A Multidimensional Compatibility Model for Partner Selection for Industrial Section of Indian Society: Integrating Neurochemistry, Psychological Traits, Socioeconomic Indicators, and Sexual Preferences

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1. Abstract

This paper proposes a multidimensional probabilistic model to assess romantic compatibility among industrial and professional populations in India. Drawing upon neurochemical typology (Fisher 2009), attachment theory (Bowlby 1988), conflict resolution frameworks (Thomas and Kilmann 1974), assortative mating principles (Watson et al. 2004), and the theory of second best (Lipsey and Lancaster 1956), the model integrates ten dimensions: neurochemistry, attachment style, conflict style, cognitive aptitude, age differential, income aggregation, mutual attraction, sexual temperament, dominance orientation, and kink openness. Each dimension is operationalized on a standardized 0–10 scale and assigned a temporally evolving weight reflecting changes in relational priorities over a ten-year horizon. Compatibility is computed as a weighted aggregation of these scores, further adjusted by a penalty factor when red-flag incompatibilities are detected. The model incorporates fuzzy logic (Zadeh 1965) to represent the graded and uncertain nature of relational attributes, enabling compatibility to be expressed both numerically and linguistically. A correlation matrix among dimensions is specified to account for interdependencies, and a neural network-based approach is proposed for future weight remodeling. This framework offers a comprehensive, theoretically grounded methodology for evaluating relational fit in high-cognition Indian populations. Limitations include reliance on self-reported data, cultural specificity, and simplification of complex constructs into numeric indices. Future research directions include longitudinal validation and integration of machine learning approaches to enhance predictive accuracy.

2. Literature Review

The multidimensional assessment of romantic compatibility has been an area of active research across psychology, sociology, and behavioral economics. This section reviews the primary theoretical and empirical contributions that inform the present model, focusing on neurochemical typology, attachment theory, conflict resolution strategies, cognitive compatibility, socioeconomic predictors, sexual and dominance dynamics, fuzzy logic, and computational modeling approaches.

Helen Fisher (2009) advanced a neurobiological framework positing that individuals exhibit stable personality constellations rooted in the predominance of four neurochemical systems: dopamine, serotonin, testosterone, and estrogen. These systems correspond to the Explorer, Builder, Director, and Negotiator types, respectively. Large-scale survey research has demonstrated that these temperaments shape not only attraction preferences but also long-term compatibility patterns. For example, Explorers tend to prefer novelty-seeking partners, while Builders often prioritize stability and social conformity.

Attachment theory, initially formulated by Bowlby (1988), conceptualizes the formation of internal working models of intimacy based on early caregiving experiences. Hazan and Shaver (1987) extended this framework to adult romantic relationships, identifying Secure, Anxious, and Avoidant attachment styles. Meta-analytic studies have confirmed that Secure–Secure dyads consistently exhibit higher relational satisfaction and resilience, whereas Avoidant–Avoidant combinations are associated with relational disengagement (Mikulincer and Shaver 2007).

Conflict resolution has been recognized as a critical determinant of relationship health. The Thomas-Kilmann Conflict Mode Instrument (Thomas and Kilmann 1974) identifies five primary styles: Collaborating, Compromising, Avoiding, Competing, and Accommodating. Longitudinal work by Gottman (1994) emphasizes that maladaptive patterns, including persistent avoidance and escalation, are predictive of dissolution. The integration of conflict style compatibility into the present model reflects this evidence base.

Assortative mating describes the observed tendency for individuals to partner with others of similar cognitive and socioeconomic status (Watson et al. 2004). Cognitive compatibility, often operationalized as IQ similarity, has been linked to shared problem-solving, value alignment, and communication efficacy. While perfect symmetry is not required, extreme discrepancies can contribute to relational strain.

Economic stress is a well-established predictor of relational discord (Kalmijn 1994). In the Indian industrial context, aspirational lifestyles and high opportunity costs further heighten the salience of income compatibility. Studies indicate that income parity not only affects daily stress but also correlates with perceived fairness and long-term stability.

While less extensively studied, sexual temperament and dominance orientation have emerged as relevant dimensions in qualitative research (Levine 2002). Mismatched sexual desire, divergent preferences for dominance or submission, and limited openness to experimentation have been cited as significant sources of dissatisfaction. The present model incorporates these factors as categorical variables.

Traditional deterministic scoring approaches often fail to capture the ambiguity inherent in subjective judgments of compatibility. Zadeh (1965) introduced fuzzy set theory to represent constructs with gradated membership rather than binary classification. Fuzzy logic enables compatibility dimensions to be modeled as continuous degrees of membership in "high compatibility," supporting more nuanced interpretation and aggregation.

Lipsey and Lancaster (1956) articulated the theory of second best, which posits that when an optimal condition is unattainable, the other conditions that would otherwise be optimal may not yield the best possible outcome. Applied to relational modeling, this implies that certain red flag incompatibilities cannot be offset by strength in other domains. Consequently, the model applies a non-compensatory penalty when such critical mismatches are detected.

Recent scholarship has explored the use of computational modeling and neural networks to predict relational outcomes (Finkel et al. 2012). Machine learning frameworks allow for dynamic recalibration of weights based on longitudinal data, improving predictive accuracy and accommodating population-specific patterns. The present model proposes a neural network-based remodeling mechanism as a future enhancement.

3. Assumptions and Scope

The proposed compatibility model is grounded in several explicit assumptions necessary for its conceptual validity and practical applicability. These assumptions clarify the scope of inference and delineate the boundaries within which the model's results should be interpreted.

3.1. Target Population

The model is designed specifically for the industrial, technical, and professional segments of Indian society, where relational decisions are increasingly shaped by hybrid influences of traditional norms and modern individual autonomy (Finkel et al. 2012). This population is characterized by:

- High educational attainment.
- Elevated cognitive aptitude (baseline IQ $\geq$120).
- Urban or peri-urban residence.
- Stable or aspirational middle- to upper-middle-class income levels.

Accordingly, the model's assumptions about income expectations, educational compatibility, and relational autonomy may not generalize to rural populations or settings with markedly different cultural dynamics.

3.2. Self-Reported Accuracy

The model assumes that individuals are able and willing to self-report accurately across all dimensions, including:

- Neurochemical temperament.
- Attachment style.
- Conflict resolution strategy.
- Sexual temperament.
- Dominance orientation.
- Kink openness.
- Perceived attraction to the partner.

Given the sensitive nature of several variables, social desirability bias and self-awareness limitations may introduce measurement error.

3.3. Stability of Traits

It is assumed that core traits are stable over short- and medium-term time horizons (1–2 years). Although personality and preferences can evolve, the model treats them as relatively fixed inputs for the purposes of calculating temporal compatibility projections over a decade.

3.4. Independence of Dimensions

While some interdependence is acknowledged (e.g., attraction may correlate with sexual temperament), the model treats each dimension as contributing unique variance to overall compatibility. A correlation matrix is introduced in Section 6 to partially account for such dependencies.

3.5. Applicability of Fuzzy Logic

The model assumes that compatibility judgments can be meaningfully operationalized using fuzzy logic constructs (Zadeh 1965), wherein membership degrees represent graded compatibility rather than binary presence or absence.

3.6. Theory of Second Best

It is further assumed that critical incompatibilities cannot be fully compensated by strengths in other areas. This reflects the theory of second best (Lipsey and Lancaster 1956), which posits that partial optimization fails in the presence of binding constraints.

3.7. Time-Evolving Priorities

The weighting of dimensions is assumed to evolve predictably over time, reflecting the natural progression of relational priorities (e.g., the growing importance of income and conflict management, and the declining salience of novelty-based attraction).

3.8. Cultural Specificity

The model reflects Indian cultural expectations regarding age differential (male older by 1–5 years), income asymmetry, and certain relational roles. It is not intended for direct application to Western, rural, or highly traditional arranged marriage contexts without recalibration.

3.9. Limitations

The model's reliance on quantitative scoring and weighting introduces simplification of complex relational constructs. Moreover, the absence of large-scale longitudinal validation

4. Theoretical Framework

This section defines the conceptual basis and operationalization of the ten dimensions incorporated into the model. Each dimension is informed by established theories, empirical findings, and cultural considerations relevant to industrial and professional Indian populations.

4.1. Neurochemical Typology

Neurochemical temperament reflects dominant neurobiological systems influencing attraction and bonding.

Classification:

- Explorer (dopamine-dominant)
- Builder (serotonin-dominant)
- Director (testosterone-dominant)
- Negotiator (estrogen-dominant)

Similarity or complementarity of neurochemical profiles predicts higher compatibility (Fisher 2009).

4.2. Attachment Style

Attachment style describes characteristic patterns of closeness, reassurance-seeking, and emotional regulation.

Classification:

- Secure
- Anxious
- Avoidant

Secure–Secure dyads yield the highest relational stability (Bowlby 1988; Hazan and Shaver 1987).

4.3. Conflict Resolution Style

Conflict style denotes preferred strategies for managing disagreement.

Classification:

- Collaborating
- Compromising
- Avoiding
- Competing

Constructive or complementary conflict styles improve compatibility, while maladaptive pairings (e.g., Competing vs. Avoiding) introduce significant risk (Thomas and Kilmann 1974).

4.4. Cognitive Compatibility

Cognitive compatibility is measured as similarity in cognitive aptitude (IQ).

Operational Rule:

$$IQ_{Score} = max\left(3, 10 - \frac{(|\mathrm{IQ_M} - \mathrm{IQ_F}|)}{4}\right)$$

Moderate IQ differences are tolerable; differences >30 points reduce compatibility substantially.

4.5. Age Differential

Age difference affects cultural acceptability and perceived maturity alignment.

Compatibility is maximized when the male partner is 1–5 years older.

4.6. Income Aggregation

Combined monthly income predicts perceived security and aspirational compatibility.

Classification:

$$\geq ₹200{,}000: Score = 10$$

$$₹100{,}000 - 199{,}999: Score = 8$$

$$₹50{,}000 - 99{,}999: Score = 6$$

$$< ₹49{,}999: Score = 4$$

Higher income levels correlate positively with satisfaction (Kalmijn 1994).

4.7. Mutual Attraction

Mutual attraction is assessed by each partner’s subjective rating of the other. Ratings <4 indicate a critical mismatch, triggering a penalty.

4.8. Sexual Temperament, Dominance, and Kink Openness

- Sexual Temperament: Exploratory vs. relational preferences.
- Dominance Orientation: Preferred power dynamics.
- Kink Openness: Comfort with non-normative sexual practices.

Alignment in these domains predicts higher sexual and relational satisfaction (Levine 2002).

4.9. Fuzzy Logic Representation

Traditional deterministic models fail to capture ambiguity and gradation inherent in subjective compatibility judgments.

Fuzzy Logic Framework: Each score X_i is interpreted as a membership degree in the fuzzy set "High Compatibility":

$$\mu_i(x) \in [0,1]$$

Scores are combined via a weighted sum of memberships, defuzzified to yield a numeric compatibility estimate.

4.10. Theory of Second Best

The theory of second best (Lipsey and Lancaster 1956) holds that if a single optimality condition cannot be satisfied, optimizing other conditions does not ensure optimal outcomes.

When a critical incompatibility (*red flag*) is present, all other dimensions are discounted by a penalty factor.

$$CompatibilitAdjusted = \lambda \times Compatibility$$

where:

$$\lambda = 0.4$$

This reflects the non-compensatory nature of certain severe mismatches.

5. Mathematical Model

The compatibility estimation framework developed in this study formalizes relationship evaluation as a deterministic mapping from a multidimensional space of measured attributes to a scalar compatibility index. This model is dynamic in time, incorporates fuzzy set representations to reflect uncertainty, and introduces an explicit penalty mechanism to handle critical incompatibilities.

Let the space of observed compatibility dimensions be defined as the closed hypercube

$$\mathcal{X} = [0,10]^{10},$$

which contains all feasible vectors of dimension scores. Each element $X \in X$ is expressed as

$$\mathbf{X} = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_{10} \end{bmatrix},$$

where each scalar X_i denotes the normalized score of the i^{th} compatibility dimension. These dimensions correspond respectively to neurochemical temperament similarity, attachment style alignment, conflict resolution style complementarity, IQ similarity, age difference, combined income, mutual attraction, sexual temperament alignment, dominance preference compatibility, and openness to sexual kinks.

At each point in time $t \in [0,10]$, the model defines a vector of raw (unnormalized) importance weights $w(t) \in \mathbb{R}^{10}_{>0}$. These weights encode the relative salience of each dimension at time t, acknowledging that relational priorities evolve as relationships mature. Specifically, each component $w_i(t)$ is interpolated from assigned reference values at the years $\tau_0 = 0,\ \tau_2 = 2,\ \tau_5 = 5,$ and $\tau_{10} = 10$. For $t \in [\tau_j, \tau_j + 1]$, the interpolation is defined by the affine mapping

$$w_i(t) = w_i^{(\tau_j)} + \frac{t-\tau_j}{\tau_{j+1}-\tau_j}\left(w_i^{(\tau_{j+1})} - w_i^{(\tau_j)}\right),$$

where $\omega_\iota^{(\tau_\kappa)}$denotes the raw weight assigned to dimension iii at reference time τ_κ. This specification ensures continuity and a smooth transition of weights over the relationship timeline.

To interpret weights as proportions, the raw weight vector is normalized to the unit simplexΔ^9, yielding the vector of normalized weights:

$$\mathbf{W}(t) = \frac{\mathbf{w}(t)}{\sum_{j=1}^{10} w_j(t)},$$

satisfying the condition

$$\sum_{i=1}^{10} W_i(t) = 1.$$

This normalization guarantees that the relative contribution of each dimension to the aggregate compatibility measure is explicitly bounded and interpretable, regardless of the scaling of raw weights.

The nominal compatibility estimate $C(t)$ is computed as the standard Euclidean inner product between the normalized weight vector $W(t)$and the dimension score vector X:

$$C(t) = \mathbf{W}(t)^\top \mathbf{X} = \sum_{i=1}^{10} W_i(t)\, X_i.$$

This quantity lies in the interval [0,10] preserving interpretability as a proportion of maximum compatibility.

Recognizing the inherently subjective and imprecise nature of many dimension scores, the model introduces a fuzzy representation. For each dimension *i*, a fuzzy membership degree $\mu_i \in [0,1]$ is defined by the linear mapping

$$\mu_i = \frac{X_i}{10}.$$

Collectively, these degrees are aggregated into the vector

$$\boldsymbol{\mu} = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_{10} \end{bmatrix},$$

which represents the degree of membership of each observed dimension in the fuzzy set "High Compatibility." The aggregate fuzzy compatibility is computed analogously:

$$\mu_C(t) = \mathbf{W}(t)^\top \boldsymbol{\mu} = \sum_{i=1}^{10} W_i(t)\, \mu_i,$$

producing a scalar in [0,1] that can be interpreted as the overall degree of perceived compatibility.

To model the impact of incompatibilities that cannot be offset by other dimensions—a phenomenon predicted by the theory of second best (Lipsey and Lancaster, 1956)—the model defines a red flag indicator variable:

$$R = \begin{cases} 1, & \text{Critical incompatibility} \\ 0, & \text{otherwise} \end{cases}$$

In this study, red flags include configurations such as severe conflict style mismatch, extreme IQ disparity (>30 points), complete absence of mutual attraction, or irreconcilable dominance preferences.

When such a condition arises, the model applies a penalty operator:

$$C_{\text{adj}}(t) = \mathcal{P}\big(C(t), R\big) = \begin{cases} \lambda\, C(t), & R = 1, \\ C(t), & R = 0, \end{cases}$$

where $\lambda \in (0,1)$ is the penalty factor. Here, $\lambda = 0.4$ reflects the assumption that critical incompatibility reduces effective compatibility by 60%.

In addition to the deterministic aggregation, the model specifies the correlation matrix

$$\mathbf{R} = \big[R_{ij}\big] \in [-1,1]^{10\times 10},$$

whose entries are given by

$$R_{ij} = \mathrm{Corr}\big(X_i, X_j\big).$$

This matrix quantifies the degree of linear association between each pair of compatibility dimensions. For example, it is empirically plausible that mutual attraction correlates positively with sexual temperament alignment and kink openness, or that attachment style correlates with conflict resolution preferences. Although the correlation matrix does not modify the aggregation function $C(t)$, it provides critical information about multicollinearity and informs error estimation and regularization during neural network–based remodeling of weights (discussed in Section 7). In future extensions of the model incorporating stochastic error terms, $\mathbf{R}$ could also be used to construct covariance-adjusted confidence intervals for compatibility estimates.

Formally, the complete model is expressed as the composite mapping:

$$\mathcal{M} : \mathcal{X} \times [0,10] \times \{0,1\} \to \mathbb{R}, \quad \mathcal{M}(\mathbf{X}, t, R) = \mathcal{P}\Big(\mathbf{W}(t)^\top \mathbf{X},\, R\Big).$$

This yields a scalar compatibility estimate at each point in time, explicitly accounting for temporal evolution of weights, the graded nature of subjective evaluations, and the possibility of non-compensable incompatibility constraints.

The model therefore produces three principal outputs: the numeric compatibility estimate $C_{adj}(t) \in [0,10]$, the fuzzy membership degree $\mu_C(t) \in [0,1]$, and a linguistic label derived from threshold mappings (e.g., "High Compatibility," "Moderate Compatibility," "Low Compatibility"). These outputs together enable a multidimensional, temporally sensitive, and partially fuzzy assessment of romantic fit, suitable for further probabilistic calibration and cross-sectional or longitudinal validation.

6. Weight Remodelling via Neural Networks

While the time-dependent weighting function $w(t)$ defined in Section 5 is specified through deterministic interpolation of expert-assigned reference weights, this approach inevitably incorporates subjective biases and fixed assumptions regarding the evolution of relational priorities over time. To enhance the adaptability and empirical grounding of the model, the framework proposes the application of supervised machine learning—specifically, feedforward neural networks—to recalibrate the weight function dynamically based on observed compatibility outcomes.

Formally, let the training dataset comprise a collection of N historical relationship records:

$$\mathcal{D} = \left\{ \left(\mathbf{X}^{(n)},\, t^{(n)},\, y^{(n)}\right) \right\}_{n=1}^{N},$$

where:

- $X(n) \in X$ denotes the vector of dimension scores for the n-th relationship,
- $t(n) \in [0,10]$ is the relationship duration at assessment,
- $y(n) \in [0,10]$ represents an empirical outcome measure of relational success (e.g., validated satisfaction score, persistence index, or expert rating).

A neural network $f_\theta : \chi \times [0,10] \to \mathbb{R}^{10}_{\geq 0}$ parameterized by weights θ is trained to predict the unnormalized weight vector $w(t)$ as a function of the observed attributes and time. The architecture of f_θ may be specified as a multilayer perceptron with ReLU or softplus activation functions to enforce non-negativity of outputs.

Given the predicted raw weights:

$$\widehat{\mathbf{w}}^{(n)} = f_\theta\left(\mathbf{X}^{(n)},\, t^{(n)}\right),$$

the corresponding normalized weights are computed by the simplex projection:

$$\widehat{\mathbf{W}}^{(n)} = \frac{\widehat{\mathbf{w}}^{(n)}}{\sum_{j=1}^{10} \widehat{w}_j^{(n)}}.$$

The predicted compatibility score is then obtained via the aggregation operator:

$$\widehat{C}^{(n)} = \left(\widehat{\mathbf{W}}^{(n)}\right)^\top \mathbf{X}^{(n)}.$$

The training objective is to minimize the empirical loss function:

$$\mathcal{L}(\theta) = \frac{1}{N} \sum_{n=1}^{N} \left(y^{(n)} - \widehat{C}^{(n)}\right)^2 + \Omega(\theta),$$

where $\Omega(\theta)$ is a regularization penalty that can be defined, for example, as an ℓ_2 norm or a covariance-informed shrinkage term incorporating the correlation matrix $\boldsymbol{R}$. The inclusion of $\boldsymbol{R}$ in regularization serves to discourage unstable solutions in which highly correlated dimensions receive disproportionately divergent weights.

Once training is complete, the neural network f_θ can be applied to any new input pair (X, t) to produce time-sensitive, empirically grounded weight vectors. These can then replace or complement the deterministic interpolation scheme described previously. The adjusted compatibility calculation proceeds identically, incorporating the fuzzy membership mapping and red flag penalty:

$$C_{\mathrm{adj}}(t) = \mathcal{P}\Big(\big(\widehat{\mathbf{W}}(t)\big)^{\top}\mathbf{X},\, R\Big).$$

This hybrid approach balances the interpretability of expert-elicited reference weights with the adaptive power of supervised learning, enabling the model to evolve as more outcome data become available and to better reflect real-world relational dynamics in the target population.

7. Limitations and Future Research Directions

While the proposed compatibility model offers a rigorous and multidimensional framework for assessing relational fit, it necessarily embodies several limitations inherent in the operationalization of complex human relationships into quantitative constructs. Acknowledging these constraints is essential for the appropriate interpretation of results and the design of future refinements.

First, the model relies heavily on self-reported data across all dimensions, including subjective perceptions of mutual attraction, sexual temperament, and openness to kinks. Self-report introduces vulnerability to biases such as social desirability, acquiescence effects, and introspective limitations, which may attenuate the reliability of the scores X. In addition, some constructs, particularly neurochemical typology and sexual dominance orientation, may be partially opaque to respondents without guided assessment instruments, further compounding measurement error.

Second, the temporal evolution of weights is specified through interpolation of expert-assigned reference values or, in the neural network implementation, through supervised learning on historical data. Both approaches implicitly assume that the relational priorities of the target population exhibit relatively stable temporal trajectories and that past patterns are predictive of future compatibility. However, in rapidly evolving cultural contexts—such as industrial segments of Indian society—these assumptions may be periodically invalidated by shifts in socioeconomic expectations, gender norms, or relationship structures. Periodic recalibration of the model is therefore essential.

Third, while the correlation matrix R captures linear interdependencies among dimensions, the model does not explicitly incorporate these correlations into the aggregation function itself. Thus, the computed compatibility scores assume conditional independence of dimensions in their contribution to aggregate compatibility. Although this simplifies computation and interpretability, it omits the possibility of synergistic or antagonistic interactions between dimensions (for example, how high mutual attraction may buffer the impact of moderate conflict style mismatch). Future extensions could explore nonlinear aggregation functions or Bayesian network structures that model such dependencies explicitly.

Fourth, the red flag penalty function is binary and deterministic: any critical incompatibility reduces compatibility by a fixed proportion. This implementation, while interpretable and conservative, may over-penalize certain combinations where compensatory factors genuinely moderate the adverse impact. A more sophisticated approach could define a probabilistic penalty function in which the magnitude of the adjustment is itself a function of secondary dimensions or the severity of the mismatch.

Finally, the model is developed primarily for industrial and professional populations in India, where socioeconomic stratification, education levels, and cultural norms shape mate selection in distinct ways. Generalization to rural populations, other cultural settings, or different socioeconomic strata would require context-sensitive adaptation of input distributions, weighting trajectories, and red flag definitions.

Future research directions include several promising avenues. First, the collection of large-scale longitudinal datasets linking baseline dimension scores to observed relationship outcomes will enable empirical estimation of dynamic weights and validation of the model's predictive performance. Second, incorporation of stochastic components—such as latent compatibility factors or random effects—would improve the model's capacity to express uncertainty and generate probabilistic forecasts. Third, the development of a modular interface for real-time visualization, including dynamic radar charts and interactive explanations, would support practical application in counseling and decision-making contexts. Finally, exploring alternative aggregation paradigms, such as fuzzy integrals, multi-criteria decision analysis frameworks, or graph-theoretic representations of compatibility, may yield richer interpretive possibilities and stronger alignment with the nuanced nature of romantic relationships.

8. Conclusions

This study has introduced a multidimensional, temporally dynamic model for estimating romantic compatibility in the context of industrial and professional populations in India. By integrating ten distinct dimensions—ranging from neurochemical typology and attachment style to socioeconomic indicators and sexual preferences—the model seeks to capture the multifaceted determinants of relational fit. The formulation combines a deterministic aggregation mechanism with fuzzy set representations to accommodate the graded and subjective nature of compatibility assessments.

The inclusion of time-dependent weight trajectories acknowledges that relational priorities evolve across the life cycle of a relationship, while the penalty operator informed by the theory of second best explicitly accounts for non-compensable incompatibilities. The specification of a correlation matrix further provides a foundation for modeling interdependencies among dimensions, highlighting potential avenues for future refinement. The proposed incorporation of neural network–based weight remodeling illustrates how the framework can progressively learn from empirical data, enhancing both predictive validity and adaptability to cultural shifts.

Despite its rigor, the model necessarily abstracts and simplifies inherently complex human experiences. Its reliance on self-reported measures, deterministic scoring functions, and fixed penalty factors imposes limitations on generalizability and interpretive nuance. Nonetheless, by offering a structured, mathematically grounded approach to compatibility estimation, the model contributes a novel analytical lens to the study of intimate relationships in contemporary Indian society.

Future work should focus on empirical validation through longitudinal datasets, exploration of alternative aggregation and penalty functions, and integration with interactive visualization platforms. Such advancements will be essential to translate this theoretical framework into a robust, user-centered tool capable of informing personal decisions, counseling interventions, and sociological research on relational dynamics.

9. References

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10. Appendix

10.1. A. Time-Indexed Weight Reference Table

This appendix presents the reference raw weights assigned to each dimension across the four anchor time points. These weights are used as input to the interpolation function defining $w_i(t)$.

Dimension	**Year 0**	**Year 2**	**Year 5**	**Year 10**
Neurochemistry	12	14	16	18
Attachment Style	15	13	10	8
Conflict Resolution	10	12	15	17
IQ Similarity	5	8	12	15
Age Difference	6	5	4	3
Income	8	12	15	20
Mutual Attraction	18	12	7	4
Sexual Temperament	12	10	8	6
Dominance Orientation	8	7	6	5
Kink Openness	6	7	8	8

Note: These values are subject to recalibration through neural network training as discussed in Section 6.

10.2. B. Dimension Category Definitions

This appendix describes the classification systems applied to categorical variables.

Neurochemical Typology (Fisher 2009):

- *Explorer*: Dopamine-dominant, novelty-seeking
- *Builder*: Serotonin-dominant, stability-oriented
- *Director*: Testosterone-dominant, analytical
- *Negotiator*: Estrogen-dominant, empathetic

Attachment Style (Bowlby 1988; Hazan and Shaver 1987):

- *Secure*: Comfortable with intimacy
- *Anxious*: Preoccupied with closeness
- *Avoidant*: Discomfort with closeness

Conflict Resolution (Thomas and Kilmann 1974):

- *Collaborating*: Joint problem solving
- *Compromising*: Mutual concession
- *Avoiding*: Withdrawal
- *Competing*: Assertive confrontation

Sexual Temperament:

- *Exploratory*: Preference for novelty
- *Relational*: Preference for bonding-focused intimacy

Dominance Orientation:

- *Dominant*: Preference for control
- *Submissive*: Preference for yielding
- *Switch*: Flexible
- *Neutral*: No preference

Kink Openness:

- Measured on a 0–10 scale from complete aversion to high enthusiasm

10.3. C. Example Correlation Matrix

Below is an illustrative correlation matrix $\boldsymbol{R}$, representing plausible associations among dimensions. Actual estimates should be derived empirically.

Dimension	Nch	Att	Con	IQ	Age	Inc	Attr	Sex	Dom	Kink
Nch	1.00	0.20	0.10	0.10	0.00	0.00	0.30	0.40	0.20	0.20
Att		1.00	0.50	0.00	0.00	0.00	0.20	0.10	0.10	0.10
Con			1.00	0.00	0.00	0.00	0.10	0.10	0.20	0.10
IQ				1.00	0.10	0.40	0.00	0.00	0.00	0.00
Age					1.00	0.20	0.00	0.00	0.00	0.00
Income						1.00	0.10	0.00	0.00	0.00
Attraction							1.00	0.30	0.30	0.40
Sexuality								1.00	0.40	0.50
Dominance									1.00	0.30
Kink										1.00

Legend:

- Nch = Neurochemistry
- Att = Attachment
- Con = Conflict
- IQ = IQ Similarity
- Inc = Income
- Attr = Attraction
- Sex = Sexual Temperament
- Dom = Dominance Orientation