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Generative AI-driven Semantic Compression and Trustworthy Transmission Mechanisms for Cross-cultural Digital Heritage

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Abstract. In the context of intensified digitalization and globalization, cross-cultural transmission of cultural heritage faces dual challenges of semantic compression and trust construction. Existing methods often fail to balance semantic fidelity, transmission efficiency, and cultural adaptability, limiting the effective flow of digital heritage across diverse contexts. This study proposes a Generative AI-based semantic compression and trustworthy transmission framework, integrating the T5 language model, semantic alignment algorithms, and a multidimensional trust model to optimize compression and delivery of digital heritage in multilingual settings. Tests were conducted on open-source UNESCO, Europeana, and Google Arts & Culture data in English, Chinese, Arabic, and French environments. Experimental results show the new approach significantly outperforms traditional approaches in semantic fidelity, compression ratio, cultural adaptability, and explainability, achieving an average 34.8% improvement in cross-cultural transmission trustiness. This work accomplishes more than verifying the technical potential of Generative AI in semantic compression but offers an expandable smart solution to global dissemination of digital cultural heritage.

Keywords: Generative AI, Semantic Compression, Cross-cultural Communication, Digital Heritage, Trustworthy Transmission

1. Introduction

Against the backdrop of intensifying globalization and digitalization, cross-cultural transmission and deep digital preservation of cultural heritage have drawn widespread concern and interest among academia and practice fields. As a significant carrier of collective memory and cultural identity, digital heritage has faced enormous barriers in achieving efficient and reliable transmission across multi-context, multi-lingual, and multicultural environments [1]. Most of the previous studies on cross-cultural communication have focused on localization of the message, contextual adaptiveness, or user acceptability, but little has investigated the transformative potential of Generative AI in semantic comprehension and compression within transmission processes. In particular, in the field of digital heritage, an important open question lies in achieving semantic compression with cultural integrity preservation and enabling low-loss, high-efficiency dissemination [2]. To fill this void, this paper proposes a novel paradigm relying on "Generative AI-driven Semantic Compression and

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Trustworthy Transmission Mechanisms," including semantic preservation, cross-cultural trust modeling, and generative representation.

2. Literature review

2.1. Application of generative AI in cross-cultural communication

Experiments have shown that Transformer models like GPT and T5 have remarkable strengths in perceiving deep semantic structures and contextual pragmatics, and are thus capable of dynamically generating linguistically proper and culturally translatable expressions. But such technological competency does not automatically translate into true intercultural understanding. These models are subject to semantic overfitting or cultural bias in output if they are tested in the context of low-resource languages or non-mainstream cultural settings [3]. As such, even though Generative AI has great potential in rebuilding the routes of cross-cultural semantic transmission, its performance has to be tempered by fine-tuning, culturally annotated corpora, and diversity-conscious semantic modeling [4]. Generative AI functions as much as an agent of enhancing transmission efficacity as a contested site of negotiating technological determinism and cultural multiplicity, but because of this constructive potential in intercultural settings, such potential has to be assessed dynamically and not statically.

2.2. Current status and challenges of semantic compression technology

State-of-the-art mainstream methods are attention-based extractive compression and encoder-decoder generative approaches. As extractive models provide reliability of information fidelity, they are however limited by the surface form of texts; generative models, on the other hand, are dependent on huge-scale semantic modeling competence and are superior in contextual inference and semantic reconstruction and have evident superiority in the retention of implicit cultural information. In cross-cultural settings, however, semantic compression encounters intensified difficulties of ambiguity and cultural disembedding [5]. Classical approaches are prone to excluding cultural metaphors, polysemous form, and background knowledge when compressing, resulting in semantic loss or miscompression. Consequently, achieving high compression levels with the retention of cultural semantic integrity requires incorporating generative modeling, semantic alignment, and cross-contextual recognition [6]. This complexity places new modeling demands on Generative AI-based compression frameworks and propels the development of compression strategies into an ever-increasing sensitivity to cultural pragmatics.

2.3. Trust and information transmission mechanisms

Whereas past research has recognized that technical efficiency may increase dissemination speed and coverage, they similarly prove that in the absence of cultural adaptability and semantic clarity, audiences are likely to form resistance or misconceptions, and thereby compromise communication effectiveness. This phenomenon has particular salience in the case of digital heritage, where the disseminated information has elevated cultural density and symbolic significance, and where any failure of the mechanisms of trust may precipitate semantic distortion and erosion [7]. Dominant technological models tend to disregard the trust architecture, favoring instead such attributes as accuracy or promptness to the detriment of cultural receptiveness and consequently fail to secure culturally diverse users' engagement. The establishment of a cross-cultural trust model, thus, necessitates more than reliable AI outputs but must integrate into its construct semantic

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transparencies, cultural alignment, and user perceptual biases [8]. The model ought to stress the dimensions of "trustful perception and cultural adaptation" as primary bases, essentially redefining the ethics and course of digital heritage transfer in an age of globalization.

3. Methodology

3.1. Design and implementation of semantic compression algorithm

To achieve low-loss compression and semantic preservation of cross-cultural digital heritage, this study constructs a semantic compression mechanism based on a generative pre-trained language model such as T5, aiming to maximize compression ratio while retaining cultural contextual information [9]. First, define the original semantic unit set as $S=\{s_1,s_2,...,s_n\}$, where each semantic unit sis_isi represents key cultural information in the digital heritage text. The encoder function $E(\cdot)$ maps S into a set of vectors in semantic embedding space $V=\{v_1,v_2,...,v_n\}$, such that:

$$V=E(S),v_i\in\mathbb{R}^d \tag{1}$$

Subsequently, the compression function $C(\cdot)$ extracts the information subset $\widehat{V}\subset V$ with minimal redundancy and maximal semantics, optimized by the following objective:

$$\widehat{V}=\text{argmax}_{\widehat{V}}\left(\text{SemanticCoverage}\left(\widehat{V},V\right)-\lambda\cdot\text{Redundancy}\left(\widehat{V}\right)\right) \tag{2}$$

Where λ is a tuning parameter controlling the trade-off between semantic preservation and redundancy.

The mechanism adopts a dual-tower structure to construct contextual semantic graphs and integrates a cross-attention mechanism for cultural context adaptation. To address semantic drift in cross-cultural scenarios, a KL-divergence-based semantic alignment penalty is introduced to guide semantic consistency between outputs across different language models.

3.2. Construction of cross-cultural trust model

Based on the generative AI compression algorithm, a multidimensional and hierarchical cross-cultural trust model is designed to evaluate the effect of information transmission under different cultural contexts. The core structure of the model includes three components semantic transparency layer cultural adaptability layer and technical interpretability layer [10]. A dual-channel feedback mechanism collects perceived trust scores from users with both culturally aligned and heterogeneous backgrounds. During modeling, trust T is formalized as a multivariable function:

$$T=f(S_c,A_c,E_t) \tag{3}$$

Where S_c represents semantic clarity metrics calculated using word sense disambiguation and contextual alignment indicators. A_c denotes cultural adaptability constructed from semantic retention rate and contextual consensus based on cross-lingual corpora. E_t refers to interpretability metrics assessed by SHAP values and visual path dependency.

In terms of structural integration the model output is linked with the semantic compression module by a semantic trustworthiness gating mechanism that determines whether compressed content is released to the target cultural user side. This mechanism dynamically adjusts the cultural

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acceptability threshold of AI-generated content enabling trust-based classification and delivery of compressed semantics and preventing distorted information from reaching target recipients. It enhances both the security and acceptance of cross-cultural communication.

3.3. Experimental setup and data collection

The corpus data primarily comes from three cross-cultural and multilingual open-access digital heritage databases: the UNESCO Intangible Cultural Heritage Dataset (2023 edition), the Europeana cultural portal (2022 edition), and the traditional narrative texts from the Google Arts & Culture platform (curated data from 2021 to 2023). Ten cultural themes were selected from each platform, such as traditional craftsmanship, ritual texts, and local legends [11]. Formal descriptive texts were extracted based on English or multilingual translated versions, with each entry limited to a length of 300 to 1000 words. All data were obtained through API access or public downloads from the respective platforms and were preprocessed to remove HTML tags, duplicate paragraphs, and non-descriptive content in order to ensure the quality of structured modeling.

4. Results

4.1. Evaluation of semantic compression effectiveness

As shown in Table 1, the proposed T5-based semantic compression mechanism significantly improves transmission efficiency and reduces bandwidth consumption while maintaining high semantic fidelity. By testing on traditional narrative texts from the UNESCO Intangible Cultural Heritage dataset, the Europeana cultural portal, and the Google Arts & Culture platform, the algorithm demonstrated strong information integrity across diverse cultural contexts. Specifically, in English, Chinese, Arabic, and French language environments, the semantic compression algorithm achieved an average compression ratio ranging from 62.3% to 68.7%, while maintaining semantic fidelity between 87.4% and 91.2%. Moreover, transmission time was reduced by 45.8% to 52.3% compared to traditional methods. More importantly, the introduction of a KL-divergence-based semantic alignment penalty effectively addressed the issue of semantic drift in cross-cultural scenarios, ensuring accurate interpretation and acceptance of compressed data by the target cultural audiences.

Table 1. Assessment results

Language	Compression Ratio (%)	Semantic Fidelity (%)	Transmission Time Reduction (%)	Bandwidth Saving (%)	Cultural Adaptability Score
English	65.2	89.7	48.3	63.8	8.4 / 10
Chinese	68.7	87.4	52.3	67.2	8.1 / 10
Arabic	62.3	91.2	45.8	59.6	8.7 / 10
French	66.8	88.9	49.7	65.1	8.3 / 10

4.2. Comparison of cross-cultural trustworthiness

The cross-cultural trustworthiness evaluation experiment systematically compared traditional transmission methods with AI-driven semantic compression approaches using a multidimensional trust model, covering three core dimensions: semantic transparency, cultural adaptability, and technical interpretability. As shown in Figure 1, in terms of semantic transparency, the AI-driven

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method received a score of 8.4, representing a 35.5% improvement over the traditional method's score of 6.2. This enhancement is primarily attributed to the superior performance of Generative AI in word sense disambiguation and contextual alignment. The cultural adaptability dimension exhibited the most significant difference, with the AI method scoring 8.7 compared to 5.8 for the traditional method, marking a 50% increase. This result validates the effectiveness of the semantic retention and contextual consensus mechanisms built upon cross-lingual corpora. For technical interpretability, evaluated through SHAP values and visual path dependency analysis, the AI method achieved a score of 8.1, while the traditional method scored 6.5, reflecting a 24.6% improvement. Integrating the three dimensions, the overall trust score for the AI-driven semantic compression method reached 8.32, a 34.8% increase over the traditional method's 6.17. These findings demonstrate that by dynamically adjusting the cultural acceptability threshold through the semantic trustworthiness gating mechanism, the AI-based transmission method exhibits outstanding performance in preventing semantic distortion and cultural misinterpretation.



Figure 1. Cross-cultural trustworthiness comparison: traditional vs AI-driven methods

5. Discussion

As shown in this paper, the Generative AI-led semantic compression model not only performs best in upholding information fidelity and transmission effectiveness across cultural backgrounds but even boosts user trust significantly. Introducing the KL-divergence alignment model effectively offsets semantic drift across language models to ensure consistency of reference in intricate cultural situations. In comparison with classical approaches, the AI-led method does best in the aspect of cultural adaptability, implying that cross-lingual corpus modeling and contextual agreement mechanisms improve cultural receptivity extensively. In addition, the technical improvement of interpretability scores reveals the significance of developing translucent and visualized transmission channels in enhancing user trust constructively.

6. Conclusion

Adaptive Generative AI-controlled semantic compression and reliable transmission scheme effectively tackles the interwoven problems of semantic integrity, efficient compression, and end-user trust in inter-cultural digital cultural communication. Experimental results confirm that the scheme achieves good semantic fidelity and compression rates under multi-lingual situations and substantially boosts cultural adaptability and acceptability. Adoption of a multi-dimensional trust

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model further corroborates the method's extensive superiority in semantic clarity, cultural congruency, and explainability. Potential future work may be devoted to multimodal cultural data and studying collaborative compression approaches across text, speech, and video data to pave the way for intelligent global dissemination of digital cultural heritage.

Contribution

Zihui Tian and Wenhao Zhang contributed equally to this paper.

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