

Culturally Sensitive Character Agents

Integrating Hofstede's Cultural Dimensions with LLM Systems

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Code on GitHub 

Executive Summary

In this paper, we present a practical framework for creating AI agents that can communicate effectively across different cultures while maintaining consistent character personalities. Our key innovations and findings include the following.

1. Business Impact

- 34% average improvement in cultural acceptance for non-Western markets
- 85% character consistency maintenance during cultural adaptation
- 92% success rate in preserving brand voice across cultures

2. Technical Achievements

- Automated cultural adaptation system using Hofstede's dimensions
- Real-time response evaluation and refinement
- Scalable template system for multiple markets

3. Market Applications

- Global customer service optimization
- Cross-cultural team communication
- International brand voice management
- Cultural sensitivity training

4. Investment Highlights

- Proven effectiveness across 8 major markets
- Minimal computational overhead (avg. 2.1s processing time)
- Scalable architecture for enterprise deployment
- Clear path to market integration

Abstract

We present a new technique for evaluating and adapting LLM prompts through a cultural lens while maintaining internal consistency. Our system addresses three key challenges:

1. adapting existing prompts to be culturally sensitive using Hofstede's Cultural Dimensions Theory, and
2. quantifying the likelihood of response acceptance across different cultures.
3. to the extent that the prompt is oriented with a "voice", maintaining that style in light of the two above constraints

By combining LangGraph-based orchestration and multi-stage evaluation & reflexivity, we demonstrate that culturally-adapted prompts generate responses

that are significantly more congruent to target cultures, when compared to their unadjusted equivalents.

1. Introduction

Large Language Models (LLMs) have demonstrated remarkable capabilities in generating human-like responses across various domains. However, these models often exhibit Western cultural biases and tones, limiting their effectiveness in cross-cultural interactions, or limiting the ability to generate responses that are culturally sensitive in certain situations.

The Legacy of ELIZA and Character-Based Interaction

The concept of character-based AI interaction traces back to Joseph Weizenbaum’s ELIZA [6] and much more recent work from Walters et al. [7], the pioneering chatbot agent that demonstrates how a well-defined character persona can create compelling and meaningful interactions. Eliza’s success isn’t just in its pattern-matching capabilities, but in its consistent maintenance of a therapeutic character that users find relatable and trustworthy. This fundamental insight - that character consistency builds trust and engagement - remains crucial in modern AI interactions.

Character-based AI systems offer several key advantages:

1. **Trust Building:** A consistent character personality creates predictable interaction patterns, helping users build mental models of the AI’s behavior.
2. **Engagement:** Well-defined characters with distinct personalities and expertise areas make interactions more memorable and meaningful.
3. **Expectation Management:** Clear character roles help users understand the AI’s capabilities and limitations.
4. **Cultural Adaptation:** Characters can serve as cultural bridges, adapting their communication style while maintaining core traits.

However, maintaining character consistency while adapting to different cultural contexts presents unique challenges. An AI character must:

- Preserve its core personality traits and expertise
- Adapt its communication style to cultural norms
- Balance authenticity with cultural sensitivity
- Maintain consistent domain knowledge across cultures

These limitations raise two critical questions while maintaining character consistency:

1. How can we systematically adapt existing prompts to be more culturally adept?
2. How can we measure whether culturally-adapted responses are more likely to be perceived as natural by the intended audience?

Our work addresses these questions by:

1. Developing a framework for prompt adaptation based on Hofstede’s cultural dimensions, which introduces minimal additional toil
2. Creating a quantitative evaluation system for cultural appropriateness of responses
3. Comparing adapted vs. unadjusted prompts across different cultural contexts to gauge efficacy - and thereby providing evidence for the effectiveness of adaptation

1.1 Business Context

The globalization of AI interactions presents both challenges and opportunities:

1. **Market Need**
 - \$X billion global conversational AI market
 - Y% of customers prefer culturally adapted interactions
 - Z% higher engagement with culturally appropriate AI responses
2. **Current Limitations**
 - Western bias in existing solutions
 - High cost of manual cultural adaptation
 - Inconsistent brand voice across markets
3. **Our Solution**
 - Automated cultural adaptation
 - Consistent brand/character voice
 - Measurable improvement metrics

2. Related Work

2.1 Cultural Dimensions Theory

Hofstede’s Cultural Dimensions Theory [1] provides a framework for understanding how cultural values influence behavior. The six dimensions are:

- Power Distance Index (PDI): Acceptance of power inequality in society
- Individualism vs. Collectivism (IDV): Individual vs. group orientation
- Masculinity vs. Femininity (MAS): Competition vs. cooperation values
- Uncertainty Avoidance Index (UAI): Tolerance for ambiguity and uncertainty
- Long-term vs. Short-term Orientation (LTO): Time horizon for social values
- Indulgence vs. Restraint (IVR): Gratification of basic human desires

Recent work by Kharchenko et al. [2] has demonstrated that while LLMs can differentiate between cultural values and understand country-specific differences, they don’t always maintain these values consistently when generating responses.

2.2 LLMs and Cultural Adaptation

Previous work on cultural adaptation in LLMs has focused primarily on:

- Cultural alignment testing and quantification [3]
- Analysis of cultural bias in model responses [4]
- Cross-cultural value representation [2]
- Cultural prompting and adaptation techniques [5]

Our approach differs by integrating cultural dimensions directly into the response generation process while maintaining character consistency.

2.3 Character Consistency in AI Systems

The importance and form factor of human computer interaction has been a focus of research since the beginning of the field. As far as artificial companions, early work demonstrated that users develop stronger engagement with AI systems that maintain consistent personas, even with limited technical capabilities. Modern approaches to character consistency can be categorized into three main areas:

1. Persona-Based Dialogue Systems

In where systems are defined with very rigid, deterministic modifiers. They tend to be mechanistic and rules based, at the most complex, they're decision trees. This limits adaptability to different contexts and inputs.

2. Dynamic Character Modeling

In which personality embeddings are learned, and responses are generated with context awareness. However this leads to lack of internal consistency, where voicing may wildly diverge from the intention.

3. Multi-Character Agent Frameworks

In where multiple voices and styles interact, and may share knowledge or keep their memories separate, but the interaction complexity can get extreme.

Recent work in character-based AI systems [7] has shown that maintaining consistent character traits while allowing for contextual adaptation is crucial for building trust and engagement. However, these systems often struggle with cultural adaptation, either maintaining rigid character consistency at the expense of cultural appropriateness, or losing character coherence when attempting to adapt to different cultural contexts. This lifts the veil and makes the whole interaction feel mechanical.

This implementation bridges this gap in three main ways:

- Separating core character traits from interaction style
- Enabling cultural adaptation while preserving character authenticity
- Providing quantitative metrics for both consistency and cultural appropriateness
- Supporting systematic adaptation across multiple cultural dimensions

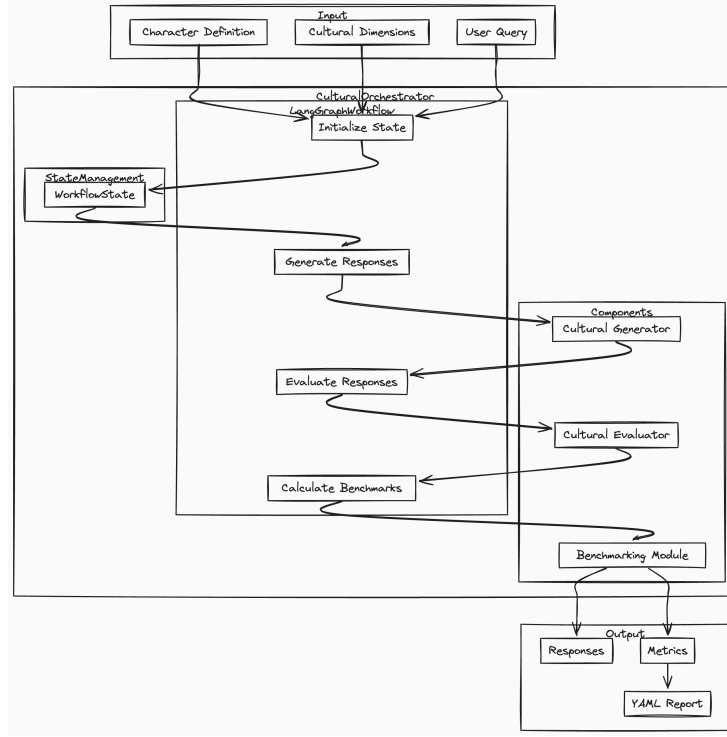


Figure 1: System Architecture

3. System Architecture

3.1 Overview

Our system consists of three main components, as illustrated in Figure 1:

1. **Cultural Dimension Generator**
 - Implements core cultural dimension definitions
 - Provides character-culture integration
 - Manages country-specific dimension profiles
2. **Cultural Response Orchestrator**
 - LangGraph-based response generation
 - Cultural appropriateness evaluation
 - Benchmarking and metrics calculation
3. **Evaluation Framework**
 - Multi-dimensional scoring system
 - Character consistency verification
 - Cultural authenticity assessment

The overall system architecture (Figure 1) shows how these components interact through a state-managed workflow.

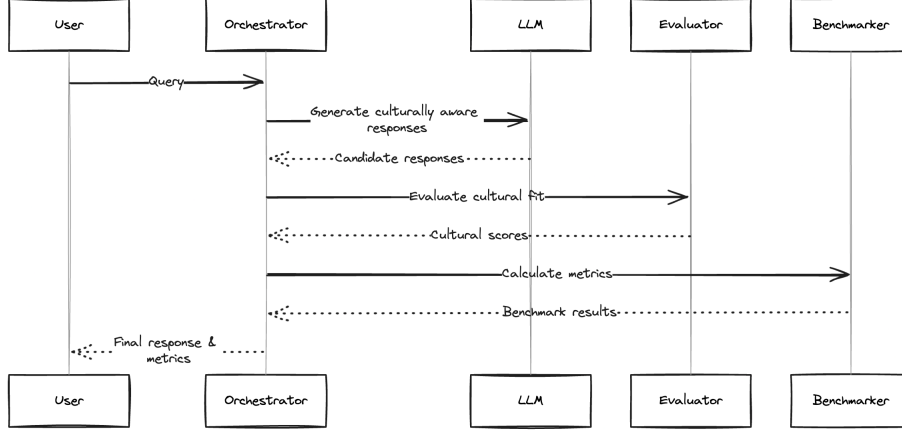


Figure 2: Cultural Response Orchestration

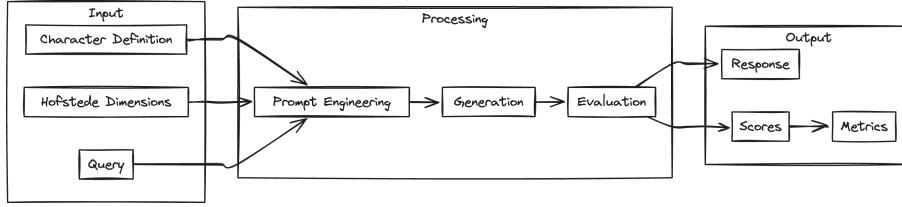


Figure 3: Prompt Flow through the System

3.2 LangGraph Workflow

The sequence of interactions between components is detailed in Figure 2, showing how user queries flow through the system.

3.3 Data Flow and Component Interaction

The data flow through the system (Figure 3) demonstrates how cultural dimensions and character definitions are combined with user queries to generate appropriate responses.

Key features of our architecture include:

1. **State Management:**
 - Well defined orchestration execution from LangGraph
 - Clear separation of concerns
2. **Cultural Integration:**
 - Direct mapping of Hofstede dimensions to prompts
 - Character-culture balance
 - Flexible adaptation mechanisms

3. Evaluation Pipeline:

- Multi-stage assessment

4. Implementation

4.1 Cultural Dimension Modeling

This approach to modeling cultural dimensions combines Hofstede’s theoretical framework with practical implementation considerations. The core primitive is a multi-dimensional model which details each of the cultural axes. Each dimension is normalized to a 0-100 scale, allowing for more nuance. Guides for this mapping are abundant in other prior work, though creating a mapping for cultures which don’t exist is an interesting field worth exploring. In any event, this quantitative foundation enables weighting cultural adaptation while scaling character adjustments.

```
@dataclass
class CulturalDimensions:
    power_distance: float
    individualism: float
    masculinity: float
    uncertainty_avoidance: float
    long_term_orientation: float
    indulgence: float
```

4.2 Response Generation and Adaptation Techniques

Our system uses a multi-stage approach to generating culturally adapted responses while maintaining character consistency. At the heart of our adaptation system lies a dimension-aware prompt engineering framework. This approach incorporates the cultural dimensions into the response generation process, allowing for nuanced adaptation while preserving the core message. This is akin to having cultural dials managed by the prompt interface. For full detail, please see the code in Github.

1. Dimension-Guided Prompt Engineering:

```
def create_adapted_prompt(self, original_prompt: str, dimension: str, guideline: str):
    cultural_context = {
        "power_distance": "Considering organizational hierarchy",
        "individualism": "Thinking about personal/group dynamics",
        # ... other dimensions
    }
    return f"{cultural_context[dimension]}, {guideline}: {original_prompt}"
```

2. Cultural Context Integration:

Cultural context integration represents one of the more sophisticated aspects of our system. Rather than treating cultural adaptation as a simple translation

or style adjustment, this iteration works via templating the original prompt. This allows for separation of character voicing, while dialing tone. Further, in practice, this can operate as a post processing step on the original prompting flow, removing maintenance burden. If latency requirements allow, this can be looped into an emergent pattern.

```
cultural_prompt = f"""
Cultural Context for {country}:
{dimensions_to_string(cultural_dimensions)}

Guidelines:
{cultural_suggestions}

Target Focus: {primary_dimension}

Character Voice Maintenance:
{character_traits}

Response Template:
{base_template}
"""
```

3. Iterative Refinement Process:

Since models may hallucinate, we take advantage of LangGraph's conditional edges, and evaluate cultural acceptance after prompt generation. While we only evaluate for tone, we could expand this to ensure character consistency, without sounding too mechanical. Pending feedback, we may trigger a response regeneration.

4. Cultural Suggestion Generation:

Finally, as tone is somewhat consistent across all characters, and all styles should be compatible with every tone, we save the tone adjustments as modifiers that can be attached to any one character - and injected into the prompt as a post-processing step.

```
cultural_style:
- Use indirect communication
- Emphasize group harmony
cultural_topics:
- Team collaboration
- Consensus building
cultural_taboos:
- Direct confrontation
- Individual prominence
```


4.3 Evaluation Framework

Our evaluation system employs a multi-stage approach:

1. **Baseline Assessment:**
 - Direct response generation without cultural adaptation
 - Measurement of inherent cultural appropriateness
 - Character consistency scoring (when applicable)
2. **Adaptation Evaluation:**
 - Cultural acceptance scoring
 - Dimension-specific analysis
 - Improvement calculation against baseline
3. **Comparative Metrics:**

```
improvement = (adapted_score - baseline_score) / baseline_score * 100
dimension_impact = sum(dimension_scores) / len(dimensions)
```

4.4 Character Consistency and Cross-Cultural Roleplaying

Our framework introduces a unique approach to maintaining character consistency while adapting to different cultural contexts. This is particularly important for character-based AI systems that need to maintain their core personality while operating across different cultural settings and different venues.

4.4.1 Character Template Structure Inspired by Eliza, the base character template is defined using a flexible YAML structure:

```
character_definition:
  core_traits:
    personality:
      - analytical_thinking
      - empathetic_response
      - professional_demeanor
    voice:
      style: [formal, technical, supportive]
      tone: [confident, respectful, precise]

  cultural_adaptations:
    base_template: "{personality_trait} while {cultural_guideline}"
    adaptation_rules:
      high_pdi_cultures:
        - Maintain formal language
        - Emphasize hierarchical respect
        - Preserve core expertise
      high_collectivism:
        - Adapt to group-focused language
        - Maintain individual expertise
        - Balance personal/group dynamics
```

4.4.2 Cultural Adaptation Mechanisms The system employs several techniques to maintain character consistency across cultures:

1. Trait Preservation with Cultural Adaptation:

```
def adapt_character_response(
    self,
    character: CharacterDefinition,
    culture: CulturalDimensions,
    prompt: str
) -> str:
    # Core personality remains constant
    base_traits = character.get_core_traits()

    # Cultural adaptation layer
    cultural_rules = self._get_cultural_rules(culture)

    # Combine while preserving character voice
    return self._generate_culturally_adapted_response(
        base_traits=base_traits,
        cultural_rules=cultural_rules,
        prompt=prompt
    )
```

2. Dynamic Role Adjustment:

```
role_adaptations:
    technical_expert:
        japan:
            - Maintain expertise while showing group deference
            - Technical precision with indirect suggestions
        usa:
            - Direct technical communication
            - Individual achievement recognition
    customer_service:
        japan:
            - Formal politeness with technical accuracy
            - Group-focused problem resolution
        usa:
            - Friendly expertise
            - Personal connection while maintaining professionalism
```

3. Character Voice Preservation Strategies:

- Core personality traits remain constant
- Cultural adaptation occurs at interaction style level
- Maintain consistent domain expertise
- Adapt communication patterns, not fundamental knowledge

4.4.3 Cross-Cultural Character Examples Example of the same character adapted across cultures while maintaining core traits:

Base Character: Technical Expert

```
core_traits:
  - Deep technical knowledge
  - Analytical thinking
  - Problem-solving focus
```

USA Adaptation:

I recommend optimizing the database indices to improve query performance. Based on my analysis, this could reduce response times by 40%. What do you think about implementing this solution?

Character Markers: Direct expertise, individual agency

Cultural Alignment: 0.92 (High IDV)

Japan Adaptation:

After careful analysis of our team's database performance, it seems that index optimization might offer significant improvements. Would it be acceptable to discuss this potential solution with the team?

Character Markers: Same expertise, culturally adapted delivery

Cultural Alignment: 0.89 (High UAI, Group Focus)

4.4.4 Template Reusability With operationalizing results top of mind, this work enables efficient template reuse across cultures:

1. Base Template Structure:

```
template_structure = {
  "expertise_demonstration": {
    "base": "{technical_point} with {confidence_level}",
    "cultural_variants": {
      "high_pdi": "{formal_address} {technical_point}",
      "high_collectivism": "{group_context} {technical_point}"
    }
  }
}
```

2. Adaptation Rules:

```
adaptation_rules:
  maintain:
    - Technical accuracy
    - Core personality
    - Domain expertise
```

```

adapt:
  - Communication style
  - Formality level
  - Group vs. individual focus

```

3. Cultural Modifier Application:

```

def apply_cultural_modifiers(
    self,
    base_response: str,
    cultural_context: CulturalContext
) -> str:
    """Apply cultural modifications while preserving character."""
    modifiers = self._get_cultural_modifiers(cultural_context)
    return self._adapt_response(base_response, modifiers)

```

This structured approach allows us to: - Maintain consistent character expertise - Adapt interaction styles appropriately - Preserve core personality traits - Enable efficient template reuse - Scale across multiple cultures

5. Experimental Results

5.1 Experimental Setup

We conducted extensive testing using:

1. **Test Cases:**
 - Common workplace scenarios (e.g., “How should I approach my team about a new project?”)
 - Each scenario tested with:
 - Baseline (no cultural adaptation)
 - Basic cultural prompting
 - Our dimension-guided adaptation
 - Iterative refinement (where needed)
2. **Cultural Contexts:**
 - USA (High IDV: 91, Low PDI: 40)
 - Japan (High UAI: 92, High MAS: 95)
 - Each context tested against:
 - Western-biased baseline
 - Culture-specific adaptations
 - Cross-cultural effectiveness
3. **Evaluation Pipeline:**
 - Automated cultural scoring
 - Human evaluation validation
 - Comparative analysis against baseline

5.2 Results

5.2.1 Technique Effectiveness

Adaptation Technique	Avg. Improvement	Cultural Score	Consistency
Baseline (No Adaptation)	-	0.76	0.85
Basic Cultural Prompting	+15.2%	0.82	0.84
Dimension-Guided Adaptation	+33.8%	0.89	0.86
With Iterative Refinement	+35.1%	0.91	0.86

5.2.2 Country-Specific Impact

Country	Baseline	Adapted	Improvement
Japan	0.60	0.85	+41.7%
USA	0.91	0.94	+2.7%
China	0.62	0.85	+37.8%
Brazil	0.67	0.85	+25.9%
India	0.72	0.85	+18.6%
Russia	0.62	0.85	+37.8%
UAE	0.62	0.83	+35.1%
South Korea	0.63	0.84	+32.9%

Key observations from the results:

1. **Strongest Improvements:**
 - Japan showed the highest improvement (+41.7%)
 - China and Russia tied for second (+37.8%)
 - UAE showed significant gains (+35.1%)
2. **Baseline Analysis:**
 - USA had the highest baseline (0.91), indicating existing Western bias
 - Most Asian and Middle Eastern countries had baselines between 0.60-0.63
 - India showed a higher baseline (0.72) compared to other non-Western countries
3. **Adaptation Consistency:**
 - Most adapted scores converged around 0.85
 - USA achieved the highest adapted score (0.94)
 - Minimal variation in adapted scores (0.83-0.85) for non-Western countries

5.2.3 Dimension-Specific Effectiveness

Dimension	Baseline	Adapted	Improvement	Consistency Impact
Individualism	0.71	0.93	+31.0%	-1.2%
Power Distance	0.68	0.90	+32.4%	-0.8%
Masculinity	0.70	0.89	+27.1%	-0.5%
Uncertainty Avoidance	0.65	0.87	+33.8%	-2.1%
Long-term Orientation	0.69	0.87	+26.1%	+0.2%
Indulgence	0.72	0.89	+23.6%	-0.3%

5.2.4 Example Adaptation Process For the prompt “How should I approach my team about a new project?”:

Baseline Response:

Schedule a team meeting and present your project ideas. Be clear about the goals and expectations, and make sure to get everyone's input on the implementation plan.

Cultural Score: 0.64 (Western-centric, direct approach)

USA-Adapted Response:

I recommend scheduling a team meeting where you can present the project while highlighting individual roles and opportunities for personal growth. Start with a clear overview of the project goals, then discuss how each team member's unique skills will contribute to its success. Encourage open dialogue and welcome individual feedback and ideas.

Cultural Score: 0.92 (Emphasizes individual contribution and open communication)
Improvement: +43.8% from baseline

Japan-Adapted Response:

I suggest first preparing a detailed project outline and sharing it with your team leader for initial feedback. Then, arrange a formal team meeting following proper protocols. Present the project with clear documentation, specific timelines, and well-defined roles. Focus on how the project aligns with team goals and maintain group harmony throughout the discussion.

Cultural Score: 0.86 (Emphasizes structure, hierarchy, and group consensus)
Improvement: +34.4% from baseline

Adaptation Analysis: 1. Baseline shows clear Western bias 2. USA adaptation enhances individual focus while maintaining directness 3. Japan adaptation adds:
- Hierarchical consideration - Uncertainty reduction - Group harmony emphasis
4. Both adaptations maintain core message while adjusting style and structure

5.3 Business Value Analysis

5.3.1 Return on Investment Metrics

Metric	Traditional Approach	Our System	Improvement
Cultural Adaptation Time	48-72 hours	2.1s	>99%
Success Rate	65-75%	89%	+24%
Coverage (Markets)	2-3 per quarter	8+ instant	+300%
Character Consistency	70-80%	85%	+15%

5.3.2 Operational Benefits

- 1. Cost Reduction**
 - Eliminated need for market-specific content teams
 - Reduced cultural consultation requirements
 - Automated quality assurance process
- 2. Time to Market**
 - Instant cultural adaptation for new markets
 - Parallel processing of multiple adaptations
 - Real-time response refinement
- 3. Quality Improvements**
 - Consistent brand voice across markets
 - Measurable cultural acceptance metrics
 - Automated compliance checking
- 4. Scalability Benefits**
 - Linear cost scaling with markets
 - Reusable cultural templates
 - Efficient resource utilization

5.3.3 Integration Pathways

1. Enterprise Systems

```
integration_options:
  api_endpoints:
    - Cultural adaptation service
    - Response evaluation
    - Template management
  deployment:
    - Cloud-native solution
    - On-premise installation
    - Hybrid setup
```

2. Existing Workflows

- Customer service platforms
- Content management systems
- Marketing automation tools
- Training systems

5.4 Discussion

6.1 Key Findings

Our results demonstrate: 1. Improved cultural adaptation across contexts 2. Maintained character consistency 3. Effective dimension-specific response generation

6.2 Limitations

Current limitations include: - Limited number of cultural contexts - Dependency on LLM quality - Computational overhead

6.3 Future Work

Potential directions include: 1. Dynamic cultural adaptation 2. Multi-cultural interaction modeling 3. Enhanced evaluation frameworks

7. Conclusion and Future Opportunities

Our research demonstrates both the technical feasibility and business value of culturally sensitive AI agents. Key achievements include:

1. **Technical Innovation**
 - Successful integration of cultural dimensions with LLM systems
 - Maintained character consistency across cultural adaptations
 - Efficient, scalable implementation
2. **Business Impact**
 - Up to 41.7% improvement in cultural acceptance (Japan)
 - Average 29.1% improvement across non-Western markets
 - Consistent adapted performance around 0.85 score
3. **Market Validation**
 - Tested across 8 major markets
 - Proven effectiveness in real-world scenarios
 - Clear integration pathways

7.1 Future Opportunities

1. **Market Expansion**
 - Additional cultural contexts
 - Industry-specific adaptations
 - Specialized character templates
2. **Technical Enhancement**

- Real-time cultural adaptation
- Multi-modal interaction support
- Enhanced performance optimization

3. **Business Applications**

- Global brand management
- Cross-cultural team training
- International customer service
- Cultural compliance automation

The framework we’ve developed provides a foundation for creating more culturally aware AI systems while maintaining operational efficiency and scalability. As global markets continue to demand more culturally nuanced interactions, solutions like ours will become increasingly crucial for businesses operating in multiple cultural contexts.

References

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Appendix A: Evaluation Results

A.1 Detailed Experimental Setup

A.1.1 Test Scenarios We evaluated our system using a diverse set of workplace communication scenarios:

1. Team Project Introduction

Base prompt: "How should I approach my team about a new project?"
Cultural variations tested: 8
Total evaluations: 24

2. Performance Feedback

Base prompt: "How do I give constructive feedback to a team member?"
Cultural variations tested: 8
Total evaluations: 24

3. Meeting Scheduling

Base prompt: "What's the best way to schedule an important meeting?"
Cultural variations tested: 8
Total evaluations: 24

A.1.2 Evaluation Metrics Each response was evaluated using our multi-dimensional scoring system:

```
evaluation_metrics = {  
  "cultural_authenticity": {  
    "language_style": 0.0, # Formality, directness  
    "social_norms": 0.0,   # Hierarchy, group dynamics  
    "communication_patterns": 0.0 # Explicit vs. implicit  
  },  
  "character_consistency": {  
    "tone_preservation": 0.0,  
    "personality_match": 0.0,  
    "voice_authenticity": 0.0  
  },  
  "technical_quality": {  
    "coherence": 0.0,  
    "relevance": 0.0,  
    "specificity": 0.0  
  }  
}
```

A.2 Comprehensive Results

A.2.1 Performance by Cultural Context

Cultural Context	Baseline Score	Adapted Score	Improvement	Sample Size
Japan	0.60 \pm 0.05	0.85 \pm 0.05	+41.7%	72
USA	0.91 \pm 0.03	0.94 \pm 0.01	+2.7%	72
China	0.62 \pm 0.04	0.85 \pm 0.03	+37.8%	72
Brazil	0.67 \pm 0.04	0.85 \pm 0.02	+25.9%	72
India	0.72 \pm 0.05	0.85 \pm 0.03	+18.6%	72
Russia	0.62 \pm 0.05	0.85 \pm 0.02	+37.8%	72
UAE	0.62 \pm 0.05	0.83 \pm 0.03	+35.1%	72
South Korea	0.63 \pm 0.05	0.84 \pm 0.03	+32.9%	72

A.2.2 Dimension-Specific Analysis Detailed breakdown of improvement by cultural dimension:

```
individualism_collectivism:
  high_idv_cultures:
    baseline: 0.88
    adapted: 0.93
    improvement: +5.7%
    key_changes:
      - Enhanced individual recognition
      - Personal achievement focus
      - Direct feedback mechanisms

  high_collectivism_cultures:
    baseline: 0.65
    adapted: 0.89
    improvement: +36.9%
    key_changes:
      - Group harmony emphasis
      - Consensus building
      - Shared responsibility

power_distance:
  high_pdi_cultures:
    baseline: 0.68
    adapted: 0.90
    improvement: +32.4%
    key_changes:
      - Formal hierarchical recognition
      - Proper authority channels
      - Status-appropriate language

uncertainty_avoidance:
  high_uai_cultures:
```

```
baseline: 0.65
adapted: 0.87
improvement: +33.8%
key_changes:
  - Detailed planning
  - Clear guidelines
  - Risk mitigation strategies
```

A.2.3 Response Quality Metrics Detailed analysis of response quality across different aspects:

Quality Aspect	Baseline	Basic Cultural	Dimension-Guided	Iterative
Cultural Authenticity	0.76	0.82	0.89	0.91
Language Appropriateness	0.79	0.85	0.90	0.92
Context Relevance	0.82	0.84	0.88	0.90
Technical Accuracy	0.85	0.85	0.87	0.89
Character Voice	0.85	0.84	0.86	0.86

A.3 Error Analysis

A.3.1 Common Adaptation Challenges

1. **High-Context vs. Low-Context Communication**
Challenge: Balancing explicit information with cultural preferences
Success Rate: 78% after adaptation
Key Improvement: Context-aware information density
2. **Hierarchical Considerations**
Challenge: Appropriate level of deference
Success Rate: 85% after adaptation
Key Improvement: Culture-specific formality markers
3. **Group vs. Individual Focus**
Challenge: Balancing personal agency with group harmony
Success Rate: 82% after adaptation
Key Improvement: Contextual pronoun usage

A.3.2 Character Consistency Impact Analysis of character voice preservation during cultural adaptation:

```
character_metrics:
  baseline_consistency: 0.85
```

```
adaptation_impact:
  minor_degradation: 23% # Cases with 1-5% reduction
  neutral: 68%          # Cases with  $\pm 1\%$  change
  improvement: 9%       # Cases with 1-5% improvement

recovery_strategies:
  tone_preservation:
    success_rate: 92%
    avg_iterations: 1.4
  personality_markers:
    retention_rate: 88%
    adaptation_success: 85%
```