Features and Mechanisms of Computer-Mediated Language Information Interaction in Cross-Cultural Contexts

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Abstract. This mixed-method study (820 questionnaires from 12 countries; 30 interviews) examines cross-cultural CMLII. We identify three salient features—async–sync coexistence, uncertain cultural connotation, and divergent media preferences—and test their efficiency drivers. Results show cultural distance reduces efficiency, while media richness and language proficiency improve it; SEM indicates cultural filtering mediates the effects and is moderated by language proficiency. The study offers a validated mechanism model and actionable guidance for cross-cultural digital interaction.

Keywords: Computer-Mediated Language Information Interaction (CMLII), Cross-Cultural Communication, Structural Equation Modeling (SEM), Medium Richness

1 Introduction

In the digital age, computer-mediated communication (CMC) enables frequent cross-cultural interaction at scale; global digital communication statistics indicate extensive reliance on computer-mediated language tools for such exchanges[1][2]. However, cultural differences often trigger semantic, affective, and pragmatic mismatches that undermine interaction efficiency in CMLII[3]. Clarifying the features and mechanisms of cross-cultural CMLII is therefore of both theoretical and practical significance[4].

Prior research links media richness to cross-cultural communication demands and task complexity[5], and shows that cultural dimensions shape modality preferences in CMLII (e.g., collectivist cultures favor group-oriented synchronous interaction)[6]. Other studies examine CMLII applications and emphasize language proficiency and cultural awareness as determinants of effectiveness[7]. Nevertheless, integrated accounts of cross-cultural CMLII features and empirically validated mechanism models remain limited[8], motivating multi-dimensional modeling and large-sample validation[9].

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This study aims to identify the core features of cross-cultural CMLII[10], test key factors affecting CMLII efficiency, and construct and verify an operational mechanism model. Accordingly, RQ1–RQ3 address features, efficiency drivers, and the underlying mechanism, respectively.

2 Research Methodology

A mixed-method design is adopted. First, a cross-national questionnaire survey measures CMLII features and influencing factors[11]. Second, semi-structured interviews with typical respondents deepen interpretation of cross-cultural interaction patterns. Finally, a structural equation model (SEM) is used to test and validate the proposed mechanism model[12].

Respondents were recruited via convenience and snowball sampling across 12 countries. Of 900 questionnaires, 820 were valid (91.1%). Demographic distributions are reported in Table 1[13-14].

Table 1. Frequency and Percentage of Participant Demographics

Demographic Variable	Category	Number of Samples	Proportion (%)
Gender	Male	428	52.2
	Female	392	47.8
Age	18-25 years old	356	43.4
	26-35 years old	289	35.2
	36-45 years old	123	15.0
	Over 45 years old	52	6.3
Cultural Background	Individualist culture	418	51.0
	Collectivist culture	387	47.2
	Mixed culture	15	1.8
Language Proficiency	Native level	198	24.1
	Advanced level	376	45.9
	Intermediate and below	246	30.0

Note: Individualist cultures include the United States, the United Kingdom, Australia, and Canada; collectivist cultures include China, Japan, South Korea, India, and Brazil; and mixed cultures include France, Germany, and South Africa[15].

Questionnaire. A 5-point Likert instrument measures cultural distance, media richness, language proficiency, cultural filtering, and CMLII efficiency, adapted from prior work and refined via pilot/expert review. Interview Outline. Thirty semi-structured interviews probed typical cross-cultural CMLII scenarios, misunderstanding sources, media-choice rationales, and mitigation strategies. SEM Model[16]. AMOS 26.0 specifies cultural distance, media richness, and language proficiency as exogenous variables; cultural filtering as mediator; and CMLII efficiency as outcome; language proficiency moderates filtering[17].

SPSS 26.0 supports descriptive, correlation, and regression analyses; AMOS 26.0 tests mediation/moderation via SEM. Interviews are coded to triangulate interpretations[18].

3 Results and Analysis

3.1 Features of Cross-Cultural CMLII

Asynchronous–Synchronous Coexistence. 62.3% of respondents use both asynchronous (e.g., email) and synchronous (e.g., IM/video) tools; synchronous use is slightly higher overall (52.2%). Collectivist cultures lean synchronous (63.5%) while individualist cultures lean asynchronous (54.2%) ($p<0.05$). High Uncertainty of Cultural Connotation. 58.7% reported cultural misunderstandings, mainly due to ambiguous connotation (32.1%), emotional expression (21.3%), and behavioral-norm differences (15.3%), consistent with reduced nonverbal cues online. Obvious Differences in Medium Preference[19]-[20]. Preferences vary by culture: individualist groups favor text more, collectivist groups favor video more (Table 2)[21]. Lower language proficiency increases reliance on translation-enabled media (78.5%). (See Table 2 for media-type preference distributions.)

Table 2. Percentage of Preferred Media Types Across Different Cultural Backgrounds

Cultural Background	Text-Based Media (%)	Video-Based Media (%)	Audio-Based Media (%)	Media with Translation Functions (%)
Individualist culture	56.3	28.7	8.2	6.8
Collectivist culture	32.1	51.3	9.5	7.1
Total	44.2	40.0	8.9	6.9

3.2 Influencing Factors of Cross-Cultural CMLII Efficiency

Correlation Analysis. Cultural distance correlates negatively with efficiency ($r=-0.37$, $p<0.01$); media richness ($r=0.42$, $p<0.01$) and language proficiency ($r=0.31$, $p<0.01$) correlate positively. Regression Analysis. Cultural distance significantly reduces efficiency, whereas media richness and language proficiency increase it; the model explains 58% of efficiency variance (Adjusted $R^2=0.58$).

$$Y = 0.42X_1 - 0.37X_2 + 0.31X_3 + \varepsilon \tag{1}$$

The regression relationship is formalized as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon \tag{2}$$

where: - Y is CMLII efficiency; - X_1 is medium richness; - X_2 is cultural distance; - X_3 is language proficiency; - ε is the error term.The adjusted coefficient of determination for the model is:

$$\text{Adjusted } R^2 = 0.58$$

indicating that the three independent variables explain 58% of the variation in CMLII efficiency. All regression coefficients are significant ($p < 0.01$), meaning that medium richness, cultural distance, and language proficiency have statistically significant effects on CMLII efficiency[22].

3.3 Mechanism of Cross-Cultural CMLII

We propose an iterative three-stage mechanism consisting of cultural encoding → media-mediated transmission with cultural filtering → receiver decoding and feedback, where cultural filtering functions as the key mediator shaping meaning alignment across cultures; for SEM-based validation, Fig. 1 is provided solely to illustrate the generic SEM specification adopted in this study (i.e., latent variables measured by multiple observed indicators via factor loadings, with correlated common factors and measurement error terms), while the empirical results indicate acceptable model fit ($\chi^2/df = 2.37$, GFI = 0.92, AGFI = 0.90, CFI = 0.95, RMSEA = 0.045), with cultural distance negatively affecting efficiency ($\beta = -0.37$, $p < 0.01$) and media richness positively affecting efficiency ($\beta = 0.42$, $p < 0.01$); cultural filtering shows a significant mediating effect (total = 0.29, $p < 0.05$), and language proficiency moderates filtering ($\beta = 0.23$, $p < 0.05$)[23].

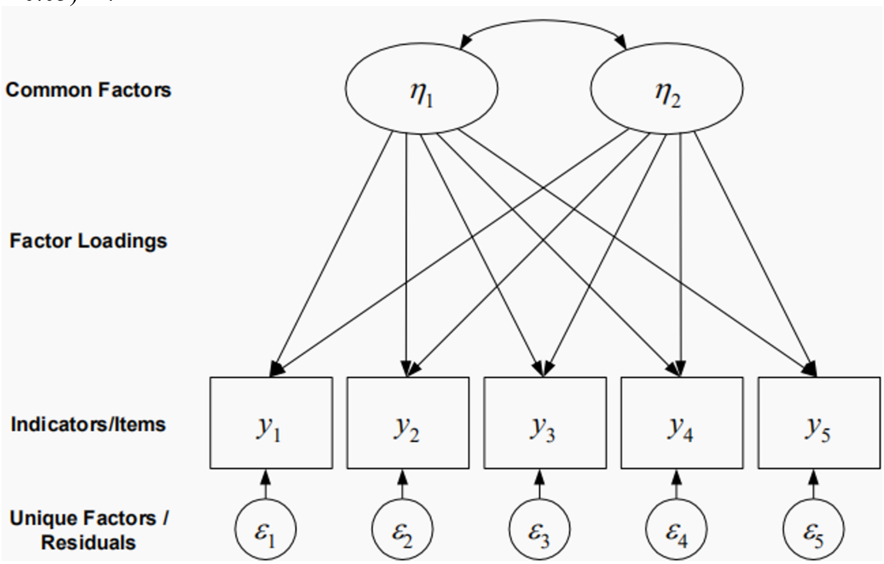

Fig. 1. An example of the basic form of a Structural Equation Model (SEM)

4 Discussion

Async–sync coexistence reflects adaptation to time zones, urgency, and culturally shaped responsiveness expectations. Richer media accelerate clarification under cultural distance; language proficiency supports precision and reduces inference load. Cultural filtering reframes messages through cultural schemas; explicit clarification and feedback mitigate misalignment, especially with stronger language skills[24].

5 Conclusion

This study identifies cross-cultural CMLII features and validates a mechanism in which cultural distance, media richness, and language proficiency influence efficiency via cultural filtering. Practical Suggestions. Align media choice with task ambiguity and cultural expectations; strengthen language and intercultural pragmatics; use translation tools cautiously and verify nuance when connotation is uncertain. Limitations include non-probability sampling and a younger sample; future work should broaden samples and incorporate evolving platform/AI-translation and task-context factors[25].

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