. This is a critical point. If 40% of premarital cohabitators break up after moving in together, as recent data show, we can expect this cohort to suffer increased difficulty in the face of past relationship failure, each negative reinforcement reducing the likelihood of future cohabitation success. Relevance and increased risk, then, provide convincing reasons for industry executives to include a cohabitation metric in their models, especially if they operate, even tangentially, in the interest of their users.

2. Origins

The CI emerged from both the rich literature surrounding social-exchange theory (as first developed by Homans, Blau, Thibaut, Kelly, etc.) and various investment models of relationship satisfaction. In broadest terms, social-exchange theory (SET) is a theory of social interaction based on economic models of exchange where *costs* and *benefits* are used to decide whether a (possibly non-romantic) relationship is worth pursuing. If the sum of the benefits ($B = b_1 + b_2 + \dots + b_m$) is greater than the sum of the costs ($C = c_1 + c_2 + \dots + c_n$) given one’s expectations and available alternatives, there exists a net profit to the relationship, and the one who profits will likely pursue (or seek to maintain) the relationship. Individuals also expect equitable compensation for costs they must incur from the relationship, and, in some cases, as we will see shortly, it may take multiple benefits to balance a heavily weighted cost. This might be formalized as follows:

$$w_k c_k = \omega_i b_i + \omega_{i+1} b_{i+1} + \dots + \omega_{i+j} b_{i+j}$$

where all indexing variables are elements of \mathbb{Z}^+ ; weights w_q and ω_r correspond to the q th cost and r th benefit, respectively, with weights summing to one (i.e., $\sum_{q=1}^n w_q = 1$, etc.); $i + j \leq m$; and $k \leq n$. When costs outweigh benefits ($C - B > 0$), individuals will very likely terminate (or reject) the relationship.

Related to costs and benefits are the concepts of similarity and complementarity, both of which inform the design of modern matching algorithms. Generally speaking, matches who are more similar represent the potential for greater benefits

while dissimilarity projects costs. Where similarity would likely generate conflict (e.g., dominant-submissive dynamics, etc.), complementarity will be preferred and viewed as a benefit.¹ Of particular interest to us was the thread running from SET through similarity measures to Murstein’s perceived-ideal model (PIM), a psychosocial framework reified in [16] where dyad exchanges are informed by perceived distances between an “ideal” (of self and partner) and what one actually “perceives” (of self and partner) (Figure 2). This model resonates with similarity concepts but moves beyond the simplicity of comparing horizontal attributes ([16]: 7).²

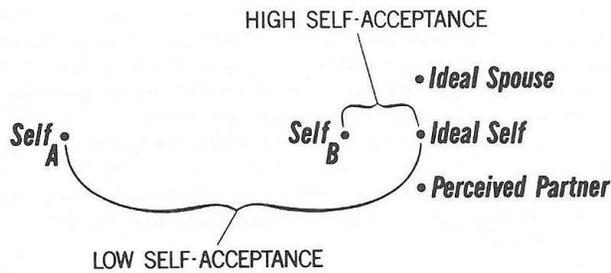


Figure 2. Murstein’s perceived-ideal distances

We appropriate this model to address cohabitation compatibility, a parameter that, as we have seen, informs long-term relationship stability and enjoys a storied history of academic support that spans nearly seven decades—from a 1953 Burgess and Wallin study that reported “broken engagements...could be predicted by...differences in leisure-time preferences...” ([3]: 84) and Femlee et al. [7] who stated the “likelihood of a couple breaking up is influenced by...[the] amount of time spent together...” (13) to recent publications from Vanover [25], Srivastava [23], and Hiekel et al. [11] that continue to champion cohabitation as an essential component of a successful relationship.

2.1 Building Blocks

The theoretical mechanism of exchange, however, varies with different approaches. The two most important of these—at least as it concerns our work on the CI algorithm—are Bernard Murstein’s Stimulus-Value-Role (SVR) theory and Peter Blau’s work on social exchange qua power dynamics. Both play a significant role in our thinking about cohabitation.

SVR Theory Murstein [16] develops a cost-benefit analysis for romantic dyads based on a progression of dating “stages” with each stage acting as a filter to the increased intimacy of the subsequent stage (Figure 3).³ The initial *stimulus* phase focuses on the non-interpersonal cataloging and evaluation

of a potential match’s surface characteristics (e.g., physical attractiveness, age, perceived wealth and status, vocalizations, behavior and mannerisms, etc.). Should a potential match pass the *stimulus* stage, he or she will likely be invited to participate in the *value* stage, an intermediate phase that involves “the appraisal of...compatibility through verbal interaction” and, consequently, a more thorough examination of the perceived physical attributes observed from the *stimulus* stage (116). Here, the pair begins investigating various “horizontal attributes” by slowly revealing details about themselves, often with the goal of validating self through the process of value comparison. Finally, the *role* stage, which usually precedes a more substantive commitment, provides a general “fitness” test for relationship longevity; the most critical factors in this stage include expected gender and career roles, sexual compatibility, and an awareness of one’s impact on the relationship dynamic.

Most people use PIM to evaluate potential matches as they progress through each stage; the decision to engage, however, is usually influenced by the likelihood of reciprocity based on the *perceived* self. Though there has been a lively debate concerning the validity of SVR theory to describe mating selection (see Rubin and Levinger [21], Murstein [17], Leigh et al., [14], etc.), the theory is palpably intuitive and resonates quite well with the way most people seem to experience the dating process. Murstein briefly discusses cohabitation as a “developmental stage of courtship that eventually terminates in marriage,” an informal phase that necessarily follows the *role* stage, but he only speculates that the “kind of people drawn to cohabitation” might explain the then-higher rate of relationship dissolution concerning cohabitators ([18]: 93). We developed the CI with the intention of taking a step toward quantifying what was, to Murstein, a largely ineffable result.

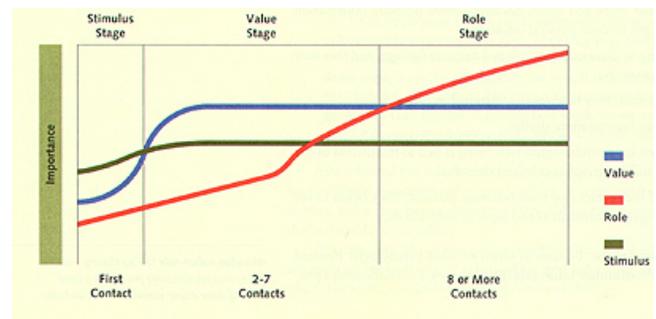


Figure 3. Stages of SVR theory

Power Peter Blau’s work in *Exchange and Power in Social Life* is a celebrated 1964 monograph that, *inter alia*, imports the mathematics of economics as a way to formalize the exchange between social groups and, thus, define emergent power structures. Blau builds a theory of group dynamics from an investigation of individual exchanges and recognizes that an imbalanced exchange, even at the dyad level, leads to unilateral power structures, an arrangement that is often used to exploit and manipulate others. (Think: Bob likes Alice

¹It is interesting to note, however, the concept of complementarity has been criticized, if not deprecated, in the literature (e.g., [16]: 125-129, [8]: 47, [24]: 53-55, etc.).

²Davidson, et al. [4] wrongly attribute this model to Wetzel and Insko [26].

³Murstein refers to “costs” and “benefits” in this context as *assets* and *liabilities*, but the appellations are essentially identical.

more than Alice likes Bob.) Though Blau has been criticized for applying indifference curves to describe social exchange within the framework of economic theory (see Heath [10], in particular), his general conceit is irresistible. Given the usual toy-model assumptions required by microeconomic theory (e.g., ranking of goods, transitivity of preferences, no satiety, etc.), indifference curves quantify the “indifferent” (i.e., invariant) satisfaction level of a consumer with respect to varying combinations of goods. The maximization of consumer satisfaction with respect to a specific indifference curve occurs when the consumer’s “budget line” is tangent to a point on the curve. It is at this point where market-substitution requirements and consumer preferences align.

But despite concerns that the rules of economic theory do not translate well to sociological inquiry, Blau suggests we can evaluate moments of social exchange (and, thus, emerging power shifts) through the prism of commodity-based preferences—assuming the orthodox restrictions on indifference curves continue to hold (e.g., crossings are prohibited, higher curves are preferred, convexity to the origin, etc.). Blau does somewhat of a disservice to his argument by constructing unnecessarily obtuse examples (e.g., problem-solving ability vs. “resources of willing compliance” ([10]: 277), etc.), but the economic link to social exchange (and SVR theory) remains clear.

Example Imagine Alice, a very desirable coed, enters a bar intent on meeting someone to start a romantic relationship. In this first *stimulus* phase, let us assume Alice will filter potential matches based on three benefits (qua commodities): money (M), age (X), and physical attractiveness (Y). Though she must infer M and X based on limited observations, these remain measurable variables. Y , too, can be considered measurable if one adjudicates attractiveness by one or more definable metrics (e.g., BMI, height, facial proportions approximating the Golden ratio $1 : \tau$, etc.), though one presumes Alice will use her visceral response to visual cues as a way to assign non-negative attraction values $y_1, y_2, \dots, y_{n-1}, y_n$ to a pool of n candidates. Figure 4 depicts the current situation.⁴ The convex \mathbb{R}^3 surface bounded by ABC represents the agglomeration of Alice’s minimum indifference combinations of benefits X , Y , and M .

Now, suppose Bob, an undergraduate studying art history, walks into the bar. Alice, using her three-commodity filter, finds him unattractive ($y = 0$), not particularly well dressed (m_2), and too young (x_1). Despite Bob’s appearance, however, Alice would still be as interested as any other possible combination of benefits lying on the indifference surface ABC if Bob were either (1) very wealthy, (2) significantly older, or (3) able to offer some acceptable combination of wealth and age that would, according to Alice, generate for her an overall profit. Such a combination in (3) would create a point on Alice’s indifference curve AB in the \mathbb{R}^2 “universe” of money and age. Unfortunately, the point $(x_1, 0, m_2)$ —call it F (not

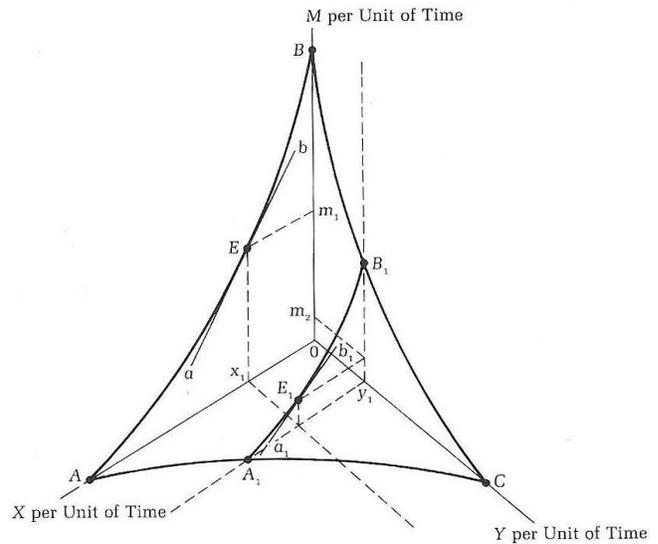


Figure 4. Indifference curves in \mathbb{R}^3

drawn)—falls below the \mathbb{R}^2 indifference curve AB on the XM plane, and no line drawn through F can be tangent to Alice’s AB indifference curve at that point. Alice thus dismisses Bob as a potential match and continues looking.

But what if Bob had wealth m_1 to compensate for the cost Alice associates with his unattractiveness? Then, he would have attained point $E = (x_1, 0, m_1)$, which does lie on Alice’s indifference curve AB with tangent line ab , as required. Given the same age and attractiveness level, Bob could also have attained point $E_1 = (x_1, y_1, m_2)$, which lies on indifference curve A_1B_1 with tangent line a_1b_1 . Using microeconomic terms, Alice considers attractiveness to be a substitute for age.⁵ Unfortunately, Bob cannot offer (read: afford) the specific combination of commodities that would cause Alice to initiate the *value* stage. For Blau, this represents the potential for exploitation as the power dynamic shifts. Bob, realizing Alice is too good for him, might signal a willingness to offer “extrinsic” benefits in the form of gifts or obsequious behavior. This could add increased value to the relationship, and in lieu of superior alternatives, the additional benefit might convince Alice to consider future overtures.

One might ask how this relates to the CI algorithm. We assume most people evaluate a potential exchange based on the (subconscious) design of one’s “indifference curves.” The CI algorithm, then, uses probability modeling to quantify cohabitation compatibility by measuring dyadic exchange within the context of benefit maximization viewed through the lens of PIM. This exchange structure can generate Blau-like power imbalances, leading to (1) interpersonal stressors that are difficult to avoid within a marriage built upon an assumption of permanence and (2) increasing personal dissatisfaction with one’s partner, which, left unresolved, could culminate in a decision to dissolve the relationship. Stated in finance terms,

⁴This graphic is taken from Leftwich [13]: 105.

⁵This is based on the decreasing slope of tangent line a_1b_1 .

the CI measures the volatility of the relationship with respect to the domestic space. Even though the CI does not import the full mathematical machinery of indifference curves, the mechanics of the algorithm are a direct outgrowth of contemplating modes of economic exchange in terms of commodity bundles, and they simulate the process in a way that dovetails with Murstein’s psychosocial model of the “ideal.” What emerges from this Frankensteinian concatenation of ideas is the industry’s best approach to domestic compatibility and, thus, relationship success.

3. Methods and Statistics

Most recent alpha testing utilizes an SRS of modest size ($n_1 = 8$, $\bar{x}_1 = 77.7$, $s_1^2 = 42.34$, $s_1 = 6.51$) taken from a population of long-term (i.e., 10+ years) married couples with unknown μ and σ^2 . The sample size was designed to mitigate both bias and various statistical anomalies (see below), and our target population emerged from logistical and methodological limitations on recruiting candidates. Many promising couples, for example, refused to take the test due to concerns about receiving (or confirming what they expected to be) a poor result. (We call these “high-investment” candidates.) There were also serious obstacles associated with locating and testing individuals who are no longer romantically involved. Former couples, the literature suggests, are unreliable and will very often provide asymmetric (and possibly untruthful) reasons for breaking up; also, too many of the variables likely responsible for relationship dissolution have nothing to do with cohabitation metrics (e.g., infidelity, finances, neuroticism, familial tension, delayed proposal, etc.). Failure to account for these exogenous stressors would lead to an ostensibly poorer performance of our algorithm, yet filtering the population for former couples who suffered specifically from cohabitation incompatibility would generate false positives and bias the sample in our favor.

Conversely, unhappy couples who would otherwise divorce might survive long-term cohabitation for reasons unrelated to shared-space compatibility. There are far too many variables to list, but some of the most common include (1) a desire to maintain a standard of living that requires two incomes, (2) labor-market and -mobility restrictions for the non-income earner, (3) stability for younger children, (4) an alignment with religious or ideological beliefs, (5) the stigma of divorce, (6) challenges of single parenthood, (7) fear of being alone, (8) financial loss, and (9) the fracturing of calcified social groups. Including these couples in the sample would clearly generate false negatives and undermine the CI’s projected efficacy.

We sought, instead, to model the academic claim that domestic compatibility is a necessary condition for successful long-term relationships, and we believe the most effective model requires a carefully crafted similarity metric based on the above material. We are not claiming a low CI score offers apodictic proof of relationship failure, and neither are we suggesting a high score guarantees future success. The

CI value only measures how well two strangers would each model the other’s ideal domestic space, and our underlying assumption, which is supported by the academic community, is that a matched dyad with above-average similarity (based on standard online-dating metrics) will possess an increased likelihood of long-term relationship success if the pair *also* exhibits above-average cohabitation compatibility. There are pointed exceptions, as mentioned above, but, all things being equal, it seems far more likely well-matched couples who experience a significant degree of cohabitation compatibility will remain together longer and report a higher degree of relationship satisfaction.

We chose to focus on the population of couples married at least ten years for two primary reasons. First, the median time to divorce for first marriages is 7.85 years (with 7.15 years for *second* marriages), so the decision to sample married couples in excess of this median would seem to increase the likelihood of measuring above-average-to-high cohabitation compatibility. Second, an SRS of this population arguably reduces the risk of outliers while limiting both biased sampling and the potential for Type I and II statistical errors. One would like to report a statistically significant result compared to a population of former cohabiting couples with low-to-average CI scores, but such a finding might be difficult to achieve in practice without engendering bias.

Limiting the population to long-term married couples allows us to quantify the degree to which the CI tracks relationship satisfaction with respect to the domestic space. A questionable CI score (≤ 60) is likely an indication of potential conflict and future dissatisfaction within the relationship, and paired users in those cases should (1) welcome an open dialogue about future expectations, (2) be prepared to make lifestyle adjustments, or (3) completely recalibrate one’s vision of the domestic landscape. Tolerance and compromise can significantly mitigate problems associated with incompatibility, but, as we opined above, no algorithm can predict the myriad trajectories of the human decision-making process. Finkel et al. [8] suggest “a dating site could...develop a highly predictive algorithm if it did no more than prevent pairings that are unlikely to succeed...” (41). Unfortunately, the CI cannot prevent such pairings, but it can provide timely warning signs when Pollyannaish modelers bathe users in the soft light of superficial similarity scores.

3.1 Testing

What we *can* say, however, is that the mean-difference between our sample and the stochastic responses provided by the pseudo-random number generator (PRNG) is very statistically significant. We selected the eight highest PRNG results (of 20) to equate sample sizes and calculate the most conservative result ($n_2 = 8$, $\bar{x}_2 = 37.99$, $s_2^2 = 2.38$, $s_2 = 1.54$). The scatterplots in Figure 5 show both sample scores with their respective density graphs. We then implemented the standard approach for two-sample mean testing with no information about the underlying populations and defined H_0 to be the

usual “no mean-difference between the sample and that of the PRNG” with H_1 as “the mean-difference of the sample is greater than that of the PRNG responses.” Formally, we have

$$H_0 : \mu_1 = \mu_2$$

$$H_1 : \mu_1 > \mu_2$$

as the template for our investigation. To address concerns about normality, we performed the Shapiro-Wilk test on both samples and found the assumption of normality applied in both cases despite the small sample size: $p(n_1) = 0.1762$ and $p(n_2) = 0.8348$.⁶ A Q-Q plot of n_1 was also used to investigate a Gaussian correlation (Figure 6, top), but the Shapiro-Wilk test provides a more robust result.

We then performed a *Welch t* test ($\alpha = 0.01$) that yielded expected results (Figure 6, bottom): $t = 16.793$, $df = 7.79$, and $p \ll 0.001$.⁷ Thus, the observed difference in means approaches 17 standard errors above the *null* hypothesis ($\mu_1 - \mu_2 = 0$). Clearly, this is a highly significant result, and it suggests the CI measures compatibility in a way that lies far beyond the reach of chance.

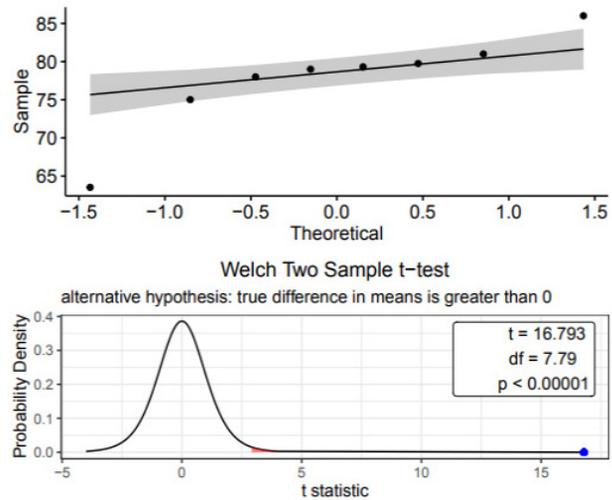


Figure 6. Statistical results in R

and $\alpha = 0.05$, the confidence interval δ for the population mean μ is given by

$$\delta_{1-\alpha} \approx \bar{x}_1 \pm t_{\alpha/2, n-1} \cdot sn^{-1/2}$$

with 77.7 ± 5.44 . We speculate LS couples would average 5-10 points lower than the CI sample, and using the lower bound for δ ($\bar{x}_\ell = 72.26$) with no reason to suggest a larger standard deviation for the LS sample (s_2), we achieve significant *effect sizes* according to Cohen’s standard d values. This invariably requires smaller sample sizes for even the most stringent α and power (i.e., $1 - \beta$) parameters. Table 1 ($d \approx 0.768$) and Table 2 ($d \approx 1.536$) represent power analyses using the usual industry-standard values for five- and ten-point mean-decreases from \bar{x}_ℓ , respectively.

Table 1. Power Analysis I

Parameters		
α	$1 - \beta$	n_2
0.05	0.8	12
0.01	0.99	40

The five-point mean-decrease of the LS sample (i.e., $\bar{x}_2 = \bar{x}_\ell - 5$) requires a more substantial sample size of $n_2 = 40$, while the usual publication standard of $\alpha = 0.05$ and $(1 - \beta) = 0.8$ only demands 12 participants. These results are expected based on the calculated d values, and assuming

Table 2. Power Analysis II

Parameters		
α	$1 - \beta$	n_2
0.05	0.8	5
0.01	0.99	13

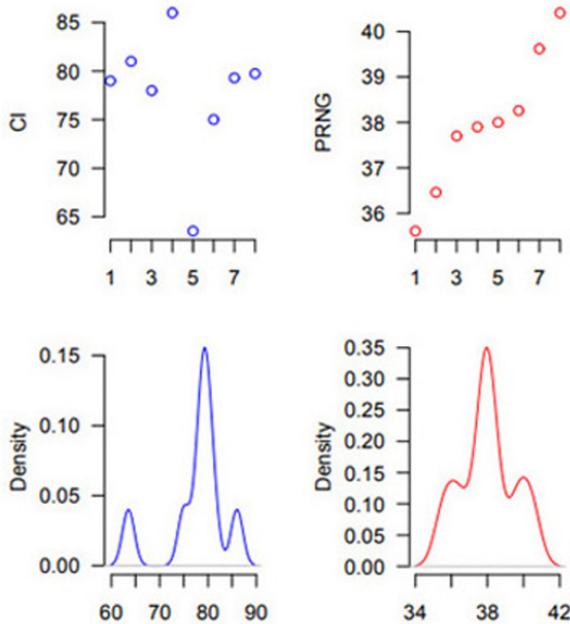


Figure 5. Sample scores and their densities

Future testing We would like to find a statistically significant difference between a large CI sample and that of a population of low-score (LS) couples whose relationships have since terminated. This, as we mentioned above, will be a difficult task in the absence of filtering for sample bias, but we can provide a general blueprint for those wishing to investigate further. Assuming a $t(7)$ distribution with $s = 6.51$

⁶All statistical tests were performed by the corresponding author using R software (RStudio version 1.3.1093).

⁷R gives a precise p -value of $p = 1.075/10^7$.

all other point estimates remain invariant, sample sizes will continue to shrink as the mean of the LS sample decreases (i.e., as the *effect size* grows). Our eagerness to avoid Type-II errors, however, suggests an implementation of the most stringent statistical parameters, though updating the CI sample would obviously require a revision to these statistical projections.

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