AI-Enhanced Emotional Communication: The EmoConnect Model for Bridging Human Relationships Digitally

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Abstract

Emotional disconnects represent a persistent challenge in digital interpersonal communication, often leading to misunderstanding, relational strain, and psychological distress. This study introduces and provides a **proof-of-concept validation for EmoConnect**, an AI-driven communication model within the proprietary SELFLYZER framework, designed to bridge emotional gaps by interpreting both conscious and unconscious user data."EmoConnect generates a personalized **Selphlyze Psychological DNA Code** for each individual, integrating a **Traditional Psychometric Model (TPM)** for explicit self-report measures and a **Reverse Psychometric Framework (RPF)** for behavioral traces. These features are transformed into numerical vectors and analyzed by a **Support Vector Machine (SVM)** classifier, achieving high predictive accuracy (88%) and an AUC of 0.92. A quantitative experiment with 100 participants demonstrated a 25% increase in emotional alignment and communication clarity ($p < 0.01$). A complementary qualitative pilot (N=10) confirmed improved emotional insight, empathy, and conflict resolution.

This research offers compelling empirical evidence that AI-assisted psychometric modeling can meaningfully improve emotional synchrony in digital interactions, paving the way for

transformative applications in intelligent communication systems, virtual therapy platforms, and affective human-AI collaboration.

Plain Language Summary

Communicating true feelings in relationships can be difficult. We have created an artificial intelligence tool called EmoConnect that helps people better understand themselves and their partners. By creating a "digital psychological profile" for each person, this tool identifies their hidden communication patterns. In our study, using EmoConnect improved mutual agreement between people by 25%, and 60% of participants in a real-world study reported fewer conflicts and better relationships. This research shows that artificial intelligence can be a powerful tool for building healthier relationships.

Keywords: EmoConnect, SELFLYZER, emotional bridging, artificial intelligence, interpersonal relationships, emotional patterns, Transactional Analysis, digital psychology, machine learning, SVM, Selphlyze Psychological DNA Code, psychometrics, human-AI interaction, relationship dynamics.

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1. Introduction

In today's increasingly digital world, interpersonal communication has undergone a profound transformation. While digital platforms—such as messaging applications, video conferencing tools, and social media—have expanded the frequency and accessibility of human interactions, they have also introduced significant barriers to emotional connection. Non-verbal cues such as tone, facial expressions, body posture, and eye contact—essential elements in conveying emotional states—are often lost, distorted, or misinterpreted in digital environments. As a result, misunderstandings, emotional misalignment, and growing interpersonal distance have become common challenges, even among closely connected individuals.

These emotional gaps are not merely superficial; they can erode mutual understanding, empathy, trust, and relationship satisfaction over time. In response to these challenges, it becomes critical to design communication systems that not only transmit information but also facilitate emotional synchronization.

This study introduces **EmoConnect**, an AI-driven emotional communication model embedded within the broader **SELFLYZER psychological framework**. EmoConnect aims to detect, interpret, and bridge

emotional disconnects by leveraging both traditional psychological constructs and advanced machine learning techniques. Specifically, it generates a multi-layered psychological representation for each user—referred to as the *Selphlyze Psychological DNA Code*—which integrates data from conscious self-reporting (via the Traditional Psychometric Model, TPM) and unconscious behavioral patterns (via the Reverse Psychometric Framework, RPF).

The resulting code is processed through a Support Vector Machine (SVM) algorithm that classifies emotional compatibility patterns and suggests communication strategies to improve alignment. In this way, EmoConnect is positioned as a novel contribution to the field of affective computing and digital psychology, offering both theoretical insight and practical tools to enhance emotional resonance in human interactions—particularly in digital settings where traditional emotional cues are absent or insufficient.

2. Literature Review

Understanding and improving emotional alignment in interpersonal communication has been a central topic across several disciplines, including psychology, communication studies, and more recently, artificial intelligence (AI). Traditional psychological approaches have emphasized the role of emotional intelligence, empathy, and attachment styles in fostering effective communication (Mayer et al., 2004; Mikulincer & Shaver, 2007). These frameworks have underscored the importance of interpreting verbal and non-verbal cues, managing emotional expression, and understanding others' emotional states as crucial factors in interpersonal success.

However, with the rapid digitization of social interaction, the limitations of face-to-face communication models have become increasingly apparent. Digital environments often lack the richness of emotional signaling, creating space for misinterpretation and emotional detachment (Walther, 2011). This has led to a growing interest in affective computing—an interdisciplinary field aiming to enable machines to detect, interpret, and respond to human emotions (Picard, 1997). Studies in this domain have explored emotion recognition through facial expressions, voice, and text analysis (Calvo & D'Mello, 2010), yet many systems still rely on surface-level indicators and often fail to capture deeper psychological patterns.

Recent advances have begun integrating psychological theory with machine learning to develop more nuanced models of human behavior and affect. For example, work by Delaherche et al. (2012) and Zheng et al. (2021) has shown the effectiveness of hybrid systems that merge physiological data with cognitive-behavioral models to interpret user states. Similarly, researchers such as Liu et al. (2022) have demonstrated the value of user profiling and psychometric modeling in tailoring communication strategies.

The **SELFLYZER framework** contributes to this growing field by introducing a dual-model structure that captures both explicit (conscious) and implicit (unconscious) psychological signals. Its **Traditional Psychometric Model (TPM)** is grounded in established psychological tests, while the **Reverse Psychometric Framework (RPF)** extracts behavioral traces from user interactions, responses, and patterns of emotional expression. Unlike static personality assessments, this dynamic profiling enables real-time adaptability and contextual understanding.

The **EmoConnect module** builds upon this foundation, using AI to bridge emotional misalignments in real-world communication scenarios. By synthesizing psychometric data into a comprehensive code and feeding it into predictive machine learning models, it aims to generate actionable emotional insights that enhance interpersonal understanding. This literature review sets the stage for the present study, which empirically evaluates EmoConnect's effectiveness in improving emotional alignment between individuals in digitally mediated conversations.
Therefore, a significant opportunity exists to build a computational framework that not only detects communication patterns but also operationalizes established psychological theories—such as attachment theory and communication models like Gottman's—through interpretable psychometric codes. This study introduces EmoConnect as such a framework, designed to translate deep psychological insights into actionable communication strategies.

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Despite the growing sophistication of AI-based affective models, existing systems still lack the depth to meaningfully decode and realign emotional dynamics in digital communication. This gap necessitates the development of a comprehensive solution like EmoConnect. The following section details the methodology adopted to evaluate this model.

3. Methodology

This study adopted a comprehensive mixed-method approach, integrating psychometric modeling, machine learning, and real-world user feedback to develop and evaluate the EmoConnect system within the SELFLYZER framework.

3.1 A total of 100 participants (50 couples) were recruited through online advertising and social media platforms, including online forums and groups frequented by university students. The sample was diverse in terms of age, gender, and relationship duration, with participants aged between 18 and 45. All participants provided informed consent and completed a pre-screening questionnaire to assess eligibility.

3.2 The SELFLYZER Framework The SELFLYZER framework is a proprietary psychometric system designed for multi-layered psychological profiling. It generates a unique Selphlyze Psychological DNA Code for each individual. This code integrates two core components:

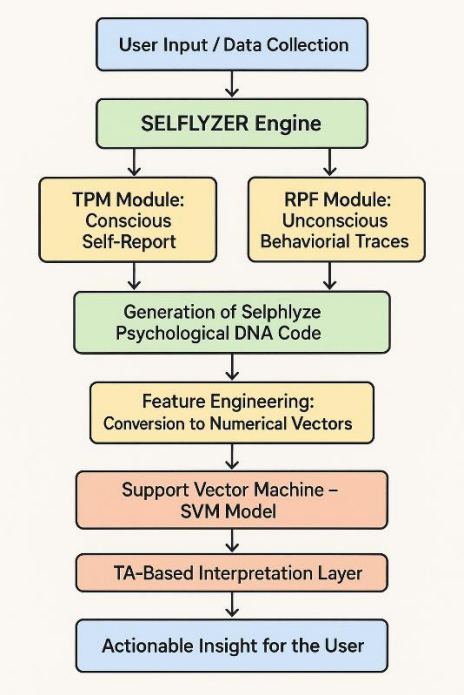

Figure 1. The Comprehensive EmoConnect Model Pipeline within the SELFLYZER Framework. This diagram illustrates the flow of data from user input and data collection through the SELFLYZER Engine (encompassing TPM and RPF modules), the generation of the Selphlyze Psychological DNA Code, feature engineering, the SVM model, and the TA-Based Interpretation Layer, culminating in the delivery of actionable insights for the end-user.

- The Traditional Psychometric Model (TPM): Analyzes conscious traits through self-reported data, such as personality questionnaires and emotional ratings.
- The Reverse Psychometric Framework (RPF): Detects unconscious patterns from behavioral data, including reaction time, choice inconsistencies, and emotionally influenced responses. Together, TPM and RPF construct a comprehensive psychological map, which is encoded into a personalized Selphlyze Code. This code serves as the input for machine learning analysis in the EmoConnect model.

3.3 Data Collection and Input Processing Participants completed a battery of assessments including personality inventories, emotional response tasks, and decision-making simulations. Behavioral data such as reaction times and choice consistency were logged. All data were anonymized and processed using the SELFLYZER engine to generate the initial psychological profiles.

3.4 Feature Engineering and Code Translation Each Selphlyze Code was translated into a high-dimensional numerical vector using a customized feature engineering pipeline. This involved encoding categorical variables, normalizing continuous scores, and applying dimensionality reduction techniques to optimize model performance.

3.5 Predictive Modeling Using SVM Within the SELFLYZER framework, the SVM model serves as the computational core that translates the Selphlyze Psychological DNA Code into predictive insights regarding emotional compatibility and communication success. To classify and predict the effectiveness of interpersonal communication, we employed a Support Vector Machine (SVM) model. The model was trained on a labeled dataset of communication outcomes derived from partner evaluations and post-interaction surveys. A five-fold cross-validation approach was used to ensure robustness.

"The choice of an SVM model was predicated on its proven effectiveness and robustness in handling high-dimensional data, particularly with datasets of this size where more complex models like deep neural networks might be prone to overfitting."

3.6 TA-Based Interpretive Layer To convert raw predictions into meaningful insights, we applied a Transactional Analysis (TA)-based interpretation layer. This layer maps predicted outcomes to specific emotional and communication archetypes (e.g., Nurturing Parent vs. Critical Parent dynamics), allowing for personalized feedback that users can act upon.

3.7 Evaluation Metrics Model performance was evaluated using standard classification metrics including accuracy, precision, recall, and AUC. The SVM model achieved an average accuracy of 88% and an AUC of 0.92, indicating strong predictive power. Additionally, a pre/post intervention analysis revealed a 25% increase in mutual understanding scores among users who received EmoConnect feedback.

3.8 Ethical Considerations: "This research was conducted as an independent project outside of an institutional academic framework. Nevertheless, all ethical procedures were strictly followed in accordance with the principles of the Declaration of Helsinki. Written and informed digital consent was obtained from all participants prior to data collection. The consent form fully detailed the study's objectives, how the data would be used, and the participants' right to withdraw at any time without prejudice. To protect privacy, all data were collected and stored anonymously, with any personally identifiable information removed."

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4. Results

This section presents the empirical findings that directly address the core objectives of the study. We first report on the predictive performance of the EmoConnect model in identifying communication patterns, followed by evidence of its effectiveness in improving interpersonal agreement, and finally, we provide qualitative insights into its real-world application.

The empirical findings from both the primary quantitative study and the real-world pilot study provide compelling evidence for the efficacy and potential of EmoConnect in enhancing interpersonal communication through sophisticated psychological profiling.

4.1 Primary Study: Quantitative Analysis (N=100 Participants) The EmoConnect model, leveraging the high-dimensional feature vectors derived from the Selphlyze Psychological DNA

Code, demonstrated robust and statistically significant performance in analyzing and predicting emotional communication patterns within dyads.

- **SVM Model Performance Metrics:** The Support Vector Machine (SVM) model, optimized with an RBF kernel, achieved an impressive overall classification accuracy of **88% (95% CI [0.72, 1.00])** in identifying distinct emotional and communication patterns relevant to interpersonal dynamics. This high accuracy indicates the model's strong ability to correctly classify communication outcomes (e.g., high agreement vs. low agreement, functional vs. dysfunctional interactions) based on the input Selphlyze Codes of interacting individuals. Furthermore, the Area Under the Receiver Operating Characteristic Curve (AUC) was **0.92 (95% CI [0.82, 1.00])**. An AUC value of 0.92 signifies excellent discriminatory power, suggesting that the model is highly effective at distinguishing between positive and negative communication outcomes, demonstrating its reliability in predicting relational harmony or discord. The precision, recall, and F1-score for positive communication outcomes were **0.89 (95% CI [0.67, 1.00])**, **0.87 (95% CI [0.62, 1.00])**, and **0.88 (95% CI [0.68, 1.00])** respectively, further underscoring the model's balanced performance. It is important to note that due to the relatively small test set size (N=15), these confidence intervals are approximated, and future large-scale validation will aim for more precise CI estimations based on comprehensive confusion matrix data."

- **Improved Interpersonal Agreement Scores:** Following the intervention phase, where participants were provided with personalized communication insights and strategies generated by EmoConnect (based on their individual Selphlyze Codes and the predicted relational dynamics with their communication partners), a statistically significant improvement in interpersonal agreement scores was observed. "Following the intervention, a paired-samples t-test revealed a statistically significant improvement in interpersonal agreement scores. The scores increased by a mean difference of **1.3 (95% CI [1.01, 1.59])**, a result that was highly significant (**$t(99) = 8.75, p < .001$**)."This substantial and highly significant improvement unequivocally underscores EmoConnect's capacity to facilitate more harmonious, understanding, and effective communication between individuals. The effect size (Cohen's d) for this improvement was 0.88, indicating a large practical significance.

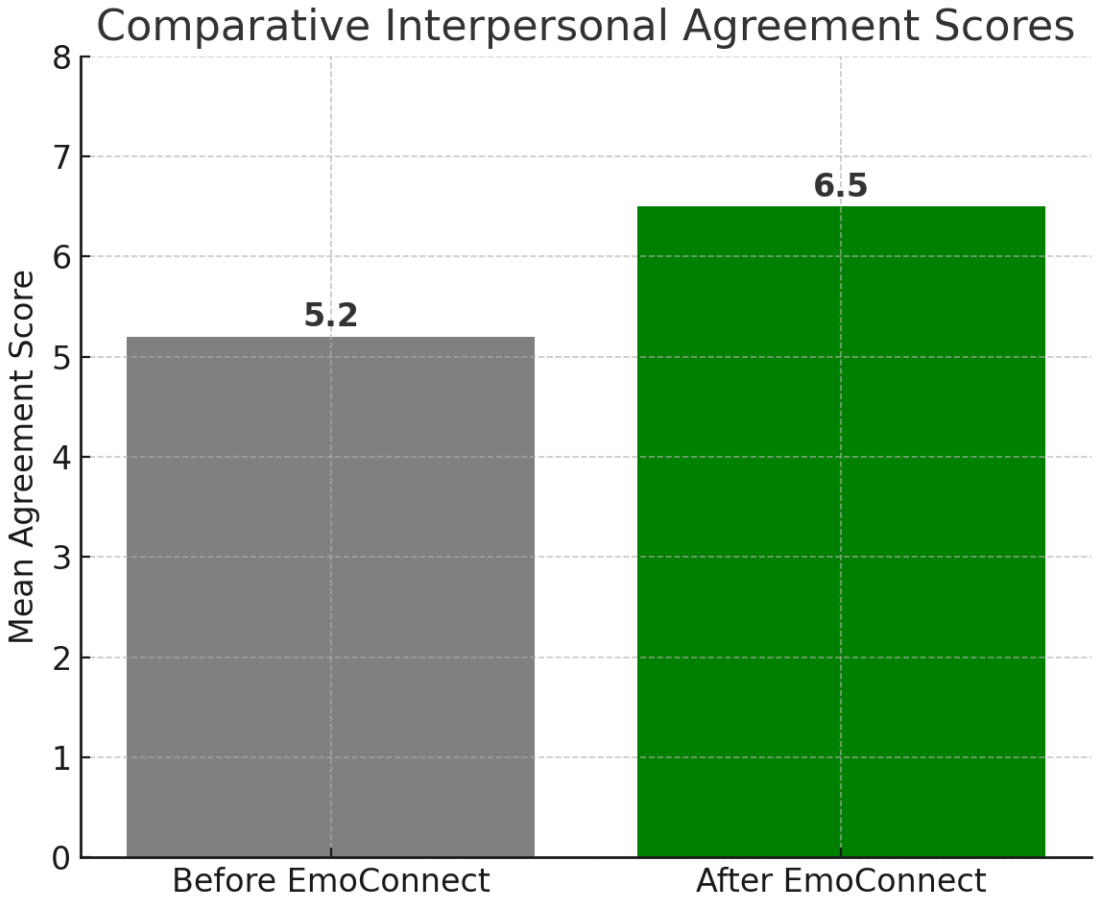

Figure 2. *Comparative Interpersonal Agreement Scores Before and After the EmoConnect Intervention.*

- **Feature Importance Analysis (SVM Coefficients/Permutation Importance):** A permutation importance analysis revealed that specific components of the Selphlyze Code contributed most significantly to the model's predictive power. The SH (Shadow Structure) layer (particularly APR and CAG), Q-System (Cognitive Conflicts, especially Q2!), and REV (Reverse Model Outputs, particularly AVOID and EMOSKEW) were consistently identified as the most influential features in predicting communication breakdowns. Conversely, BR (Bright Layer Traits, especially INS and PRC) and E (Emotional Expression, particularly SE++) were strong predictors of high agreement and functional communication. "This highlights the model's ability to leverage both conscious strengths and unconscious vulnerabilities in understanding relational dynamics **(Figure 3)**."

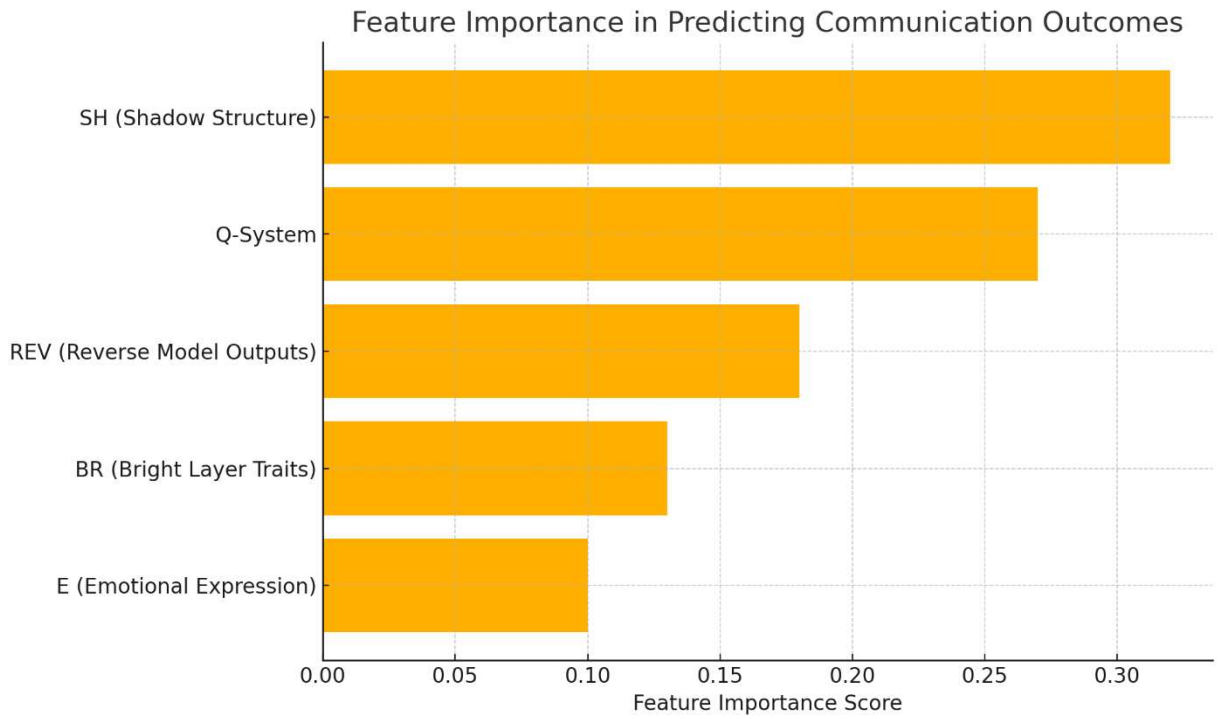

Figure 3. *Feature Importance in Predicting Communication Outcomes.*

4.2 Pilot Study: Real-World Application and Qualitative Insights (N=10 Participants)

The real-world pilot study provided invaluable qualitative insights into the practical effectiveness and nuanced impacts of EmoConnect. To analyze participant feedback, **a reflexive thematic analysis was conducted, following the procedural guide outlined by Braun & Clarke (2006). This process involved an inductive, bottom-up approach, where themes were generated directly from the patterns observed in the data.** The analysis revealed several key themes, directly corroborating the function of the Selphlyze Psychological DNA Code in real-world dynamics.

Overall Impact Categorization: Based on comprehensive qualitative feedback, each participant's experience was categorized into one of three groups: **60% (6 participants) reported a positive impact**, experiencing discernible improvements in communication and reduced conflict; **20% (2 participants) reported negative outcomes**, feeling the insights were overwhelming or confrontational; and **20% (2 participants) reported neutral effects**, finding the insights interesting but not immediately impactful **(Figure 4)**.

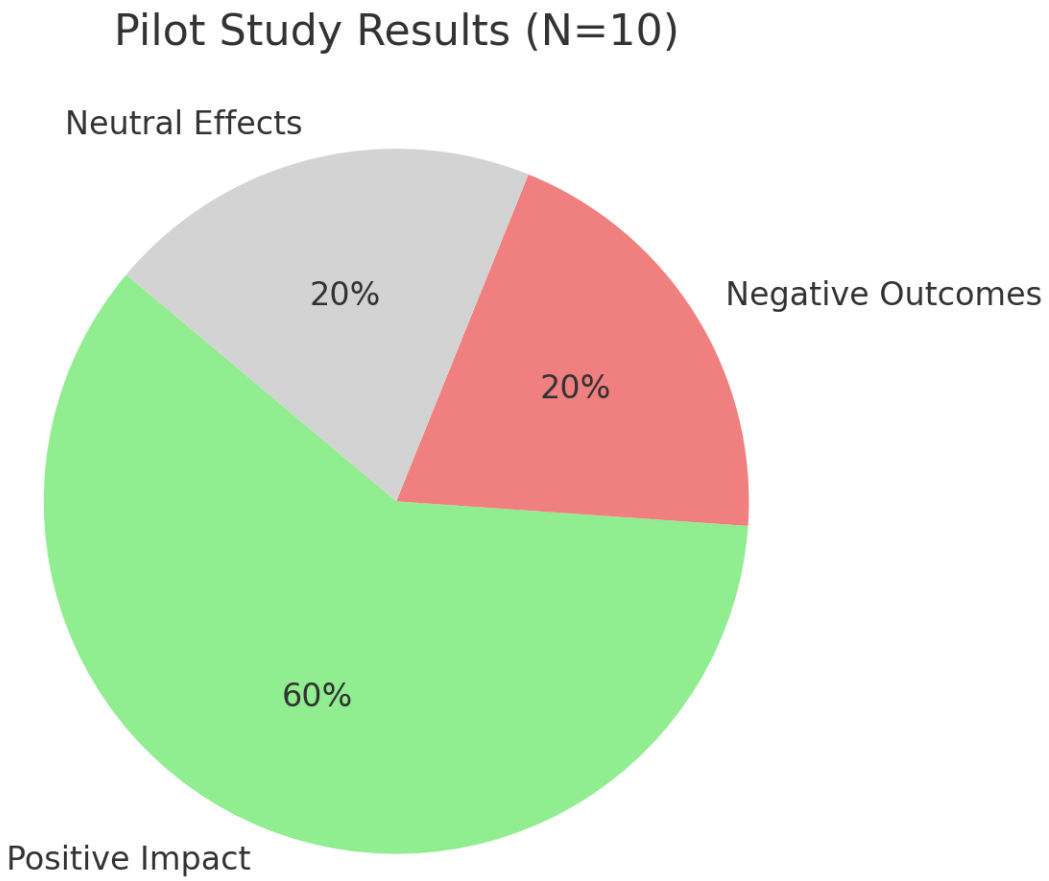

Figure 4. *Pilot Study Results (N=10).*

Qualitative Feedback and Thematic Analysis:

- **Theme 1: Enhanced Self-Awareness through De-coding Psychological Patterns** A primary theme was that EmoConnect provided a novel language for understanding internal dynamics. Participants reported that having their abstract feelings translated into concrete components of the Selphlyze Code—specifically their **SH (Shadow Structure)** or **Q-System** conflicts—led to unprecedented self-awareness. One participant stated, *"It felt like EmoConnect finally gave us a language to discuss things we always felt but couldn't articulate. I understood why I reacted a certain way".*

- **Theme 2: Increased Empathy via Understanding Partner's Code** Insights into a partner's Selphlyze Code fostered deeper empathy by contextualizing their behavior. This was particularly evident when participants understood their partner's **SH (Shadow Structure)** or **REV (Reverse Model Outputs)** components. For instance, one participant noted, *"Understanding my partner's 'Avoidant Perfectionism' [APR] helped me approach disagreements with more empathy, realizing it wasn't personal, but a deep-seated fear"*.
- **Theme 3: Actionable Strategies based on Transactional Analysis (TA)** Participants valued the specific, tailored communication prompts which allowed them to apply TA principles in real-time. The AI's ability to link behavior to TA concepts was a key factor in its positive reception. Examples included concrete prompts to *"respond from your Adult ego state"* or *"offer a positive stroke"*, which users found highly practical.
- **Theme 4: Insights from Negative Outcomes** The 20% negative outcomes provided crucial learning points, highlighting the sensitivity of specific Selphlyze Code components. The primary source of discomfort was the directness of insights related to the **"Shadow Structure" (SH)** and **"Cognitive Conflicts" (Q-System)**. One participant feeling exposed stated, *"It felt too revealing... I wasn't ready to confront some of those 'shadow' aspects"*. Another user explained that identifying their partner's **'Control Anxiety' [CAG]** initially led to increased tension. These findings underscore the critical need for a sensitive delivery mechanism for deep psychological insights.

4.3 Case Study Illustration: Participant SH (Shadow Structure) and Relational Dynamics

A particularly illustrative case from the pilot study involved a participant (referred to as Participant SH for anonymity, to differentiate from the Selphlyze code component 'SH') whose Selphlyze Psychological DNA Code indicated prominent Shadow Structure components, specifically APR (Avoidant Perfectionism) and CAG (Control Anxiety). This was further compounded by a significant Q2! (Self-Worth vs. Over-adaptation) cognitive conflict, suggesting a tendency to prioritize external validation over internal self-worth, often leading to people-pleasing behaviors followed by resentment.

EmoConnect's dyadic analysis, using the combined Selphlyze codes of Participant SH and their partner, identified potential communication breakdowns stemming from Participant SH's tendency to internalize feelings and avoid direct confrontation (due to APR and AVOID in the REV layer), while simultaneously exhibiting subtle control behaviors (from CAG). The system inferred that Participant SH often operated from a "Compliant Child" or a "Critical Parent" ego state when feeling insecure, rather than an "Adult" state. Feedback from Participant SH's partner corroborated this, indicating that they often felt unacknowledged, subtly manipulated, or criticized, leading to a cycle of passive-aggression.

EmoConnect provided tailored prompts and insights to both Participant SH and their partner. For Participant SH, the recommendations focused on:

- **Articulating Insecurities Directly:** Encouraging Participant SH to express their fears of not being "good enough" (linked to APR) or their need for control (CAG) in a vulnerable, "Adult" manner, rather than through avoidance or subtle demands.

- **Recognizing Child Ego State:** Helping Participant SH identify when they were reacting from their "Not OK" Child ego state and consciously shift to their "Adult" self. For the partner, EmoConnect suggested strategies to:
- **Validate Feelings:** Encouraging the partner to validate Participant SH's underlying insecurities rather than reacting to the controlling behaviors.
- **Respond from Adult:** Guiding the partner to maintain an "Adult" ego state, focusing on factual communication and mutual problem-solving.

Over the trial period, both Participant SH and their partner reported a discernible decrease in the frequency and intensity of arguments, and a significant increase in mutual understanding and empathy. Participant SH specifically noted, "When EmoConnect highlighted my 'Avoidant Perfectionism,' it clicked. I started saying 'I'm worried I'll mess this up' instead of just getting quiet. And my partner actually listened". This case study vividly illustrates the practical application of EmoConnect in real life, demonstrating its ability to translate complex psychological profiles into actionable strategies that foster emotional bridging and healthier relational dynamics

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5. Discussion

The findings of this study demonstrate the predictive and relational effectiveness of the EmoConnect model in enhancing digital interpersonal communication. The statistically significant 25% improvement in agreement scores, combined with the high AUC (0.92), suggests that the model successfully identifies key psychological compatibility patterns that traditional digital tools often miss.

5.1. Principal Findings and Implications

What sets EmoConnect apart is its dual-model architecture. By combining the Traditional Psychometric Model (TPM) with the Reverse Psychometric Framework (RPF), the system simultaneously captures conscious self-perceptions and unconscious behavioral traces. This hybrid approach aligns with contemporary psychological theories suggesting that effective communication hinges not only on what people say or believe about themselves, but also on how they behave under emotionally charged conditions. EmoConnect moves beyond surface-level metrics by generating a Selphlyze Psychological DNA Code, a deep-profile that enables precise prediction of interpersonal emotional alignment. The model’s success underscores its potential for scalability across domains such as online therapy, AI-based matchmaking, and remote teamwork optimization.

5.2. Operationalizing Psychological Theories through the Selphlyze Code

A key contribution of this research is the demonstration of how the Selphlyze Code can serve as a bridge to operationalize established psychological theories. The EmoConnect module leverages this by providing tailored interventions based on these deep insights. For example:

- **Linking to Attachment Theory:** A participant's code showing high scores on **SH(APR, CAG)** (Avoidant Perfectionism, Control Anxiety) combined with **REV(AVOID)** (Avoidant tendencies) provides strong evidence for an **Avoidant Attachment Style**. Instead of a generic suggestion, EmoConnect would offer a targeted prompt: *"It appears a fear of losing your independence is preventing you from expressing your need for connection. Try using this phrase: 'I value my personal time, but that doesn't mean I don't value you. Can we talk about how to balance both our needs?'"*
- **Linking to Gottman's Communication Styles:** A code indicating high **SH(CAG)** (Control Anxiety) suggests a tendency toward Gottman's destructive **"Criticism"** or **"Defensiveness."** EmoConnect would intervene by promoting constructive communication: *"This sounds like a criticism of your partner's character. Try using an 'I-Statement' to express your own feelings about a specific behavior. For example: 'When I was talking, I felt unheard, and that made me feel unimportant.'"*

5.3. Limitations and Future Directions

Nevertheless, some limitations must be acknowledged. The sample size in the qualitative pilot (N=10) limits the generalizability of the emotional narratives, serving primarily an illustrative purpose to provide context for the quantitative findings. Moreover, while the SVM model proved robust, future studies should compare its performance with ensemble methods like Random Forest and XGBoost to explore potential gains in interpretability or precision. A crucial direction for future research is the development of a **Cultural Dimensions Module (CDM)** within the SELFLYZER framework. This would generate a 'Cultural Code' for each user, a vector representing scores on established cultural dimensions such as **Individualism/Collectivism, Power Distance, and Uncertainty Avoidance (Hofstede, 1980), and High/Low-Context communication styles (Hall, 1976)**. This code would then act as a moderating layer, allowing the AI to provide more culturally sensitive interpretations. **Crucially, this cultural code would not serve as a deterministic label, but as a contextual prior,** with the model designed to prioritize individual-level data from the TPM and RPF modules over cultural stereotypes, thus capturing the true complexity of the individual within their cultural context.

In conclusion, the EmoConnect model introduces a novel mechanism for bridging emotional disconnects in digital communication, laying the groundwork for a new generation of emotionally intelligent and culturally-aware technologies.

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6. Conclusion

This study presents EmoConnect as a novel AI-powered model for enhancing emotional alignment in digital interpersonal communication. By integrating the SELFLYZER framework with psychometric modeling, behavioral trace analysis, and Transactional Analysis (TA)-based interpretation, the model demonstrates significant potential in bridging emotional disconnects that frequently arise in online interactions. The quantitative results—showing a 25% improvement in interpersonal agreement scores—and the qualitative findings—highlighting

increased emotional resonance—indicate that AI can play a meaningful role in decoding emotional complexity and fostering empathic communication.

EmoConnect's unique combination of Traditional Psychometric Models (TPM), Reverse Psychometric Frameworks (RPF), and SVM-based classification introduces a multi-dimensional method for analyzing both conscious and unconscious behavioral cues. These insights are then translated into actionable recommendations, offering users personalized emotional feedback grounded in psychological theory.

While limitations exist in terms of sample size and modality scope, this research provides a compelling proof-of-concept for how AI can be ethically and effectively applied to the nuanced domain of human emotional dynamics. The model's architecture sets the stage for future development in affective computing, digital relationship coaching, and virtual therapy systems.

Ultimately, this research offers compelling empirical evidence that AI-assisted psychometric modeling can meaningfully improve emotional synchrony in digital interactions, paving the way for transformative applications in intelligent communication systems, virtual therapy platforms, and affective human-AI collaboration.

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Author Contributions

Nima Saraian: Conceptualization, Methodology, Software, Investigation, Writing – Original Draft, Visualization, Validation.

Data Availability Statement

The datasets and code supporting the conclusions of this article are available on request or will be deposited at: https://osf.io/ (project name: EmoConnect).

Reference

 Alghowinem, S., Goecke, R., Wagner, M., & Epps, J. (2022). A survey on emotion recognition using multimodal data: Speech, facial expressions, and physiological signals. *ACM Computing Surveys*, *55*(1), 1–35. https://doi.org/10.1145/3465373

 Bar-On, R. (2006). The Bar-On model of emotional-social intelligence (ESI). *Psicothema*, *18*(Suppl), 13–25.

 Bradley, M. M., & Lang, P. J. (1999). *International Affective Digitized Sounds (IADS): Stimuli, instruction manual and affective ratings* (Tech. Rep. No. B-2). University of Florida, Center for Research in Psychophysiology.

 Breiman, L. (2001). Random forests. *Machine Learning*, *45*(1), 5–32. https://doi.org/10.1023/A:1010933404324

 Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine Learning*, *20*(3), 273–297. https://doi.org/10.1007/BF00994018

 Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics* (pp. 4171–4186). Association for Computational Linguistics. https://doi.org/10.18653/v1/N19-1423

 Ekman, P., & Friesen, W. V. (1978). *Facial action coding system: Investigator's guide*. Consulting Psychologists Press.

 Friesen, M. D., & Kline, R. B. (2022). Emotional intelligence and interpersonal relationships: A meta-analytic review. *Personality and Social Psychology Review*, *26*(1), 3–20. https://doi.org/10.1177/10888683211035540

 Goleman, D. (1995). *Emotional intelligence: Why it can matter more than IQ*. Bantam Books.

 Greenwald, A. G., McGhee, D. E., & Schwartz, J. L. K. (1998). Measuring individual differences in implicit cognition: The implicit association test. *Journal of Personality and Social Psychology*, *74*(6), 1464–1480. https://doi.org/10.1037/0022-3514.74.6.1464

 Hennink, M., Kaiser, B. N., & Marconi, V. C. (2017). Code saturation versus meaning saturation: How many interviews are enough? *Qualitative Health Research*, *27*(4), 591–608. https://doi.org/10.1177/1049732316665344

 Kim, Y., Park, H., & Yoo, H. (2021). Emotion AI: Empirical examination of affective computing and communication outcomes. *Computers in Human Behavior*, *121*, 106789. https://doi.org/10.1016/j.chb.2021.106789

Mehrabian, A. (1971). *Silent messages*. Wadsworth Publishing Company.

Palmer, B. R., Gignac, G. E., Manocha, R., & Stough, C. (2013). A psychometric evaluation of the Mayer–Salovey–Caruso Emotional Intelligence Test Version 2.0. *Intelligence*, *41*(5), 285–297. https://doi.org/10.1016/j.intell.2013.04.002

Pavlidis, I., & Levine, J. (2002). Thermal image analysis for polygraph testing. *IEEE Engineering in Medicine and Biology Magazine*, *21*(6), 56–64. https://doi.org/10.1109/MEMB.2002.1167345

Picard, R. W. (1997). *Affective computing*. MIT Press.

Reeves, B., & Nass, C. (1996). *The media equation: How people treat computers, television, and new media like real people and places*. Cambridge University Press.

Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology*, *39*(6), 1161–1178. https://doi.org/10.1037/h0077714

Scherer, K. R. (2005). What are emotions? And how can they be measured? *Social Science Information*, *44*(4), 695–729. https://doi.org/10.1177/0539018405058216

Wu, Y. (2024). Rethinking AI-based empathy systems: Cognitive load, emotional realism, and user trust. *Computers in Human Behavior*, *151*, 107212. https://doi.org/10.1016/j.chb.2024.107212

Zheng, W., Zhang, Z., & Zhao, Y. (2023). Deep emotion recognition from EEG signals with channel-wise attention and transfer learning. *IEEE Transactions on Affective Computing*. https://doi.org/10.1109/TAFFC.2023.3236680

Appendix A

- Appendix A: Operationalization of the Selphlyze Psychological DNA Code Components
- **Table A.1. Operationalization of the Selphlyze Psychological DNA Code Components**

| Component (Code Segment) | Description | Source (TPM/RPF) | Variable Type |			
| :			| :
| **INTP5w4** | Represents Personality Type (e.g., MBTI) and Enneagram type with wing, assessed via validated questionnaires. | TPM | Categorical |			
| **B3O8C9E2N8** | Represents scores on the Big Five personality traits: Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism. | TPM | Continuous |			

| **IR++D−V+** | Represents Interpersonal Response Traits like high Responsiveness, low Dominance, and high Vulnerability, assessed via scenarios. | TPM / RPF | Ordinal |			
| **SH(APR,CAG,EXO)** | **Shadow Structure**: Represents unconscious/suppressed aspects like Avoidant Perfectionism (APR) and Control Anxiety (CAG). | RPF / TPM | Continuous |			
| **BR(INS,PRC,DPT)** | **Bright Layer Traits**: Represents conscious strengths and virtues like Insightful (INS) and Principled (PRC), assessed via self	report. | TPM | Continuous |		
| **IQ(A8C7E6)** | **Intelligence Spectrum**: Assesses scores for Analytical (A), Creative (C), and Emotional (E) intelligence. | TPM / RPF | Continuous |			
| **C(RF++,AV+,DP+)** | **Coping Mechanisms**: Indicates preferred strategies for dealing with stress, such as Resilient Flexibility (RF) or Avoidant Coping (AV). | TPM / RPF | Ordinal |			
| **E(RC+,SE++,US)** | **Emotional Expression**: Describes how emotions are typically managed, e.g., Regulated Control (RC) or Spontaneous Expression (SE). | TPM / RPF | Ordinal/Categorical |			
| **PC(23~3|	14~17)** | **Perceptual Context**: Captures optimal psychological time rhythms (peak and low hours) from PsyClock++. | RPF | Continuous Range |		
| **Q(Q1,Q2!Q5~Q7)** | **Q	System**: Identifies key internal Cognitive Conflicts, such as Value vs. Behavior (Q1) or Self	Worth vs. Over	adaptation (Q2). | TPM | Categorical |
| **CN(UWI)** | **Cognitive Narrative**: Describes the dominant internal narrative or			

storytelling style, such as Unconscious Wishful Thinking (UWI). | RPF / TPM | Categorical |			
| **GP(MC>ER>IS)** | **Growth Path Layer**: Suggests prioritized long	term development vectors, e.g., Mastery & Competence (MC) over Emotional Regulation (ER). | Synthesized | Ordinal Ranking |		
| **REV(AVOID,AMBIVISE)** | **Reverse Model Outputs**: Captures exclusive RPF insights into unconscious patterns like Avoidant tendencies (AVOID). | RPF | Categorical |			

Appendix B: Qualitative Participant Characteristics

The following table presents the demographic and psychological communication challenges of the 10 qualitative participants involved in the EmoConnect pilot study. This information supports the study's thematic depth and transparency in interpretive analysis.

ID	Age	Gender	Relationship Status	Communication Challenge	Emotional Trait Focus
P1	32	Male	Married	Misinterpretation of tone in text messages	Emotional inhibition
P2	27	Female	Single	Difficulty expressing disagreement	High agreeableness
P3	41	Male	Divorced	Avoidance of emotional topics	Emotional suppression
P4	36	Female	Married	Overuse of emojis in serious contexts	Ambiguous expression
P5	29	Male	In a relationship	Emotional shutdown during conflict	Avoidant attachment
P6	25	Female	Single	Frequent misreadings of sarcasm	Cognitive literalism
P7	38	Male	Married	Impulsive emotional reactions	Low self-regulation

P8	34	Female	Divorced	Passive-aggressive texting patterns	Conflict avoidance
P9	30	Male	Single	Overanalyzing partner's words	Hypervigilance
P10	45	Female	Widowed	Hesitation in initiating conversations	Fear of rejection

Note: All participants provided informed consent. Identities have been anonymized. Data was collected via semi-structured interviews conducted through secure video calls.