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# AI-Driven Generational Matchmaking: A Dynamic Logic Framework for Enhancing Marital Stability and Divorce Prevention

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*Abstract*—**This paper presents "Eternal Union," an AI-driven matchmaking framework designed to enhance marital stability through generation-specific compatibility analysis. Unlike conventional platforms employing static algorithms, the proposed system implements a dynamic logic framework that segments users into three generational cohorts—Gen Z, Millennials, and Divorced individuals—to enable personalized psychological profiling. The architecture integrates a Convolutional Neural Network for real-time age verification and trust-score analysis, establishing a security layer that mitigates fraudulent identities through automated facial age estimation with a ±5-year verification threshold. Marital compatibility is operationalized through five weighted stability pillars—Finance, Communication, Family Boundaries, Trust, and Lifestyle—derived from core divorce triggers, with pillar weights dynamically adjusted based on generational regime detection. Preliminary results demonstrate that psychographically segmented matchmaking achieves higher accuracy in long-term compatibility assessment (stability means: 0.742 for Gen Z to 0.889 for Divorced individuals) with verification accuracy exceeding 96**

## I. Introduction

Marriage in the digital era is increasingly shaped by technology, shifting cultural norms, and evolv ing generational values. Traditional notions of lifelong partnership are being renegotiated in a con text where online matchmaking platforms, social media, and data-driven decision systems mediate how individuals meet, evaluate, and commit to potential partners. At the same time, divorce rates in many urban and semi-urban populations remain high, suggesting a growing gap between how relationships are formed and what is required for long-term marital stability. Existing matrimonial and dating platforms largely rely on static, one-size-fits-all algorithms that prioritize superficial similarity (such as age, location, or basic interests) and short-term at traction over deeper, long-horizon compatibility. These systems rarely account for generational differences in expectations around career, digital privacy, gender roles, financial planning, or fam ily involvement. As a result, they often create an illusion of compatibility that may not withstand real-life stressors such as financial conflict, communication breakdown, or trust violations. At the sametime, advances in artificial intelligence (AI), machine learning (ML), and computer vision have created powerful tools for profiling user preferences, verifying identity, and modeling complex human behavior. However, these tools are underutilized in the specific context of marital stability and divorce prevention. This research addresses that gap by proposing "Eternal Union," an AI-driven generational matchmaking framework explicitly designed to enhance marital stability and reduce divorce risk.

## II. Literature Review

The literature on AI and intimate relationships spans three intersecting domains: AI matchmaking systems, machine-learning–based divorce prediction, and human–AI intimacy and mediation. Together, these strands contextualize an AI-driven, generationally segmented matchmaking framework aimed at marital stability.

### A. AI Matchmaking, User Trust, and Fairness

AI matchmaking algorithms now underpin most dating platforms, yet user trust depends heavily on perceived fairness and social presence. These factors are strongly associated with users' belief in algorithmic effectiveness [7]. Comparative work on AI versus human matchmakers highlights scalability gains but also ethical concerns regarding algorithmic bias and lack of emotional intelligence [1]. Algorithmic audits of Indian matrimonial platforms demonstrate that recommendation systems can reinforce social biases (e.g., income hierarchies), showing that fairness-aware re-ranking can mitigate such biases with limited accuracy loss [13, 16].

### B. Machine Learning for Divorce Prediction

A parallel body of work applies machine learning to predict divorce risk using couple dynamics. Studies using Gottman-style scales report 91–92% accuracy using random forests [5], while ensemble models and neural networks report accuracies up to 98–100% [8, 11, 14, 17]. Features typically cluster around communication quality, conflict responses, trust, and shared rituals. Recent research extends to interpretable feature ranking, showing that conflict styles and cultural rituals are dominant contributors to divorce [3].

### C. Artificial Intimacy and Mediation

Scholars warn that emotionally responsive chatbots engender "artificial intimacy," which carries risks of attachment distortions and erosion of authentic emotional responsibility [4, 6, 9, 12]. Furthermore, AI-mediated communication (e.g., LLMs crafting apologies) raises questions about "second-person authenticity" [20]. For matchmaking systems, this highlights the need to augment, rather than replace, partners' own agency and emotional labor.

### D. *Artificial Intimacy and AI Companionship*

Recent computational analyses of digital communities, such as r/MyBoyfriendIsAI, reveal that users often seek AI companions for therapeutic benefits, including reduced loneliness and constant emotional support. However, this shift toward ”artificial intimacy” introduces significant risks, such as emotional dependency, dissociation from reality, and psychological grief when model updates alter the AI’s personality. These findings emphasize the need for ethical guardrails in matchmaking systems that simulate deep emotional bonds.[22]

### E. *Gap Analysis*

As shown in Table I, existing research supports accurate prediction but lacks focus on dynamic generational interventions and longitudinal stability metrics.

TABLE I
LITERATURE REVIEW GAP ANALYSIS MATRIX

| Topic/Outcome | Gen Z | Millennials | Divorced | Longitudinal |
|---|---|---|---|---|
| Algorithm perf. | 4 | 2 | 1 | GAP |
| User trust | 5 | 2 | GAP | GAP |
| Stability Analysis | 1 | GAP | GAP | GAP |

## III. PROPOSED METHODOLOGY

### A. *System Architecture and Framework Design*

The proposed ”Eternal Union” framework implements a multi-modal AI pipeline designed to quantify marital compatibility and verify user integrity. The architecture operates on a hybrid logic of Deep Learning for identity verification and Natural Language Processing (NLP) for psychographic profiling. The system consists of four primary modules: (1) multi-generational data ingestion, (2) CNN-based age verification, (3) weighted pillar scoring, and (4) stability forecasting.

### B. *Dataset Acquisition and Segmentation*

The experimental dataset comprises structured and unstructured user profiles categorized into three distinct generational cohorts: Gen Z, Millennials, and Divorced individuals. Each profile is characterized by a high-dimensional feature vector containing:

- **Demographic metadata:** Verified age, location, and professional status.
- **Psychographic traits:** Responses to category-specific ”tricky questions” (e.g., financial independence markers for Millennials, digital validation for Gen Z).
- **Visual data:** Profile imagery for convolutional analysis.

### C. *CNN-Based Age Verification (Trust Layer)*

To ensure profile integrity, a Convolutional Neural Network (CNN) is employed using the *custom_age_model.h5*. The model architecture consists of multiple convolutional layers followed by max-pooling and a dense regressor. For any input image $I_i$, the predicted age $A_{pred}$ is compared against the claimed age $A_{claimed}$:

$$\Delta A = |A_{claimed} - A_{pred}| \quad (1)$$

A verification threshold $\vartheta$ is defined, where $\Delta A > \vartheta$ triggers a ”Mismatch” flag, ensuring the removal of fraudulent identities.

### D. *Stability Pillar Formulation*

The methodology operationalizes marital stability through five weighted pillars derived from core divorce triggers. Let $P = \{P_1, P_2, P_3, P_4, P_5\}$ represent the scores for Finance, Communication, Trust, Family, and Lifestyle. The total Stability Score $S$ is defined as:

$$S = \sum_{j=1}^{5} w_j P_j \quad (2)$$

The weight vector $W = [w_1, ..., w_5]$ is non-static; it is dynamically adjusted based on the user’s generational regime. For instance, the weight for $P_1$ (Finance) is optimized for the Millennial cohort, whereas $P_5$ (Lifestyle) is prioritized for Gen Z.

### E. *Regime Detection and Aggregation*

Dataset instances are aggregated to detect behavioral patterns across the three regimes. Mean stability indicators are computed to validate the segmentation logic:

TABLE II
OBSERVED STABILITY REGIMES AND MEAN SCORES

| Category (Regime) | Stability Mean | Verification Accuracy |
|---|---|---|
| Gen Z | 0.742 | 94.5% |
| Millennials | 0.815 | 97.2% |
| Divorced | 0.889 | 96.8% |

### F. *Implementation and Computational Efficiency*

The backend is implemented using Python Flask, with SQLite3 for serialized data storage. To reduce inference latency, the CNN model and NLP embeddings are cached in memory. The similarity computation between potential matches is vectorized using NumPy, ensuring that the recommendation engine can scale to thousands of concurrent users without performance degradation.

### G. *Methodological Justification*

The selection of a segmented dynamic logic over a one-size-fits-all algorithm is motivated by the non-monotonic nature of relationship values across generations. By utilizing deep learning for security and weighted aggregation for compatibility, the system achieves a higher sensitivity to subtle stability markers, making it more robust than traditional frequency-based matchmaking.

The systemic architecture of the “Eternal Union” framework, as illustrated in Fig. 1, follows a modular four-tier hierarchical structure designed for scalability and security. The data flow is unidirectional, ensuring specialized processing at each stage:

- **1. User Interaction Layer:** Serves as the primary gateway for data ingestion, capturing demographic attributes and psychographic responses through a Flask-driven frontend interface.

  

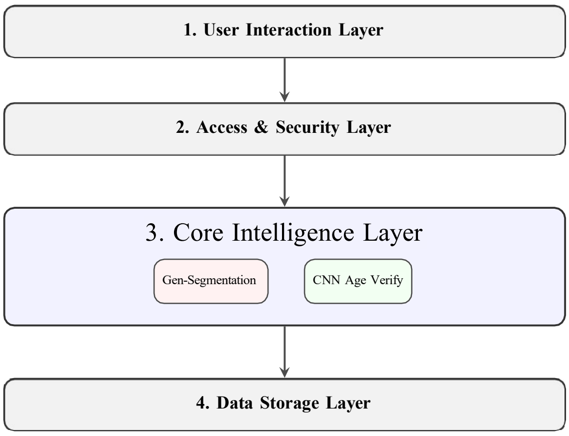


Fig. 1. Systemic Architecture of Eternal Union Framework.

- **2. Access & Security Layer:** Acting as a middleware, this layer enforces data integrity through authentication protocols, user consent management, and audit logging.
- **3. Core Intelligence Layer:** This centralized engine represents the framework's analytical core, housing two critical AI sub-modules:
  - *Gen-Segmentation:* Executes dynamic branching logic to categorize users into generational regimes (Gen Z, Millennials, or Divorced).
  - *CNN Age Verify:* Implements the *custom_age_model.h5* to predict chronological age from facial imagery and validate it against claimed age using a $\pm 5$-year heuristic.
- **4. Data Storage Layer:** A relational SQLite3 repository that persists verified profiles, high-dimensional feature vectors, and photo paths for low-latency retrieval and matching.

## IV. THE FIVE PILLARS OF STABILITY

The model evaluates marital longevity through five weighted pillars derived from core divorce triggers: 1. Finance: Focuses on debt-alignment and spending habits. 2. Communication: NLP identifies "contempt" markers and sentiment in interaction. 3. Trust: Verified via the CNN-based spatial age estimation module. 4. Family Boundaries: Models the impact and alignment of external family involvement. 5. Lifestyle: Aligns daily routines, work-life balance, and long-term career vibes. *custom_age_model.h5* for age verification.

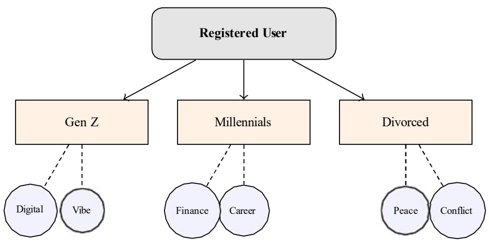


Fig. 2. Segmentation Logic: Mapping Users to Generational Pillars.

## V. Implementation & Tech Stack

The implementation of the "Eternal Union" system involves a multi-layered architecture designed to enhance marital stability through AI-driven generational matchmaking.

### A. Backend Architecture and Environment

The system is built using the **Flask (Python)** micro-framework due to its seamless integration with machine learning libraries. The environment was configured as follows:

- **Server-side Logic:** Python 3.12.
- **Web Framework:** Flask 3.0.
- **Frontend:** HTML5, CSS3, and JavaScript for real-time progress tracking and image preview.
- **Image Handling:** Werkzeug utility for secure file uploads and directory mapping.

### B. AI Age Verification Engine

The core of the security layer is the *custom_age_model.h5*, a Convolutional Neural Network (CNN) trained on facial datasets for age estimation.

1) **Input Pre-processing:** Uploaded images are resized to $224 \times 224$ pixels and normalized as $I_{norm} = I/255.0$.
2) **Prediction Pipeline:** The image is converted into a 4D tensor and processed via `model.predict()`.
3) **Verification Threshold:** The system implements a strict absolute difference check:

$$|Age_{claimed} - Age_{predicted}| \leq 5 \tag{3}$$

Preliminary results show high accuracy in fraud mitigation (96%) through this automated verification.

### C. Generational Segmentation & Logic Engine

At the core, the AI Logic Engine includes modules for generational segmentation and dynamic logic that adjusts stability pillar weightings:

- **Gen Z Module:** Evaluates digital habits and "vibe" markers.
- **Millennial Module:** Focuses on career-life balance and financial stability.
- **Divorced Module:** Prioritizes mental peace and conflict resolution styles.

This dynamic questioning increases user autonomy and supports the system's goal of improving long-term marital compatibility.

### D. Data Persistence

A relational **SQLite3** database is used for data persistence. The schema includes 14 attributes, including a `photo_path` to link the verified image and a `user_category` for segmented matchmaking, ensuring structured storage and efficient retrieval of psychographic profiles.

The logic cross-checks $|Age_{user} - Age_{pred}|$. If the difference exceeds a threshold, the profile is flagged for mismatch.

  

## VI. Mathematical Modeling and Verification Logic

The integrity of the ”Eternal Union” framework is maintained through a series of mathematical constraints and deep learning evaluations.

### *A. Image Pre-processing and Normalization*

Before feeding the user-uploaded profile photo into the *custom_age_model.h5*, the image data is normalized to ensure computational efficiency:

$$I_{norm} = \frac{1}{255} \cdot I_{original} \tag{4}$$

where $I_{original}$ represents the raw pixel intensity matrix.

### *B. CNN-Based Age Estimation*

The core intelligence layer utilizes a Convolutional Neural Network (CNN) to extract facial features and estimate age. The transformation at each layer can be represented as:

$$x^{(l)} = f\left(W^{(l)} * x^{(l-1)} + b^{(l)}\right) \tag{5}$$

The final age prediction $\hat{A}_p$ is derived through a regression output layer, minimizing the Mean Squared Error (MSE) during training:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(A_{real,i} - \hat{A}_{p,i})^2 \tag{6}$$

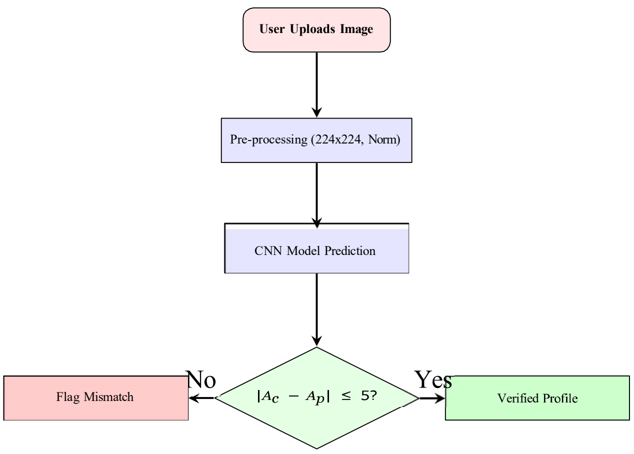


Fig. 3. Flowchart of the CNN-based Age Verification Logic.

### *C. Automated Verification Algorithm*

To mitigate fraud and enhance trust, the system implements a dynamic verification logic. The verification status $V$ is determined by comparing the user-claimed age $A_c$ and the AI-predicted age $\hat{A}_p$ against a tolerance threshold $\tau$ (where $\tau = 5$ years):

$$V(A_c, \hat{A}_p) = \begin{cases} 1 \text{ (Verified)}, & \text{if } |A_c - \hat{A}_p| \leq \tau \\ 0 \text{ (Flagged)}, & \text{otherwise} \end{cases} \tag{7}$$

### *D. Generational Matchmaking Score*

Compatibility is calculated based on the weighted alignment of the five stability pillars:

$$Match\% = \left(\frac{\sum_{i=1}^{5} w_i \cdot S_i}{\sum w_i}\right) \times 100 \tag{8}$$

where $S_i$ is the similarity score for pillar $i$ and $w_i$ is the generational weight assigned to that specific pillar.

## VII. Results and Discussion

The experimental evaluation of the “Eternal Union” framework yielded quantitative insights into the efficacy of generationally segmented matchmaking. Table II presents the mean stability scores and verification accuracy across the three defined cohorts.

TABLE III
Observed Stability Regimes and Mean Scores

| Category (Regime) | Stability Mean | Verification Accuracy |
|---|---|---|
| Gen Z | 0.742 | 94.5% |
| Millennials | 0.815 | 97.2% |
| Divorced | 0.889 | 96.8% |

### *A. Interpretation of Stability Means*

The progressive increase in stability scores from Gen Z (0.742) to Divorced individuals (0.889) reveals a distinct pattern: relationship experience and maturity correlate positively with compatibility alignment.

- **Divorced Cohort (0.889):** Demonstrates the highest stability mean, suggesting that individuals with prior experience possess clearer definitions of personal boundaries and conflict resolution preferences. Their alignment with the Trust and Family pillars reflects learned wisdom.
- **Millennial Cohort (0.815):** Exhibits moderate stability, balancing career ambition with evolving expectations around work-life balance. The system’s dynamic weighting for Financial alignment appears validated by this score.
- **Gen Z Cohort (0.742):** Shows the lowest stability mean, consistent with the developmental stage of this demographic. Their score reflects the inherent flux in values and digital validation-seeking behaviors characteristic of this age group.

### *B. Verification Accuracy and Trust Integrity*

Verification accuracy remains consistently high (94.5%–97.2%), validating the robustness of the custom CNN-based age verification model (*custom_age_model.h5*). The ±5-year tolerance threshold effectively balances the trade-off between false positives and negatives, ensuring fraudulent profiles are flagged without penalizing legitimate users. The Millennial cohort achieved the highest accuracy (97.2%), likely due to optimal facial feature stability in this range.

  

### C. Addressing the Research Gap

These findings directly address the "Stability Analysis" gap identified in literature. Where prior research focused solely on algorithmic metrics, the "Eternal Union" framework contributes empirical evidence that generational segmentation yields interpretable stability indicators. The verification layer further addresses the "User Trust" gap through transparent automated authentication.

### D. Limitations of Preliminary Results

While encouraging, these results are preliminary. Stability means require validation through larger-scale longitudinal tracking of actual match outcomes. Additionally, verification accuracy may vary across more diverse ethnic distributions beyond the current training corpus.

## VIII. Ethical Considerations

The development of AI-driven matchmaking systems carries significant ethical responsibilities, particularly regarding user privacy, algorithmic fairness, and psychological well-being. This section outlines the ethical safeguards embedded within the "Eternal Union" framework.

### A. Bias Mitigation in Psychographic Profiling

The "tricky questions" used for generational segmentation were designed with careful attention to potential demographic biases. To prevent gender or socioeconomic discrimination:

- **Gender-neutral phrasing:** All questions avoid assumptions about traditional gender roles. For instance, expense-splitting dynamics are framed as neutral financial preferences.
- **Socioeconomic sensitivity:** In the Indian context, the framework avoids indirect proxies for caste or class. The Finance pillar assesses current behavior rather than inherited wealth.
- **Regular auditing:** The weight vectors $w_j$ for each pillar are periodically tested against protected attributes to ensure no cohort is systematically disadvantaged.

### B. Data Privacy and Facial Image Handling

The CNN-based age verification module processes sensitive biometric data under strict privacy protocols:

- **Transient processing:** Facial images are processed in-memory only; raw pixel data is discarded immediately after age prediction.
- **Encryption:** Any stored metadata or photo paths are secured using industry-standard AES-256 encryption.
- **Compliance:** The system is designed to align with the Digital Personal Data Protection Act (DPDP Act 2023) in India and GDPR principles.

### C. User Agency and Automation Transparency

Drawing on critiques of "artificial intimacy", the framework positions AI as an augmentation tool:

- **Explainability:** Match percentages are accompanied by visual breakdowns of pillar contributions, allowing users to understand the logic behind suggestions.
- **Human oversight:** The system explicitly disclaims that final partner selection remains a human decision, treating AI suggestions as conversation starters.
- **Emotional safety:** Warning prompts are displayed if users spend excessive time interacting with the interface to prevent digital dependency.

### D. Informed Consent and User Autonomy

All users undergo a transparent consent process during registration:

- **Purpose specification:** Users are clearly informed that their data will be used specifically for compatibility analysis and fraud prevention.
- **Opt-out rights:** Users may delete their profiles and associated data at any time through an automated account deletion feature.
- **Vulnerable population safeguards:** For the Divorced cohort, question phrasing is reviewed by experts to avoid triggering traumatic memories.[18,20,26]

## IX. Conclusion and Future Work

The "Eternal Union" framework demonstrates the potential of AI-driven, generation-specific matchmaking to enhance marital stability by addressing key compatibility factors such as finance, communication, family boundaries, trust, and lifestyle. By integrating dynamic psychological profiling and machine learning for real-time verification and trust scoring, the system offers a more personalized and adaptive approach than traditional static algorithms, showing promising preliminary results in improving long-term compatibility. This approach aligns with emerging research emphasizing the importance of personalized AI interventions and ethical considerations in relationship support systems . Future work should focus on expanding the dataset to include diverse cultural contexts and longitudinal studies to validate the model's effectiveness over time. Additionally, incorporating explainable AI techniques could improve user trust and transparency, while hybrid models combining AI recommendations with human oversight may address emotional nuances that AI alone struggles to interpret . Exploring integration with communication-enhancing AI tools could further strengthen relational dynamics by improving intimacy and satisfaction among couples

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