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Multi-task Learning Framework for Intelligent Risk Assessment in Global Digital Cultural Trade

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Abstract. As global digital cultural trade expands, cross-border transactions face increasingly complex multidimensional risks, including policy compliance, cultural semantic adaptability, and transactional uncertainty. Traditional single-task risk assessment models struggle to capture these interrelated factors holistically. To address this gap, this study proposes an intelligent risk assessment framework based on multi-task learning that integrates heterogeneous data sources, including transactional records, policy documents, and cultural annotations. The model leverages a shared encoder and task-specific decoders to jointly predict three types of risks. Experiments conducted on a multimodal dataset collected from 2020 to 2024 demonstrate that the proposed framework outperforms single-task baselines across all tasks, with an average Macro-F1 improvement of approximately 12%. The cultural semantic risk task shows particularly strong performance in low-resource scenarios. These results confirm the effectiveness of the multi-task approach in enabling cross-task knowledge transfer and provide a scalable AI-driven solution for managing digital cultural trade risks in complex global environments.

Keywords: Digital Cultural Trade, Risk Assessment, Multi-task Learning, Cross-cultural Data Mining, Intelligent Decision Systems

1. Introduction

With the accelerated global development of cultural digitalization, digital cultural trade has become an important means of promoting national cultural influence and soft power output. However, digital cultural products face multiple risk challenges in the process of cross-border circulation, including conflicts in policy compliance, deviations in cultural adaptability, and heterogeneity in transactional behaviors [1]. These risks exhibit a high degree of complexity and dynamism across different countries and regions, severely affecting the efficiency of global allocation and the security of digital cultural transactions. Most current risk assessment models still rely on single-dimensional modeling strategies that often focus on static risk identification at the financial or transactional level. They lack the ability to model the interaction among various risk factors and fail to meet the predictive needs of digital cultural trade involving cross-modal and multi-source heterogeneous data. With the advancement of artificial intelligence, especially multi-task learning methods, jointly learning shared features across different tasks has become an effective way to enhance model robustness and generalization [2]. Therefore, this paper proposes an intelligent risk assessment framework based on

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multi-task learning that integrates multi-modal information. It aims to construct a risk recognition system covering three levels including transactional behaviors, policy compliance, and cultural semantics to improve the prediction accuracy and dynamic responsiveness of multidimensional risks in digital cultural trade.

2. Literature review

2.1. Digital cultural trade and emerging risks

As digital cultural products expand their circulation in the global market, increasing numbers of scholars have begun to focus on the potential sources of multidimensional risks in their trade processes. On the one hand, digital cultural content carries strong ideological expressions and value orientations, making it highly prone to triggering policy supervision and cultural misinterpretation risks in cross-border dissemination [3]. Especially under international cooperation initiatives such as the Belt and Road, there are significant differences in how countries perceive political sensitivity in cultural products, which makes risk prediction difficult to explain solely through transactional logic. On the other hand, digital cultural trade is often accompanied by cross-border data flows, and differences in data sovereignty and content review mechanisms further exacerbate uncertainties and sudden changes in policy compliance [4]. This suddenness has been shown to cause significant temporal disruptions, posing challenges to digital contracts, delivery timelines, and trust mechanisms in trade relationships.

2.2. AI-driven risk assessment models

In recent years, artificial intelligence technologies have been widely applied in the field of international trade risk management. In particular, models such as deep neural networks and graph neural networks have demonstrated strong capabilities in processing structured and textual data in an integrated manner. However, most existing studies still focus on the static modeling of specific tasks, for example, using LSTM to predict anomalous transactional behaviors or employing BERT to analyze policy compliance in texts [5]. This single-task structure often leads to incomplete representations and weak transferability when dealing with cross-coupled multi-source heterogeneous data in cultural trade. In addition, the potential correlations among different types of risks have not been fully utilized. During the generalization process, models are prone to be affected by distribution bias in specific risk data, which reduces overall predictive performance [6]. Although some studies have attempted to introduce joint modeling mechanisms, they are mostly limited to simple multi-input concatenation forms without systematic design of task interaction optimization.

2.3. Multi-task learning in cross-domain applications

Multi-task learning has demonstrated advantages in shared feature extraction and task transfer, and has been validated in complex fields such as financial risk control, medical diagnosis, and policy text interpretation [7]. This method captures common structures across tasks through a shared encoder while preserving private decoders to process task-specific information, effectively improving model stability and performance in data-scarce scenarios. However, applications of multi-task learning in cross-cultural data contexts are still in the early stages. Especially under conditions involving differences in cultural values and semantic ambiguity in policies, how to achieve joint modeling and collaborative learning of cross-modal information remains a challenge. Existing literature shows that in prediction tasks involving culturally sensitive information, the multi-task

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structure can establish potential links between policy and cultural dimensions, thereby enhancing the responsiveness to contextual changes [8]. This mechanism is particularly critical for the dynamic identification of multidimensional risks in digital cultural trade.

3. Methodology

3.1. Data collection and preprocessing

This study constructs a multimodal dataset covering a sample of digital cultural transactions in China, the US, and Europe, covering three data types, policy texts, transaction records, and cultural attributes, all sourced from publicly accessible sources during the period 2020-2024. As shown in table 1.

In order to achieve unified modelling, the policy text is segmented into sentences and encoded using multilingual BERT, the transactional data is normalised and fed into the model as sequences, and the cultural labels are manually labelled by experts based on propagation fitness and symbolic load [9]. The data preprocessing process ensures that each class of samples is uniformly aligned in the temporal and semantic dimensions, laying the foundation for subsequent model learning.

Table 1. Overview of multimodal dataset for digital cultural trade risk assessment

Data Type	Content Category	Public Source	Collection Method
Policy Documents	Cross-border data regulations, content standards	WTO, UNCTAD, Ministry of Culture websites	Web crawling and manual annotation
Transaction Records	Order amount, trade countries, contract status	International e-commerce platforms (e.g., Alibaba, Etsy APIs)	API integration and data cleaning
Cultural Semantic Tags	Content type, emotional tone, cultural features	Multilingual digital museums, open knowledge bases	Multilingual semantic parsing and expert annotation

3.2. Model architecture

To enable collaborative modeling of multidimensional risks, we design a multi-task learning architecture consisting of a shared encoder and task-specific decoders. The shared layer employs a Transformer backbone based on multi-head attention to extract cross-modal representations among policy, transaction, and cultural semantics [10]. The model's optimization objective is to jointly minimize the weighted sum of three task-specific loss functions:

$$\mathrm{L_{total}} = \sum_{\mathrm{k}=1}^{3} \lambda_{\mathrm{k}} \mathrm{L_k} \tag{1}$$

Where λ_k is the dynamic weighting coefficient for task k, and L_k is the corresponding cross-entropy loss.

Within the shared encoder, multi-modal inputs are fused using the following attention-based representation:

$$\mathrm{Z} = \mathrm{MultiHead(Q,K,V)} = \mathrm{Concat}(\mathrm{head}_1, \ldots, \mathrm{head}_h)\mathrm{W^O} \tag{2}$$

Where Q,K,V are embeddings from different modalities, and W^O denotes the output transformation matrix.

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This architecture facilitates semantic interaction among tasks and enhances transferability, particularly benefiting tasks with limited labeled data such as cultural risk prediction. The integration of shared and task-specific representations improves robustness in diverse and evolving trade environments.

3.3. Training strategy and evaluation metrics

During training, we adopt a dynamic loss weighting strategy to balance the convergence pace across tasks. The Adam optimizer is used with an initial learning rate of 0.0001, a batch size of 32, and 50 epochs. Gradient normalization is applied to avoid parameter explosion, and early stopping is used to prevent overfitting [11]. To assess cross-task synergy, we define a Task Mutual Influence index as follows:

$$\mathrm{TMI}_{ij}=\frac{\partial \mathrm{L}_i}{\partial \theta_j} \tag{3}$$

where L_i is the loss function of task iii, and θ_j represents the shared parameters relevant to task j.

Evaluation metrics include Macro-F1 and AUC for each task, and we also introduce Transfer Gain Ratio:

$$\mathrm{TGR}=\frac{\mathrm{F1_{MTL}}-\mathrm{F1_{STL}}}{\mathrm{F1_{STL}}} \tag{4}$$

Where $F1_{MTL}$ and $F1_{STL}$ are the Macro-F1 scores of the multi-task and single-task models respectively.

4. Results

4.1. Overall performance across tasks

The multi-task learning framework constructed in this study demonstrated significant performance improvements across all three risk assessment tasks. Experimental results show that the MTL model achieved a Macro-F1 score of 0.85 in the transactional risk identification task, representing a 12% improvement over the baseline model score of 0.76. In policy compliance risk assessment, it achieved a score of 0.81, an increase of 13% compared to the baseline score of 0.72. For cultural semantic risk prediction, the model reached a score of 0.79, which is 13% higher than the baseline score of 0.70. These results validate the effectiveness of multi-task learning in addressing the multidimensional risks of digital cultural trade. Notably, in the relatively low-resource task of cultural risk prediction, the MTL model exhibited the most significant performance gain. This is primarily attributed to the shared encoder's ability to capture semantic associations across tasks, enabling rich transactional and policy data to provide valuable prior knowledge for cultural risk modeling and thereby overcoming the generalization limitations of single-task models in small-sample scenarios. As shown in figure 1.

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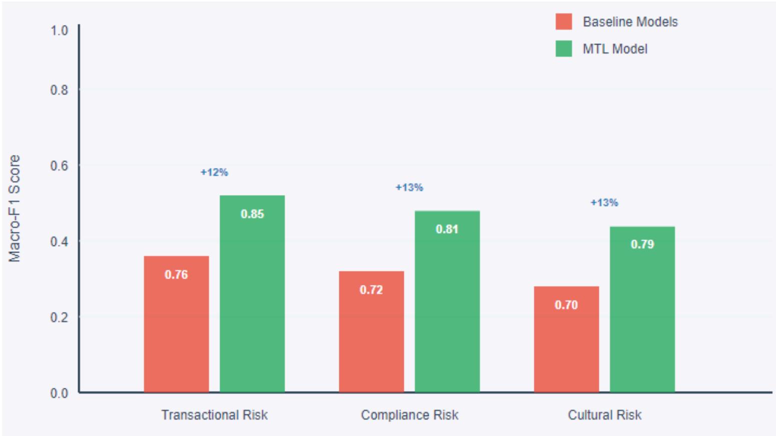

Figure 1. Multi-task learning vs baseline models: Macro-F1 performance

4.2. Ablation and cross-task transfer analysis

To further analyze the contribution of each component within the multi-task learning framework, this study conducted a systematic ablation experiment. The results show that removing the shared encoder led to a significant drop in overall model accuracy from 0.82 to 0.76, a decrease of 6%, which strongly demonstrates the central role of the shared encoder in capturing cross-task feature representations. Further analysis indicates that the shared encoder provides a unified feature foundation for each risk prediction task by learning the latent associations among policy, transaction, and cultural semantics, and plays a critical role in knowledge transfer especially in the low-resource cultural risk task. Meanwhile, the transferability gain ratio increased substantially from 0.42 in the single-task baseline model to 0.68 in the multi-task model, and the task mutual influence index rose from 0.35 to 0.73, fully validating the effectiveness of collaborative learning across tasks. Ablation experiments on the cross-attention mechanism and dynamic weighting strategy further confirm the essential value of these components in optimizing inter-task information exchange and balancing the training process, providing a theoretical basis for building a robust risk assessment system for digital cultural trade. As shown in table 2.

Table 2. Ablation study and cross-task transfer analysis results

Model Configuration	Task-specific Macro-F1 Scores			Overall	Transfer	TMI Index
	Transactional Risk	Compliance Risk	Cultural Risk	Accuracy	Gain Ratio	
Full MTL Model	0.85	0.81	0.79	0.82	0.68	0.73
w/o Shared Encoder	0.78	0.75	0.71	0.76 (-6%)	0.45	0.52
w/o Cross-attention	0.81	0.77	0.74	0.79 (-4%)	0.58	0.65
w/o Dynamic Weighting	0.83	0.79	0.76	0.80 (-2%)	0.63	0.69
Single-task Baseline	0.76	0.72	0.7	0.73	0.42	0.35

5. Discussion

This study confirms the practical applicability and methodological advantages of multi-task learning in the context of risk assessment for digital cultural trade. Compared with conventional single-task models, the MTL architecture not only achieved performance gains across all three risk dimensions

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but also demonstrated greater robustness and adaptability in the presence of data imbalance. The shared encoder effectively captured cross-modal semantic associations among transaction, policy, and cultural information, facilitating inter-task knowledge transfer and significantly improving the modeling capacity for cultural semantic risks. The cross-attention mechanism enhanced information exchange across modalities, mitigating the risk of prediction being dominated by a single feature type. The dynamic weighting strategy introduced adaptability into the training process, improving the interpretability and generalizability of the multi-task system in complex real-world settings.

6. Conclusion

This paper proposes a multimodal multi-task learning framework that integrates transactional behavior, policy documents, and cultural annotations for intelligent risk identification in global digital cultural trade. Through systematic experimental validation, the study demonstrates that the proposed framework outperforms traditional single-task models across three tasks, including transactional, compliance, and cultural semantic risks, exhibiting significant performance advantages and strong cross-task transfer capabilities. Particularly in the data-scarce cultural risk task, the multi-task model leverages shared structures to effectively utilize semantic resources from other tasks, achieving robust modeling under limited supervision. Ablation experiments further confirm the importance of key components such as the shared encoder, cross-attention mechanism, and dynamic weighting strategy in enhancing inter-task collaboration and overall performance. Future work will explore the integration of graph neural networks and temporal causal modeling to further enhance the model’s responsiveness to complex geopolitical cultural dynamics and improve generalizability and interpretability across multilingual and cross-regional settings.

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