Synchronous Emotional Dynamics in Human-AI Collaborative Networks: A Temporal Graph Neural Network Approach

Supplementary Materials

A Technical Implementation Details

A.1 Network Architecture Specifications

Graph Neural Network Layers:

- Input dimension: 240 (concatenated multimodal features)
- Hidden layers: [240, 512, 256, 128, 64]
- Activation functions: LeakyReLU ($\alpha = 0.2$)
- Dropout rates: [0.1, 0.2, 0.3, 0.2, 0.1]
- Batch normalization after each layer

Temporal Attention Mechanism:

```
class TemporalAttention(nn.Module):
    def __init__(self, hidden_dim=128, num_heads=8):
        super().__init__()
        self.multihead_attn = nn.MultiheadAttention(
            hidden_dim, num_heads, dropout=0.1
        )
        self.temporal_pe = PositionalEncoding(hidden_dim)

    def forward(self, x, mask=None):
        x = self.temporal_pe(x)
        attn_output, _ = self.multihead_attn(x, x, x, key_padding_mask=mask)
        return attn_output
```

A.2 Loss Function Implementation

```
def tarn_loss(outputs, targets, physiological_data, alignment_weights):
    # Reconstruction loss
    reconstruction = F.mse_loss(outputs.predicted, targets.emotional_state)

    # Temporal consistency loss
    temporal_diff = torch.diff(outputs.predicted, dim=1)
    change_indicators = detect_genuine_changes(physiological_data)
    temporal = torch.mean(temporal_diff ** 2 * (1 - 0.8 * change_indicators))

    # Physiological grounding loss
```

```
    physiological = F.mse_loss(
        outputs.physiological_pred,
        physiological_data.processed
    )

    # Human-AI alignment loss
    human_states = outputs.predicted[:, :, 0]  # Human nodes
    ai_states = outputs.predicted[:, :, 1:]    # AI nodes
    alignment = -torch.mean(
        F.cosine_similarity(human_states.unsqueeze(2), ai_states, dim=-1)
        * alignment_weights
    )

    return reconstruction + 0.3 * temporal + 0.2 * physiological + 0.1 * alignment
```

A.3 Real-Time Processing Pipeline

The system processes multimodal inputs through a synchronized pipeline:

1. Sensor Fusion (10ms): Temporal alignment of physiological streams
2. Feature Extraction (15ms): Parallel processing of EEG, GSR, HRV, and linguistic features
3. Graph Construction (5ms): Dynamic edge weight computation based on communication patterns
4. TARN Forward Pass (45ms): Temporal graph convolution and VAE inference
5. Response Generation (25ms): Emotional state mapping to agent behaviors

Total Latency: <100ms end-to-end processing time

B Supplementary Results

B.1 Ablation Study Results

Component removal analysis showing the contribution of each TARN module:

Configuration	Task Performance	Trust Rating	Emotional Intelligence
Full TARN	8.4±1.1	8.1±0.7	4.2±0.6
No Temporal Loss	7.1±1.4	7.2±0.9	3.6±0.8
No Physiological	6.8±1.6	6.9±1.1	3.4±0.7
No Graph Structure	6.2±1.8	6.4±1.2	3.1±0.9
Basic GNN Only	5.9±2.0	6.1±1.3	2.9±0.8

Table 1: Ablation study results for TARN components.

B.2 Individual Difference Analysis

Personality Correlations (Big Five Inventory):

- Extraversion: Stronger response to TARN emotional mirroring ($r = 0.43$, $p < 0.001$)
- Agreeableness: Higher trust ratings across all conditions ($r = 0.38$, $p < 0.01$)
- Neuroticism: Greater sensitivity to emotional consistency ($r = -0.41$, $p < 0.001$)

Technical Expertise Impact:

- High Tech: Appreciated system transparency, focus on performance metrics
- Low Tech: Emphasized emotional comfort, anthropomorphic qualities
- No significant interaction between expertise and TARN effectiveness