

What's the difference? A clarification of the statistical assumptions in
congruence modeling

by

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Abstract

This report translates statistical research on congruence modeling to family science. In particular, it highlights the limitations of the latent congruence model (LCM; Cheung, [2009](#)), which was recently re-branded as the dyadic score model (Iida et al., [2018](#)). A general model for congruence research based on polynomial response surface analysis is presented, along with unconstrained and constrained examples of first- (linear), second- (quadratic), and third-order (cubic) polynomial models. Following Edwards' ([2009](#)) critique, the LCM coefficients are shown to be equivalent to compound coefficients of the linear polynomial model that conceal the effects of its components. The implicit constraints and limitations of the LCM are demonstrated using an exploratory empirical example of sexual desire discrepancy's effects on sexual satisfaction for heterosexual couple therapy clients. These results are discussed, followed by key takeaways for family scientists.

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Dedication

This report is dedicated to my father, Gordon Eisert, who was the first person to teach me about variables. Your excitement for science ignited my passion for learning.

I would also like to dedicate this report to my 17-year-old self, who didn't get the score he wanted on the AP Statistics exam. Like you, my deep curiosity drives me to learn—but unlike you, my worth isn't based on numbers anymore.

Chapter 1

Introduction

Historically, difference scores have been used to operationalize the level of difference—or inversely, the level of congruence—between two constructs (Edwards, [2002](#)). The motivating force behind this is the idea that beyond the levels of the variables themselves, their relative difference or congruence affect outcomes. In family science, difference scores have been used to examine the effects of sexual desire discrepancy between partners on various outcomes, such as sexual or relationship satisfaction (Mark, [2012](#); Willoughby & Vitas, [2012](#)).

Unfortunately, difference scores suffer from many limitations and can mislead researchers (see Section [2.1.2](#)). Some scientists have attempted to overcome these limitations by including level (or average) terms that ostensibly control for the level of the variables used to make the difference score in the analysis (Eisert, [2021](#); Willoughby et al., [2014](#)). One such proposed solution was latent congruence modeling, which was recently re-branded as “dyadic score modeling” (Iida et al., [2018](#)). This model was created to overcome the problems with difference scores and to allow for latent variable modeling to improve construct measurement (Cheung, [2009](#)).

The latent congruence model (LCM) and linear difference score models (with or without level terms) have implicit constraints and assumptions that go unchecked by many scholars. The LCM was examined by Edwards ([2009](#)) and found to struggle with many of the very issues it aspired to overcome. Similar to the LCM, models adding level terms make as-

sumptions about the relationships between the variables that are imposed, but untested (see Section 2.1.2). Despite this, the LCM has continued to be used in family science (e.g., Leth-Nissen et al., 2023; Stadler et al., 2023). Therefore, the purpose of this paper is to translate statistical findings from other disciplines to family science by highlighting the problems with the LCM, given the implicit constraints it imposes on model variables. This will be done by first providing a general form of congruence models based on polynomial regression using response surface analysis and demonstrating the implied constraints on its various levels (linear, quadratic, and cubic). The LCM will then be shown to be a linear form of the general model (Chapter 2). An illustrative example will be presented to demonstrate how sexual desire discrepancy's influence on sexual satisfaction might be misunderstood when using the LCM (Chapter 3). Finally, the findings of the empirical example will be discussed and key takeaways for family scientists will be considered (Chapter 4).

Chapter 2

Modeling Congruence

In this paper, congruence and discrepancy are used interchangeably as they represent two sides of the same construct: how similar or different something is. The way congruence is conceptualized determines how it is operationalized into statistical models. For example, assume x and y represent the level of sexual desire reported by a man and woman in a heterosexual relationship, and z_m and z_w represent their individual sexual satisfaction scores, respectively. If a researcher expected sexual desire congruence to be linear, they would observe that as either x or y changed, z changed. If the relationship were assumed to be polynomial (second order or higher), they might observe that as x and y grow closer together, z increases.

In family science, we are particularly interested in the second operationalization of congruence: we would expect that partners who match each other's sexual desire levels have more sexual satisfaction. Unfortunately, many of the statistical frameworks used have been inadequate in testing this relationship. To demonstrate this, I introduce a general form of congruence models and explain how different orders of polynomial regressions are needed to answer different research questions. I will highlight the latent congruence model as a nested form of linear modeling and explain the criticism it has received. In the next chapter, I will provide an empirical illustration using clinical data to demonstrate how the relationship between sexual desire discrepancy and sexual satisfaction can be misunderstood when the

LCM is used.

2.1 Congruence/Discrepancy Models

2.1.1 A General Form of the Congruence Model

Many statistical models of congruence based on regression are nested within the polynomial regression framework (Edwards, 2002). Recent congruence scholarship has highlighted the use of polynomial regression models up to the third order (cubic), expressed as

$$z = b_0 + b_1x + b_2y + b_3x^2 + b_4xy + b_5y^2 + b_6x^3 + b_7x^2y + b_8xy^2 + b_9y^3 + \varepsilon, \quad (2.1)$$

where z is the outcome, b_0 is the unstandardized intercept, b_1 to b_9 are unstandardized coefficients, and ε is the residual error (Humberg et al., 2022). While polynomial congruence models can be expanded to higher orders (Edwards, 2002), few—if any—go above the third order in practice. Therefore, this paper treats the cubic congruence model as the general form from which constrained and lower-order models are created.

A Note on Syntax

In this paper, I follow the style of Schönbrodt (2016) by using b_i identifiers for regression weights on unconstrained models, c_i on constrained models, and a_i weights on models that use variables other than x and y (e.g., the latent congruence model).

2.1.2 First-Order (Linear) Models

It is becoming increasingly common knowledge that first-order congruence models are often insufficient for modeling discrepancy relationships. Among other issues, they reduce the three-dimensional relationship between x , y , and z to two dimensions. This model constrains all higher-order terms in the full general model (2.1) to zero ($b_3 = b_4 = b_5 = b_6 = b_7 = b_8 =$

$b_9 = 0$), such that

$$\begin{aligned} z &= b_0 + b_1x + b_2y + 0x^2 + 0xy + 0y^2 + 0x^3 + 0x^2y + 0xy^2 + 0y^3 + \varepsilon \\ &= b_0 + b_1x + b_2y + \varepsilon. \end{aligned} \tag{2.2}$$

One of the most common linear congruence models is the raw difference score $(x - y)$. Edwards (1994) explains that raw difference scores assume that x and y have equal but opposite weights in predicting z ,

$$\begin{aligned} z &= c_0 + c_1(x - y) + \varepsilon \\ &= c_0 + c_1x - c_1y + \varepsilon, \end{aligned} \tag{2.3}$$

such that the implied constraint on the full linear model (2.2) is $b_1 = -b_2$. Edwards (1994, 2002) also explains that researchers using the raw difference score usually do not test whether this constraint is appropriate—a bold assumption—but rather use it in null hypothesis testing to see whether c_1 is different from zero. Additionally, these scores are problematic in that the component (x and y) with higher variance may dominate the difference score, the relative contribution of the components is concealed by their difference score, and the difference score cannot explain more variance than the variance of both components considered jointly (Edwards, 1994). Linear models can be appropriately used to test for congruence, but only after the assumptions implicit in this type of modeling are tested.

Level Term

Some researchers introduce a level term in an attempt to control for the “baseline levels of the variables” used to make the discrepancy score (Willoughby et al., 2014, p. 556). In other words, they attempt to test whether the discrepancy (or congruence) itself predicts the outcome once the level of those variables is controlled in the regression. Some examples of this at the linear level include simply adding x and y together or taking the mean of the two ($\frac{x+y}{2}$). As will be shown, latent congruence modeling is another example of this type of

linear model that can mislead researchers in terms of inference (see 2.2).

2.1.3 Second-Order (Quadratic) Models

Second-order polynomial regression models have been receiving increased acceptance and validation (e.g., Humberg et al., 2019). Quadratic models can model congruence as the similarity or overlap between two variables, where more similarity is associated with higher outcomes than less. Usually, these relationships are modeled with an inverted U shape, as

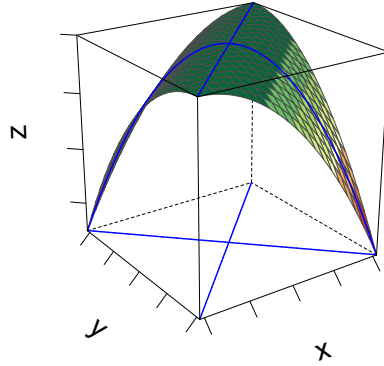


Figure 2.1: *Inverted U Shape*

shown in Figure 2.1. These relationships can also be modeled with an inverted V shape using the absolute value if theoretically indicated (see Edwards, 1994).

The full second-order quadratic model is expressed as

$$\begin{aligned} z &= b_0 + b_1x + b_2y + b_3x^2 + b_4xy + b_5y^2 + 0x^3 + 0x^2y + 0xy^2 + 0y^3 + \varepsilon \\ &= b_0 + b_1x + b_2y + b_3x^2 + b_4xy + b_5y^2 + \varepsilon, \end{aligned} \tag{2.4}$$

where third-order terms are constrained to zero ($b_6 = b_7 = b_8 = b_9 = 0$). Common—but criticized—quadratic models include those with squared ($[x - y]^2$) or absolute ($|x - y|$) difference scores that impose implicit, untested constraints on the component variables. For

example, Edwards (1994) highlights that the model using the squared difference score,

$$\begin{aligned} z &= c_0 + c_1(x - y)^2 + \varepsilon \\ &= c_0 + c_1x^2 - 2c_1xy + c_1y^2 + \varepsilon, \end{aligned} \tag{2.5}$$

is a constrained version of the full quadratic model (2.4) where $b_1 = b_2 = 0$, $b_3 = b_5$, and $b_4 = -2b_3 = -2b_5$. Again, using models that apply untested constraints can lead researchers to false conclusions regarding the true relationships between the variables. The squared difference score *might* be the appropriate model for the data, but this should be tested and not assumed. Interested readers are referred to Edwards (1994) and Edwards (2002) for a review of other scoring examples beyond the scope of this study.

Response Surface Analysis

Response surface analysis (RSA) refers to the visual display of three-dimensional models, where the predicted values of the model are depicted on a “response surface,” as shown in Figure 2.2. These graphs serve as a visual aid in the interpretation of congruence models because coefficients are generally unable to be interpreted in isolation, unlike lower-order regression models (Humberg et al., 2022). In fact, coefficients must be derived from those in the estimated model to test the quadratic model for significant congruence (see Humberg et al., 2019 for details). Several key features of a response surface include bagplot polygons, the line of congruence, and the line of incongruence.

Bagplot Polygons

The two black polygons projected onto the response surface comprise a bagplot (see Figure 2.2). A bagplot is similar to a univariate boxplot, but at the bivariate level. The inner polygon—called the bag—contains the inner 50% of points, while the outer polygon separates the in- and outliers (Schönbrodt, 2016). Bagplots are included on response surfaces to help visualize its interpretable region; response surfaces are not interpretable where observations do not exist.

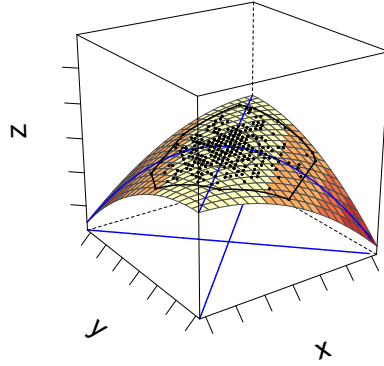


Figure 2.2: *Quadratic RSA example*

Line of Congruence and Incongruence

The line of congruence (LOC) is depicted as the blue line running from the lowest corner to the upper corner in Figure 2.2. When the scales of x and y are comparable, this line represents the graphical position of perfect congruence between the two variables (e.g., where $x = y$). When assessing for congruence effects, it is important to ensure that the first principal axis does not differ from the LOC (Edwards, 2002), which might indicate that the highest levels of the outcome z are actually the result of incongruence (see Humberg et al., 2019). The line of incongruence (LOIC) is where perfect incongruence exists between x and y (i.e., where $y = -x$). This line runs perpendicular to the LOC in Figure 2.2 and the presence of a congruence effect necessitates that the shape of the response surface is an inverted U maximized on the point at the intersection with the LOC (see Humberg et al., 2019).

Strict Versus Rising Ridge Congruence

Within quadratic RSA, researchers can assess hypotheses related to strict or rising ridge congruence. Strict congruence refers to models where the LOC is flat along the z -axis, implying that the effect of congruence between x and y is constant regardless of the levels of the variables (such as the relationships shown in Figures 2.1 and 2.2). In contrast, rising ridge congruence implies that the values along the LOC change as the levels of x and y

change (see Figure 2.3). For example, couples who congruently score higher in sexual desire, say (5,5), might score higher in sexual satisfaction than those congruent on lower levels (1,1). Interested readers can refer to Humberg and colleagues (2022) for example hypotheses and equations for these two constructs.

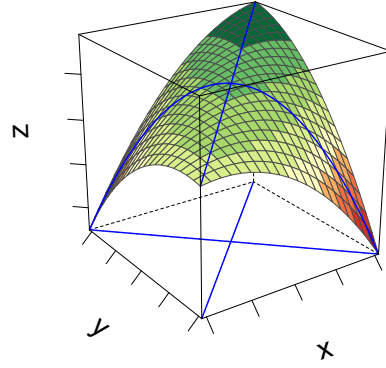


Figure 2.3: *Quadratic rising ridge RSA example*

Shift and Rotation

Schönbrodt (2016) provides extensions of the quadratic RSA models in which the response surface may be shifted and/or rotated to provide a better fit to the data. The shift occurs laterally by adding a constant (C) to one of the predictor terms in the model (e.g., $([x + C] - y)^2$) to move the ridge of the response surface away from the numerical LOC to the appropriate position. Rotations occur when the ridge of the response surface is not parallel to the LOC and must therefore be rotated to fit the data. This is performed by adding a scaling parameter, S , to one of the predictor terms and is usually used in conjunction with the shift term (e.g., $([Sx + C] - y)^2$). This can be done for both strict and rising ridge congruence models. For more details and figures see Schönbrodt (2016).

2.1.4 Third-Order (Cubic) Models

Recently, Humberg and colleagues (2022) suggested that third-order (cubic) polynomial regression models are necessary to test certain hypotheses in congruence research. Quadratic RSA is adequate for testing simple congruence, or whether two variables x and y being closer together leads to higher or lower values of the outcome variable z . However, it falls short when asymmetric or level-dependent congruence effects exist because these relationships cannot be tested below the third order (Humberg et al., 2022). Similar to quadratic models, coefficients that were created from the model coefficients are used to determine the significance and sign of effects (Humberg et al., 2022). Asymmetric and level-dependent congruence phenomena will now be reviewed.

Asymmetric Congruence

Symmetric congruence assumes that the effect of incongruence on either side of the LOC is the same, regardless of whether $y > x$ or $x > y$. Cubic models allow researchers to test whether this is a tenable assumption by allowing the response surface on either side of the ridge to have its own slope. Figure 2.4 visualizes a strict¹ cubic asymmetric response

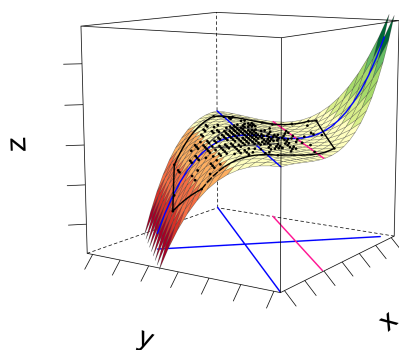


Figure 2.4: *Cubic asymmetric RSA example*

surface where the slope on $x > y$ is less steep than the slope on $y > x$. As an example

¹Rising ridges are also possible.

of asymmetric congruence, Humberg and colleagues (2022) cite Bar-Khalifa and colleagues (2018), who found that romantic partners providing the same level of social support for one another are better adjusted, but providing more support for one’s partner costs more than receiving more support. Asymmetric patterns create several complexities in the analysis of response surfaces, including the possibility of lines parallel to the LOC where response surfaces change shape and rise above the ridge at the LOC (see the pink line in Figure 2.4). Readers are referred to Humberg and colleagues (2022) for a more detailed explanation and ways to navigate this phenomenon.

Level-Dependent Congruence

In addition to the possibility of asymmetric congruence, models may display different effects of congruence depending on the levels of the x and y variables. Quadratic RSA assumes no level dependence, but cubic models can model and test for this. Humberg and colleagues (2022) cite Ilmarinen and colleagues (2016) who found that people with similarly dark personality traits like each other more, especially when people had lower levels of these traits. Figure 2.5 demonstrates an example of strict² cubic level-dependent congruence. Higher

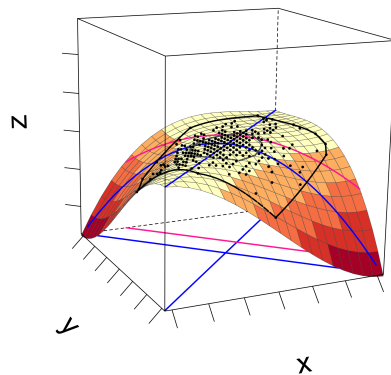


Figure 2.5: *Cubic level-dependent RSA example*

levels of x and y do not have a significant congruence effect, whereas lower levels do. The

²Rising ridges are also possible.

pink line depicted separates the two regions, where values above the line are in the non-significant region and those below the line are in the negative significance region. Refer to Humberg and colleagues (2022) for more information, including how to construct the regions of significance.

2.1.5 Limitations of Polynomial RSA

It is important to note that limitations of polynomial RSA exist. First, the equations and implementation of RSA (Schönbrodt & Humberg, 2023) are implemented with manifest variables that include measurement error. More work is needed to implement this with latent variables, including latent interactions, which is an open area of study (Schönbrodt, 2016) and can be computationally intensive in some implementations (e.g., MPlus; Muthén & Muthén, 2017). In addition, when the predictors are incommensurable—or not on similar scales—the range of testable hypotheses is restricted to fit patterns rather than numerical congruence, and the LOC and LOIC become meaningless (Schönbrodt, 2016). Polynomial models are also susceptible to overfit, where the model fits the data so well that it is not generalizable. This can be mitigated by using constraint patterns (Schönbrodt, 2016).

2.2 The Latent Congruence Model

The latent congruence model (LCM) was introduced by Cheung (2009) to harness the power of structural equation modeling to account for measurement error in modeling. Latent variables are created from indicators and compared for congruence effects on an outcome variable, which can also be latent. Cheung (2009) presents the LCM as a model that overcomes the shortcomings of difference scores. Unfortunately, Edwards (2009) points out that the LCM still falls short in adequately describing congruence relationships. To properly understand the LCM and its shortcomings, a brief overview of the model and Edwards' (2009) criticisms is in order.

2.2.1 An Overview of the LCM

As shown in Figure 2.6, the basic LCM has two major components: congruence and level. Congruence represents the difference between x and y and is modeled as a latent factor with fixed factor loadings of -0.50 on x and 0.50 on y . Note that x and y can be latent variables themselves, formed by multiple indicator variables. Level represents the mean of x and y , and it is formed by constraining the factor loadings on both x and y to each be 1. The congruence and level factors have means and variances, and they are permitted to covary. The residuals for x and y are constrained to 0. Cheung (2009) also suggested that

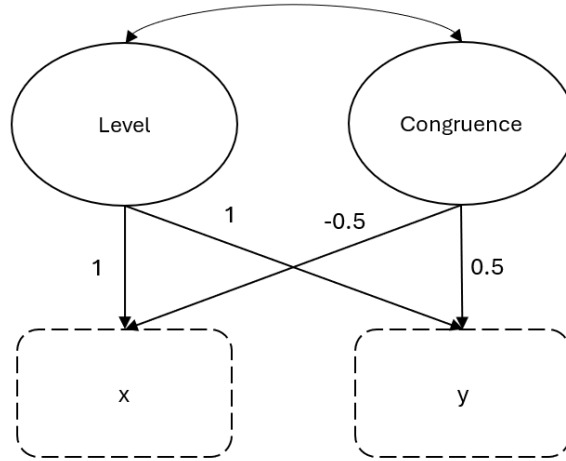


Figure 2.6: *The latent congruence model (outcome not shown)*

one can predict level and congruence as an outcome, even using level and congruence for other variables as predictors. In this report, I will focus on using level and congruence as predictors of a singular outcome, z .

Cheung (2009) provides the equations for x and y , which are

$$x = Level - 0.5 \cdot Congruence \quad (2.6)$$

and

$$y = Level + 0.5 \cdot Congruence, \quad (2.7)$$

which can be re-expressed as

$$Level = \frac{x + y}{2} \quad (2.8)$$

and

$$Congruence = y - x. \quad (2.9)$$

Interested readers should refer to Appendix A of Cheung (2009) for the derivation of other model parameters (e.g., variances and covariance).

2.2.2 Edwards' Critique of the LCM

Edwards (2009) takes issue with the LCM and explains the pitfalls of using the congruence and level variables as predictors, outcomes, and both predictors and outcomes. He clarifies that the LCM can be expressed as

$$z = a_0 + a_1 \cdot Level + a_2 \cdot Congruence + \varepsilon, \quad (2.10)$$

where z is the outcome, a_0 , a_1 , and a_2 are unstandardized coefficients, and ε is a residual. Edwards (2009) notes that coefficients a_1 and a_2 mask the true relationships between x , y , and z . The effects of x and y can be shown using a_1 and a_2 by substituting *Level* (2.8) and *Congruence* (2.9) into the LCM (2.10) using their respective equations:

$$\begin{aligned} z &= a_0 + a_1 \left(\frac{x + y}{2} \right) + a_2 (y - x) + \varepsilon \\ &= a_0 + 0.5a_1x + 0.5a_1y + a_2y - a_2x + \varepsilon \\ &= a_0 + (0.5a_1 - a_2)x + (0.5a_1 + a_2)y + \varepsilon. \end{aligned} \quad (2.11)$$

The coefficients a_1 and a_2 are two elements of the compound coefficients for x and y . Furthermore, the LCM coefficients can be obtained from the full linear model (2.2). Edwards (2009) demonstrates this by substituting x and y for their LCM counterparts (2.6 and 2.7,

respectively):

$$\begin{aligned}
z &= b_0 + b_1x + b_2y + \varepsilon \\
&= b_0 + b_1(Level - 0.5 \cdot Congruence) + b_2(Level + 0.5 \cdot Congruence) + \varepsilon \\
&= b_0 + (b_1 + b_2)Level + 0.5(b_2 - b_1)Congruence + \varepsilon.
\end{aligned} \tag{2.12}$$

This demonstrates that the coefficients for *Level* (a_1) and *Congruence* (a_2) are $a_1 = b_1 + b_2$ and $a_2 = 0.5(b_2 - b_1)$, or transformations of the coefficients for x and y . Problematically, a_1 and a_2 mask the true relationships between x , y , and z (e.g., b_1 and b_2). This becomes clear through a close examination of Table 2.1, which contains example coefficient values for b_1 and b_2 and the resulting LCM coefficients. As shown, *Level* and *Congruence* may appear to have effects when the relationship with z is driven by only one variable (see examples 1 and 2). In this situation, there is little use for the notion of level or congruence, but the LCM coefficients mislead one to believe that there is an effect (Edwards, 2009). In addition, when the effects of $x = y$, the effect of *Congruence* = 0. Similarly, when $x = -y$ or $-x = y$, the effect of *Level* = 0. This is a demonstration of the fact that in the LCM, “support for level requires lack of support for congruence and vice versa, meaning that level and congruence effects cannot coexist” (Edwards, 2009, p. 40).

Table 2.1: *LCM comparison of effects*

Example	Effect of x b_1	Effect of y b_2	Effect of <i>Level</i> $b_1 + b_2$	Effect of <i>Congruence</i> $0.5(b_2 - b_1)$
1	0	0.90	0.90	0.45
2	0.90	0	0.90	-0.45
3	0.45	0.45	0.90	0
4	0.45	-0.45	0	-0.45
5	-0.45	0.45	0	0.45

Edwards (2009) suggests that instead of using the LCM directly, congruence and level are tested using constraints once the effects of x and y on z are understood. However, this approach also assumes that the first-order (linear) relationship is suitable for modeling congruence. As demonstrated in this chapter, linear congruence models assume parameter

constraints on higher-order coefficients that may not be appropriate. Instead, I recommend scholars carefully define their conceptualization of congruence and verify—through statistical tests—whether their hypotheses are tenable, given the data. An empirical example using exploratory analyses follows to demonstrate this.

Chapter 3

An Empirical Example

To illustrate the problems with the latent congruence model within the realm of family science, I will use real data to compare the LCM with the polynomial RSA approach. Therefore, it is necessary to briefly discuss the literature background, methods, and results.

3.1 Brief Background

Many couples struggle with differences in the desired frequency of sex. Population estimates of low sexual desire range from 15 to 25% for men and 20 to 43% for women (Laumann et al., 2005; Lewis et al., 2010). A sexual desire discrepancy (SDD) between partners has been associated with lower relational and sexual satisfaction, less positive communication, increased conflict, and lower marital stability (Bridges & Horne, 2007; Davies et al., 1999; Mark & Murray, 2012; Willoughby et al., 2014; Willoughby & Vitas, 2012). Not surprisingly, SDD is a common presenting issue in couple therapy (Ellison, 2002). Understanding the effects of sexual desire discrepancy on relationship functioning is of paramount importance so that clinicians and scholars can intervene.

To date, much of the research on SDD has used first-order models to represent the construct. I am only aware of one study that has used response surface analysis to examine this issue (Kim et al., 2021). In the following example, I demonstrate the importance of empir-

ically testing the assumptions made about the model imposed on the data. I will perform an exploratory analysis on the influence of sexual desire discrepancy on sexual satisfaction among heterosexual outpatient couple therapy clients. In this analysis, I will include control variables for sexual frequency and relationship length, as these have been found to be important factors influencing sexual satisfaction (Mark & Murray, 2012; Willoughby et al., 2014). In this analysis, I will first compare various polynomial models to one another, followed by a presentation of the LCM coefficients and a comparison of the results. The results will be presented for men’s sexual satisfaction, followed by the results for women.

3.2 Methods

3.2.1 Procedure and Participants

The data acquisition procedures for this study were approved by the Institutional Review Board at the author’s university. The participants for this study included 464 heterosexual couples from a dataset provided by an outpatient relationship clinic in the Midwest United States. The dataset comprised secondary, de-identified therapy intake information. The sampling frame for this study was heterosexual, adult couples who sought services at the clinic, who have had sex, and who wanted sex more than never. Many individuals in the couples were married in their first marriage (64.44%) and identified as White (83%). The average relationship length was 10.10 years ($SD = 8.56$) and ranged from 0.25 to 53 years. The average age of men in the sample was 39.3 years ($SD = 9.06$) and that of women was 37.3 ($SD = 8.63$) with a combined range from 19 to 74. Most of the sample had at least a four-year college degree (52.17%), with those who had attended college (34.38%) following. About thirteen-and-a-half percent (13.45%) had never attended college.

3.2.2 Measures

Sexual Desire

Sexual desire assessed how frequently one wanted sex and was measured using one item, “What is your ideal frequency for sex in your relationship,” with the response options Never (0), Once or twice per year (1), once per month or less (2), 2-3 times per month (3), once per week (4), 2-3 times per week (5), and more than 4 times per week (6). As mentioned previously, couples with an individual who never wanted sex were excluded from the study because they represent a different population. Therefore, sexual desire was an ordinal variable with a possible range from 1 to 6, with increasing values indicating a desire for more frequent sex.

Sexual Satisfaction

Sexual satisfaction was assessed as the subjective amount of satisfaction derived from a person’s sexual relationship with their partner and was measured using the four-item Brief and Diagnostic Anderson Sex Scale (BADASS; Anderson & Eisert, 2024). Items included “Overall, how satisfied are you in your sexual relationship with your partner,” “In general, how connected do you feel to your partner during sex,” “In general, there is a lot of passion and excitement in our sexual relationship,” and “Our sex life has become stale and boring” (reverse coded). Responses ranged from extremely unhappy (0) to perfect (6) for the first item, not at all (0) to completely (5) for the second item, and not at all true (0) to completely true (5) for the last two items. Scores were summed, with a higher score indicating greater sexual satisfaction. The reliability of this measure was good for both men ($\alpha_{std} = 0.87$) and women ($\alpha_{std} = 0.90$).

Control Variables

Sexual Frequency

Sexual frequency assessed how frequently one had sex and was measured using one item, “How often, on average, have you had sex in your relationship during the past three months,” with the response options I have never had sex (0), not in the past 3 months (1), once per month or less (2), 2-3 times per month (3), once per week (4), 2-3 times per week (5), and 4 or more times per week (6). As mentioned previously, couples with an individual who never had sex were excluded from the study as they represent a different population. Sexual frequency was an ordinal variable with a possible range from 1 to 6, with increasing values indicating more frequent sex. This variable was standardized to assist in the convergence of the various models.

Relationship Length

Relationship length represented how long, in years, the couple had been in their relationship. It was assessed using the question “How long have you been in your current relationship” and was open-ended. Responses were coded into a numeric format and then compared between partners for fit. When a discrepancy arose between the years partners had been together, the higher value was retained as some individuals responded with the number of years they had been married, not together in general. A squared term was also included to account for the nonlinear relationship with sexual satisfaction. Both variables were log-normalized and standardized to assist with the convergence of the various models.

3.2.3 Data Preparation

As noted by Humberg and colleagues (2022), certain data characteristics are necessary to explore and report when conducting polynomial RSA. First, the variables to be compared (x and y) should be on the same scale, or transformed to be on the same scale after careful consideration. In this case, the variable is the same (sexual desire) for both men and women.

Next, the predictor combinations should be examined to ensure that there are sufficient observations to cover the three general response categories of incongruence ($x < y$), congruence ($x = y$), and incongruence ($x > y$). Their suggestion was to calculate the standardized difference between x and y and to report the percentage of data in each group, as shown in Table 3.1. Those who were within 0.5 standard deviations from being equal ($x = y$) were

Table 3.1: *Discrepancy categories of sexual desire*

Man < Woman $x < y$	Man = Woman Congruence	Man > Woman $x > y$
22%	43%	35%

assigned to the congruence group, and those falling outside of that group in either direction were classified as such. As seen in Table 3.1, most of the couples were congruent, with fewer women having more desire than men compared to men having more desire than women. Although the distribution of percentages is not equal (i.e., 33% in each category), there is no alarming discrepancy in group sizes.

Data transformations were conducted on study variables because some cubic RSA models had difficulty converging (see Humberg et al., 2022). The grand mean and standard deviation were used to standardize sexual desire. Grand means were used so that possible mean differences between groups would not artificially affect the model results. The response variables, sexual satisfaction for men and women, were similarly standardized.

3.2.4 Analysis Plan

To demonstrate the limitations of using the LCM to model discrepancy scores, I split my analyses into two major components: polynomial regression models using response surface analysis and the latent congruence model. Given that there are two response variables, men’s (z_m) and women’s (z_w) sexual satisfaction, I compared the RSA models and LCM for men and women separately. Modern structural equation modeling capabilities allow for the use of an actor-partner interdependence model (APIM), but I will keep the outcomes in separate models for the specific purpose of this study: to demonstrate the importance of examining

the implicit constraints we impose when using LCM techniques. APIM models require additional considerations and constraint tests, which are beyond the scope and complexity of this report.

Exploratory analyses are used in this report. In practice, it is best to conduct confirmatory analyses in which specific hypotheses are tested using specific statistical models. For example, my evaluation of whether there are asymmetric congruence effects or not should be founded in theory and hypothesized, then tested using the appropriate cubic RSA model. Here, I examine whether these (and other) effects exist as part of a methodological demonstration. If confirmatory inference is desired, specific hypotheses should guide model creation.

Polynomial Regression using RSA

The *RSA* package in R (Schönbrodt & Humberg, 2023) was used to examine the various levels of polynomial regression models (cubic, quadratic, linear). This package conveniently contains tools to estimate (using *lavaan*), assess, and plot polynomial regressions for evaluating congruence. Polynomial models with the constraint patterns provided by *RSA* were estimated and compared based on their bias-corrected Akaike Information Criterion (AICc). This metric converges to the AIC as the sample size increases (Hurvich & Tsai, 1989) and balances the accuracy and complexity of models (Schönbrodt, 2016). Schönbrodt (2016) cites previous literature and clarifies that models with $\Delta\text{AICc} < 2$ are roughly equivalent, $\Delta\text{AICc} < 7$ have some support, and $\Delta\text{AICc} > 10$ are likely implausible compared to the best-fitting model. Some scholars use a likelihood ratio test instead of the AICc, which is also acceptable as long as the comparison process uses one or the other, not both (Burnham et al., 2011). Once estimated, models with $\Delta\text{AICc} < 2$ will be compared amongst one another in terms of their CFI, ΔR^2_{adj} from the null model, other absolute fit indices, and parameter significance patterns. The congruence models will be accepted if they outperform the null model, which contains only the control variables (sexual frequency, relationship length, and relationship length squared). Parameter inference will be conducted using 10,000 bootstrap resamples, as previously suggested for polynomial RSA (Schönbrodt, 2016).

Latent Congruence Modeling

As clarified in the previous chapter, the latent congruence model assumes linear relationships, and its coefficients for level and congruence can be calculated from the coefficients of the full linear model (2.2) as $a_1 = b_1 + b_2$ and $a_2 = 0.5(b_2 - b_1)$, respectively (see 2.12). The results and relative fit of this model will be explored and compared with the best polynomial RSA model found in the previous step.

3.3 Results

The descriptive statistics and Pearson correlations for the model variables are shown in Tables 3.2 and 3.3, respectively. Five cases had missing information on sexual satisfaction (1.07%) and seven had missing information on relationship length (1.51%), so full information

Table 3.2: *Study variable descriptive statistics*

Variable	Mean	SD	Min	Max	Skew	Kurtosis
Male Desire	4.76	0.95	1.00	6.00	-1.07	1.69
Female Desire	4.57	0.94	1.00	6.00	-0.89	1.18
Male Frequency	3.15	1.40	1.00	6.00	0.28	-0.80
Female Frequency	3.14	1.32	1.00	6.00	0.22	-0.78
Male Satisfaction	11.04	5.54	0.00	21.00	-0.02	-0.82
Female Satisfaction	9.81	5.83	0.00	21.00	0.11	-1.10
Relationship Length	10.10	8.56	0.25	53.00	1.66	3.61

Note. The reported numbers are prior to the variable transformations.

maximum likelihood estimation with robust standard errors was used. The exploratory polynomial regression results precede the latent congruence model results and are compared. The results for men and women are presented.

Table 3.3: *Pearson correlations between study variables*

	1	2	3	4	5	6	7
1. S.D. (M)	–						
2. S.D. (W)	0.29***	–					
3. S.F. (M)	0.46***	0.42***	–				
4. S.F. (W)	0.42***	0.42***	0.78***	–			
5. S.S. (M)	0.22***	0.27***	0.56***	0.46***	–		
6. S.S. (W)	0.23***	0.28***	0.46***	0.55***	0.57***	–	
7. R.L.	-0.19***	-0.26***	-0.26***	-0.25***	-0.24***	-0.22***	–
8. R.L. ²	-0.03	0.07	0.16***	0.15**	0.13**	0.10*	-0.12**

Note. S.D. = sexual desire, S.F. = sexual frequency, S.S. = sexual satisfaction, R.L. = relationship length, and R.L.² = relationship length squared. Variables were standardized prior to correlation calculations. Relationship length was also log-transformed prior to standardization and squaring.

* $p < 0.05$

** $p < 0.01$

*** $p < 0.001$

3.3.1 Men's Sexual Satisfaction

Polynomial Model Selection (Men)

The models estimated from the *RSA* package are presented in Table 3.4. Given the number of models with $\Delta\text{AICc} < 2$, a sensitivity analysis was conducted where the sexual desire variable was reversed and log-normalized (previous to grand mean/standard deviation centering) because of its left skew over a limited, discrete range. To preserve the sign of the coefficients, the outcome variable was reverse-coded before centering in these models. The log-normalized models (see Table A.1 in Appendix A) that continued to have $\Delta\text{AICc} < 2$ were the linear difference, null, linear x -only, quadratic shifted squared difference, and linear additive models. Note that the null model consisting of only the control variables (men's sexual frequency, relationship length, and relationship length squared) performed well, such that the change in R^2_{adj} was small among the original ($0.001 < \Delta R^2_{adj} < 0.003$) and log-normalized ($0.002 < \Delta R^2_{adj} < 0.005$) models. Given that the R^2_{adj} increased, and the theoretical justification for including sexual desire in the analyses, the congruence models rejected the null and were compared for fit.

Table 3.4: *Men's polynomial models*

Order	Model	K	LL	AICc	ΔAICc	W_{AICc}	CFI	R^2	R^2_{adj}
1	Difference [†]	6	-526.50	1,065.18	—	0.157	1.000	0.323	0.318
1	Null [†]	5	-527.83	1,065.80	0.62	0.116	1.000	0.319	0.315
1	Only $x^\dagger$	6	-526.92	1,066.02	0.84	0.103	1.000	0.322	0.316
2	SSQD [†]	7	-526.30	1,066.85	1.67	0.068	1.000	0.324	0.317
2	Only x^2	7	-526.34	1,066.92	1.74	0.066	1.000	0.324	0.316
1	Additive [†]	7	-526.44	1,067.12	1.94	0.060	1.000	0.324	0.316
1	Only y	6	-527.49	1,067.16	1.98	0.058	0.998	0.320	0.314
2	Interaction	8	-525.66	1,067.63	2.45	0.046	1.000	0.326	0.317
2	SQD	6	-527.73	1,067.65	2.47	0.046	0.995	0.319	0.313
2	SRSQD	8	-525.71	1,067.73	2.55	0.044	1.000	0.326	0.317
1	Mean	6	-527.77	1,067.73	2.55	0.044	0.995	0.319	0.313
2	Strong	8	-526.10	1,068.52	3.34	0.030	1.000	0.325	0.316
2	SRR	8	-526.29	1,068.90	3.72	0.024	1.000	0.324	0.315
2	Only y^2	7	-527.39	1,069.03	3.85	0.023	0.993	0.321	0.313
3	CA	7	-527.45	1,069.14	3.96	0.022	0.993	0.320	0.313
2	SRRR	9	-525.42	1,069.23	4.05	0.021	1.000	0.327	0.316
2	RR	7	-527.71	1,069.67	4.49	0.017	0.989	0.319	0.312
3	CL	7	-527.73	1,069.71	4.53	0.016	0.989	0.319	0.312
2	Full	10	-524.70	1,069.89	4.71	0.015	1.000	0.329	0.317
2	Weak	10	-525.15	1,070.78	5.60	0.010	1.000	0.327	0.316
3	RRCA	8	-527.43	1,071.17	5.99	0.008	0.987	0.320	0.311
3	RRCL	8	-527.71	1,071.74	6.56	0.006	0.984	0.319	0.310
3	Cubic	14	-523.30	1,075.54	10.36	0.001	1.000	0.333	0.315

[†]Model had $\Delta\text{AICc} < 2$ in the sensitivity analysis (Table A.1)

The absolute fit indices among the four top performing and null models were compared, and the $\text{RMSEA}_{\text{scaled}}$ for the linear difference model slightly outperformed the other models (see Table A.2). The 95% bootstrap confidence intervals for the coefficients of both the original and log-normalized models revealed that the SSQD model did not have a significant fit effect (original: $a_4 = 0.034$ $[-0.074, 0.128]$, $p = 0.505$; log-normalized: $a_4 = -0.065$ $[-0.191, 0.081]$, $p = 0.353$), so this model was rejected. None of the b_1 or b_2 coefficients in the original linear models were significant at $\alpha = 0.05$, but the difference model had marginally significant weights ($p = 0.084$) that became significant in the log-normalized model ($p = 0.034$). Given its overall model performance and coefficient significance, the linear difference model was retained as the best-fitting model of men's sexual desire discrepancy.

Latent Congruence Model Comparison (Men)

The LCM coefficients for level and congruence were computed from the linear additive model coefficients and are shown in Table 3.5. Interestingly, the coefficients for both linear addi-

Table 3.5: *LCM coefficients for men's sexual satisfaction*

Model	Men's Desire x		Women's Desire y		<i>Level</i>		<i>Congruence</i>	
	b_1	95% CI	b_2	95% CI	L	95% CI	C	95% CI
Add	-0.06	[-0.16, 0.03]	0.04	[-0.05, 0.13]	-0.02	[-0.15, 0.11]	0.05 [†]	[-0.01, 0.11]
Add _{L-N}	-0.07 [†]	[-0.16, 0.01]	0.06	[-0.04, 0.15]	-0.02	[-0.15, 0.11]	0.06 [*]	[0.00, 0.13]
Diff	-0.05 [†]	[-0.11, 0.01]	0.05 [†]	[-0.01, 0.11]	0.00	[0.00, 0.00]	0.05 [†]	[-0.01, 0.11]
Diff _{L-N}	-0.07 [*]	[-0.13, -0.01]	0.07 [*]	[0.01, 0.13]	0.00	[0.00, 0.00]	0.07 [*]	[0.01, 0.13]

Note. The L-N subscript refers to the log-normalized model. Also note that these coefficients represent the standardized variables with 95% bootstrapped confidence intervals (R=10,000).

[†] $p < 0.10$

^{*} $p < 0.05$

tive models are not significant, but the LCM congruence coefficient is significant. The top polynomial model (linear difference) was linear, so it was also included in the table. The coefficients are similar to those of the additive model, except that $b_1 = -b_2$ in the difference model. The interpretation of the significantly positive congruence variable is difficult to determine without examining the b coefficients; therefore, a response surface of the linear additive model was created (see Figure 3.1). This figure demonstrates that when women's sexual desire is greater than that of men, men's sexual satisfaction is higher. When men's sexual desire is higher than that of women, men's sexual satisfaction is lower.

3.3.2 Women's Sexual Satisfaction

Polynomial Model Selection

Similar to the process for men, the top models with a $\Delta AIC_c < 2$ were considered for women (see Table 3.6). The sensitivity analysis (Table A.3) revealed that several models performed best: the quadratic squared difference, the cubic level-dependent, the null, the linear y -only, and the cubic rising ridge level-dependent models. To determine whether the congruence

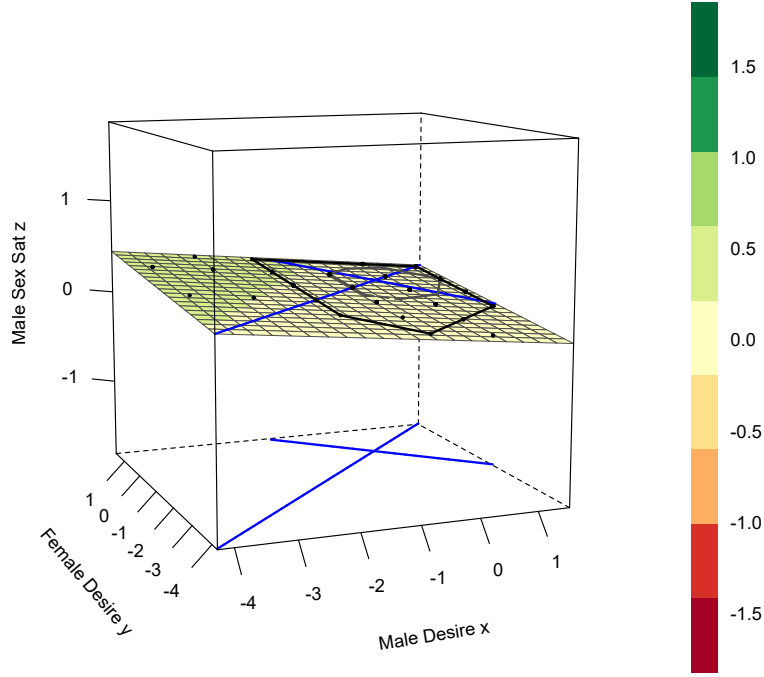


Figure 3.1: *Men's linear additive model*

models were better than the null model, the R_{adj}^2 values were compared and found that the change was small among the original ($0.000 < \Delta R_{adj}^2 < 0.004$) and log-normalized ($-0.001 < \Delta R_{adj}^2 < 0.004$) models. However, given that the R_{adj}^2 increased for most of the congruence models and the theoretical justification for including sexual desire in the analyses, the congruence models rejected the null and were compared for fit.

The absolute fit indices among the four top performing and null models were compared, and the $RMSEA_{scaled}$ for the cubic and quadratic models slightly outperformed the others (see Table A.4). The 95% bootstrap confidence intervals for the coefficients of both the original and log-normalized models revealed that the SQD model did not have a significant fit effect (original: $a_4 = -0.110 [-0.220, 0.0053]$, $p = 0.058$; log-normalized: $a_4 = 0.068 [-0.070, 0.223]$, $p = 0.300$) and the R_{adj}^2 did not improve in the log-normalized model; therefore, this model was rejected. The b_2 coefficient was not significant in the linear only- y models (original: $b_2 = 0.045 [-0.047, 0.131]$, $p = 0.336$; log-normalized: $b_2 = 0.033 [-0.065, 0.127]$, $p = 0.527$) and the R_{adj}^2 decreased in the log-normalized model, so this model was

Table 3.6: *Women's polynomial models*

Order	Model Name	K	LL	AICc	ΔAICc	AICcWt	CFI	R^2	R^2_{adj}
2	SQD [†]	6	-551.93	1,116.04	—	0.157	1.000	0.318	0.312
3	CA	7	-551.10	1,116.44	0.41	0.128	1.000	0.320	0.313
3	CL [†]	7	-551.36	1,116.97	0.93	0.099	1.000	0.319	0.312
1	Null [†]	5	-553.74	1,117.62	1.58	0.071	1.000	0.313	0.308
2	SSQD	7	-551.76	1,117.78	1.74	0.066	1.000	0.318	0.311
2	RR	7	-551.92	1,118.09	2.06	0.056	1.000	0.318	0.310
3	RRCA	8	-551.10	1,118.51	2.48	0.046	1.000	0.320	0.311
1	Only y [†]	6	-553.23	1,118.65	2.62	0.043	1.000	0.314	0.308
2	SRSQD	8	-551.25	1,118.81	2.78	0.039	1.000	0.320	0.311
2	Strong	8	-551.25	1,118.81	2.78	0.039	1.000	0.320	0.311
3	RRCL [†]	8	-551.28	1,118.88	2.84	0.038	1.000	0.320	0.311
2	Only y^2	7	-552.32	1,118.89	2.86	0.038	1.000	0.317	0.309
1	Difference	6	-553.47	1,119.12	3.08	0.034	0.997	0.313	0.307
1	Mean	6	-553.51	1,119.21	3.18	0.032	0.996	0.314	0.308
1	Only x	6	-553.74	1,119.67	3.64	0.026	0.994	0.313	0.307
2	SRR	8	-551.76	1,119.85	3.81	0.023	1.000	0.318	0.309
1	Additive	7	-553.23	1,120.70	4.67	0.015	0.994	0.314	0.307
2	SRRR	9	-551.23	1,120.85	4.82	0.014	1.000	0.320	0.309
2	Interaction	8	-552.44	1,121.21	5.17	0.012	0.997	0.316	0.307
2	Only x^2	7	-553.73	1,121.70	5.67	0.009	0.988	0.313	0.305
2	Weak	10	-550.95	1,122.38	6.35	0.007	1.000	0.320	0.308
2	Full	10	-550.95	1,122.38	6.35	0.007	1.000	0.320	0.308
3	Cubic	14	-549.22	1,127.37	11.33	0.001	1.000	0.325	0.307

[†]Model had $\Delta\text{AICc} < 2$ in the sensitivity analysis (Table A.3)

also rejected.

The two cubic level-dependent models were examined for fit. While usually only the AICc or difference tests should be used to compare models, Humberg and colleagues (2022) suggested that one must compare the constrained level-dependent models against the full cubic model to show that there is not a significantly worse fit. The strict level-dependent model was not significantly worse fitting than the full cubic model (original: $\chi^2(7) = 4.757$, $p = 0.690$; log-normalized: $\chi^2(7) = 2.917$, $p = 0.893$). The 95% bootstrap confidence intervals for the level dependency effect approached marginal significance in the original model and was significant in the log-normalized model (original: $c_3 = 0.010$ $[-0.006, 0.024]$, $p = 0.215$; log-normalized: $c_3 = 0.023$ $[0.001, 0.043]$, $p = 0.039$). The rising-ridge level-dependent model

was similarly not significantly different from the full cubic model (original: $\chi^2(6) = 4.129$, $p = 0.549$; log-normalized: $\chi^2(6) = 2.801$, $p = 0.833$). It had level-dependency effect significance pattern similar to that of the strict model (original: $c_3 = 0.011$ $[-0.006, 0.026]$, $p = 0.205$; log-normalized: $c_3 = 0.027$ $[0.001, 0.053]$, $p = 0.045$), but did not show a significant rising ridge effect (original: $u_1 = -0.027$ $[-0.179, 0.123]$, $p = 0.742$; log-normalized: $u_1 = -0.039$ $[-0.203, 0.123]$, $p = 0.635$). Therefore, the cubic strict level-dependent model was selected as the most appropriate polynomial model to represent the data.

Latent Congruence Model Comparison

The LCM coefficients for level and congruence were computed for women from the linear additive model coefficients and are shown in Table 3.7. No significant effects were observed

Table 3.7: *LCM coefficients for women’s sexual satisfaction*

Model	Men’s Desire x		Women’s Desire y		<i>Level</i>		<i>Congruence</i>	
	b_1	95% CI	b_2	95% CI	L	95% CI	C	95% CI
Add	0.00	[-0.10, 0.09]	0.05	[-0.05, 0.13]	0.04	[-0.09, 0.17]	0.03	[-0.04, 0.09]
Add _{L-N}	0.00	[-0.09, 0.09]	0.03	[-0.06, 0.13]	0.03	[-0.10, 0.16]	0.02	[-0.05, 0.08]

Note. The L-N subscript refers to the log-normalized model. Also note that these coefficients represent the standardized variables with 95% bootstrapped confidence intervals (R=10,000).

among the components (b_1 and b_2) or the LCM variables (L and C). The selected cubic polynomial model was not included in the table because it is not a linear model. While the LCM suggests that a congruence effect does not exist, the cubic level-dependent model suggests that there may be a level-dependent effect of congruence on women’s sexual satisfaction. Figure 3.2 displays the response surface from the cubic model. For low sexual desire levels, congruence seems to effect women’s sexual satisfaction, but not at higher levels. In other words, women experiencing sexual desire discrepancy may only experience reduced sexual satisfaction when the sexual desire is lower in their partnership. Humberg and colleagues (2022) report that no standard method for correcting for multiple tests exists yet in determining the regions of level-dependent outcomes, but they suggested that using $\alpha = 0.01$

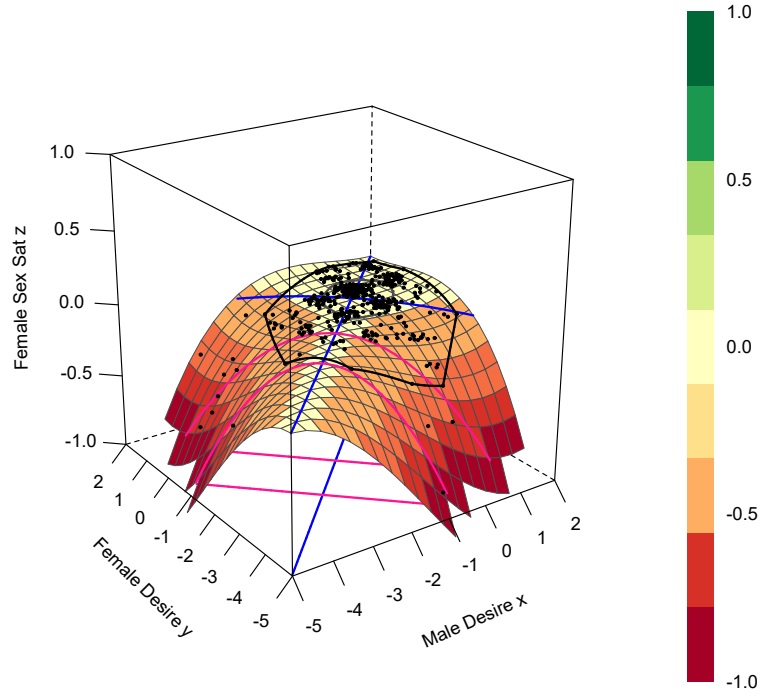


Figure 3.2: *Women's strict cubic level-dependent model*

could be useful. Table 3.8 contains the region information for both $\alpha = 0.01$ and $\alpha = 0.05$ for the original and log-normal models.

Table 3.8: *Women's strict level-dependent regions*

α	Model	Region	Lower Bound	Upper Bound	Data Points	Percent Data
0.01	Original	n.s.	$-\infty$	-2.65	1	0.22
		negative	-2.65	-1.50	20	4.31
		n.s.	-1.50	$+\infty$	443	95.47
0.01	L-N	n.s.	$-\infty$	$+\infty$	464	100.00
0.05	Original	n.s.	$-\infty$	-4.49	0	0.00
		negative	-4.49	-1.18	59	12.72
		n.s.	-1.18	$+\infty$	405	87.28
0.05	L-N [†]	negative	$-\infty$	-0.61	123	26.51
		n.s.	-0.61	4.17	341	73.49
		positive	4.17	$+\infty$	0	0.00

Note. Regions with no data points are not able to be interpreted.

[†]L-N region was reversed to reflect the direction of the original relationships.

Chapter 4

Discussion

4.1 Empirical Example Discussion

As demonstrated in the empirical example, the effect of congruence/discrepancy can be misunderstood when the assumptions behind the models used are untested. The findings of this report tentatively indicate that sexual desire discrepancy has different conceptualizations and applications for heterosexual men and women presenting for couple therapy. The men's results supported the use of a linear model of sexual desire discrepancy. On average, men's sexual satisfaction was higher when their partner's desire was higher than their own, and lower when it was lower than their own, controlling for sexual frequency and relationship length. This effect explained a small amount of additional variance in sexual satisfaction above and beyond sexual frequency and relationship length.

The results for women further demonstrate the danger of blindly applying linear models, such as the latent congruence model, to congruence/discrepancy hypotheses. The linear models of congruence did not fit the data as well as the cubic models, and the LCM coefficients indicated no significant congruence effect. In contrast, the exploratory cubic results suggested that women may experience a level-dependent congruence effect, where higher sexual satisfaction is predicted by congruent sexual desire, but only at low levels of sexual desire; at higher levels, congruence/discrepancy had no significant effect on sexual satisfaction. Put

differently, sexual desire discrepancy negatively impacted women’s sexual satisfaction only when sexual desire was relatively lower between them and their partner.

These results contradicted findings in previous sexual desire discrepancy studies that applied only linear models (e.g., Eisert, 2021, Willoughby et al., 2014, Willoughby & Vitas, 2012, Mark & Murray, 2012; Mark, 2012) in that discrepancy may have different effects based on different levels of desire for women. Research that has found null results for sexual desire discrepancy should be reassessed through the lens of polynomial RSA, particularly for results about heterosexual women.

4.2 Key Takeaways for Family Scientists

Overall, this report highlights the importance of understanding the models used to answer our research questions. Every statistical model is laden with assumptions about the nature of the data-generating process, the variable relationships, and the conceptualization of the variables. These assumptions must be assessed for appropriateness each time a model is used. This is particularly true in the case of latent congruence modeling, which was recently re-branded as the dyadic score model by Iida and colleagues (2018). If family scientists are not made aware of alternatives to the LCM and its limitations, we are doomed to embody Abraham Maslow’s law of the instrument: “I suppose it is tempting, if the only tool you have is a hammer, to treat everything as if it were a nail” (Maslow, 1966, pp.15-16).

4.3 Limitations

There are several limitations to this report. First, the empirical example used an exploratory, not a confirmatory, approach. Therefore, these results must be replicated using other datasets before they can be considered generalizable. The analyses were cross-sectional, so longitudinal studies should be designed to assess these relationships. In addition, the problem of multiple statistical tests is still an open area of research for polynomial RSA (Humberg et al., 2022); therefore, the level-dependent results for women should be inter-

preted with caution. Due to the scope of this study, the empirical example did not employ the actor-partner interdependence model, which could help to test whether there are gender-invariant actor or partner effects on sexual satisfaction. Future research should consider testing these effects. Finally, the empirical findings of this study are only generalizable to the demographics represented in the dataset: Midwestern, heterosexual couples who initiated couple therapy.

4.4 Conclusion

This report highlights the dangers of haplessly using the latent congruence model by reviewing a general form of congruence modeling using RSA, demonstrating how the LCM is nested within it, presenting an empirical example, and discussing the findings of the example. Just as scholars should regularly self-reflect on their implicit biases and prejudgements, we must do the same with our statistical models. Family science is becoming a diverse, evolving discipline that can continue to grow as appropriate methodologies are used.

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Appendix A

Supplementary Analyses

Table A.1: *Men's log-normalized polynomial models*

Order	Model Name	K	LL	AICc	ΔAICc	AICcWt	CFI	R^2	R^2_{adj}
1	Difference	6	-525.84	1,063.86	—	0.208	1.000	0.326	0.320
2	SSQD	7	-525.46	1,065.17	1.30	0.109	1.000	0.327	0.319
1	Only x	6	-526.58	1,065.35	1.49	0.099	1.000	0.323	0.317
1	Null	5	-527.83	1,065.80	1.94	0.079	1.000	0.319	0.315
1	Additive	7	-525.79	1,065.83	1.97	0.078	1.000	0.326	0.318
1	Only y	6	-527.33	1,066.85	2.98	0.047	1.000	0.321	0.315
2	SRR	8	-525.40	1,067.11	3.25	0.041	1.000	0.327	0.318
2	Interaction	8	-525.43	1,067.18	3.32	0.040	1.000	0.327	0.318
2	SRSQD	8	-525.44	1,067.20	3.34	0.039	1.000	0.327	0.318
2	Strong	8	-525.44	1,067.20	3.34	0.039	1.000	0.327	0.318
2	Only x^2	7	-526.52	1,067.28	3.42	0.038	1.000	0.323	0.316
1	Mean	6	-527.74	1,067.66	3.80	0.031	1.000	0.319	0.313
2	SQD	6	-527.77	1,067.73	3.87	0.030	1.000	0.319	0.313
3	CA	7	-526.77	1,067.79	3.93	0.029	1.000	0.322	0.315
2	Only y^2	7	-527.21	1,068.67	4.81	0.019	1.000	0.321	0.314
2	SRRR	9	-525.17	1,068.73	4.87	0.018	1.000	0.328	0.317
2	RR	7	-527.67	1,069.58	5.72	0.012	0.999	0.320	0.312
3	RRCA	8	-526.69	1,069.70	5.84	0.011	1.000	0.323	0.314
3	CL	7	-527.73	1,069.70	5.84	0.011	0.999	0.319	0.312
2	Full	10	-524.93	1,070.34	6.48	0.008	1.000	0.328	0.317
2	Weak	10	-524.94	1,070.36	6.50	0.008	1.000	0.328	0.317
3	RRCL	8	-527.66	1,071.64	7.78	0.004	0.993	0.320	0.311
3	Cubic	14	-524.10	1,077.14	13.28	0.000	1.000	0.331	0.313

Table A.2: *Men's top model absolute fit indices*

Model Name	RMSEA _{scaled}	RMSEA _{scaled} 90% CI	SRMR
Difference	0.000	[0.000 , 0.055]	0.009
Null	0.019	[0.000 , 0.060]	0.010
Only x	0.015	[0.000 , 0.062]	0.012
SSQD	0.000	[0.000 , 0.060]	0.009
Additive	0.017	[0.000 , 0.066]	0.010

Table A.3: *Women's log-normalized polynomial models*

Order	Model Name	K	LL	AICc	Δ AICc	AICcWt	CFI	R^2	R^2_{adj}
3	CL	7	-551.47	1,117.18	—	0.185	1.000	0.319	0.312
1	Null	5	-553.72	1,117.57	0.39	0.152	1.000	0.313	0.308
2	SQD	6	-553.33	1,118.84	1.66	0.081	1.000	0.314	0.308
3	RRCL	8	-551.31	1,118.94	1.77	0.077	1.000	0.319	0.310
1	Only y	6	-553.47	1,119.13	1.95	0.070	1.000	0.313	0.307
1	Mean	6	-553.59	1,119.37	2.19	0.062	1.000	0.313	0.307
1	Difference	6	-553.61	1,119.41	2.24	0.061	1.000	0.313	0.307
1	Only x	6	-553.71	1,119.61	2.43	0.055	1.000	0.313	0.307
2	Only y^2	7	-553.07	1,120.39	3.21	0.037	1.000	0.315	0.307
2	RR	7	-553.16	1,120.57	3.39	0.034	1.000	0.314	0.307
3	CA	7	-553.22	1,120.68	3.51	0.032	1.000	0.314	0.307
2	SSQD	7	-553.30	1,120.84	3.66	0.030	1.000	0.314	0.306
1	Additive	7	-553.47	1,121.19	4.01	0.025	1.000	0.313	0.306
2	Only x^2	7	-553.69	1,121.63	4.45	0.020	0.998	0.313	0.305
2	SRSQD	8	-552.84	1,122.00	4.82	0.017	1.000	0.315	0.306
2	Strong	8	-552.84	1,122.00	4.82	0.017	1.000	0.315	0.306
3	RRCA	8	-553.03	1,122.37	5.19	0.014	1.000	0.315	0.306
2	SRR	8	-553.12	1,122.56	5.39	0.013	0.999	0.314	0.305
2	Interaction	8	-553.40	1,123.12	5.95	0.009	0.996	0.313	0.304
2	SRRR	9	-552.78	1,123.95	6.77	0.006	0.997	0.315	0.305
2	Weak	10	-552.74	1,125.96	8.79	0.002	0.992	0.315	0.303
2	Full	10	-552.74	1,125.96	8.79	0.002	0.992	0.315	0.303
3	Cubic	14	-550.05	1,129.03	11.85	0.000	1.000	0.323	0.305

Table A.4: *Women's top model absolute fit indices*

Model Name	RMSEA _{scaled}	RMSEA _{scaled} 90% CI	SRMR
SQD	0.000	[0.000 , 0.049]	0.009
CL	0.000	[0.000 , 0.047]	0.011
Null	0.018	[0.000 , 0.060]	0.013
Only y	0.020	[0.000 , 0.063]	0.012
RRCL	0.000	[0.000 , 0.059]	0.010