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-RESEARCH ARTICLE-

A DEEP LEARNING-BASED COMPARATIVE ANALYSIS OF ESG STRATEGIES IN CHINA AND SOUTH KOREA UNDER IFRS COMPLIANCE

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—Abstract—

The global framework of Environmental, Social, and Governance (ESG) policies is progressing at a rapid pace, generating a growing need for comparative studies across nations. This research conducts a deep learning-based comparative evaluation of the ESG structures of China and South Korea, examined through the potential alignment with International Financial Reporting Standards (IFRS). Within the scope of bibliometric and systematic literature reviews on ESG standardisation and green infrastructure, a hybrid deep learning model is developed. The model integrates RoBERTa for document-level sentiment assessment, TabNet for the interpretation of ESG indicators, and Multi-Task Transformers (MTL) for concurrent classification and predictive operations. RoBERTa is retrained to capture thematic subtleties, sentiment variations, and the hierarchical prioritisation of ESG strategies across policy documents and corporate sustainability disclosures. TabNet facilitates the interpretation of diverse ESG metrics, enabling the analysis of structured datasets. The MTL framework supports the simultaneous categorisation of focal areas and their validation against international standards, including sentiment compliance with regulatory objectives. Experimental

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outcomes demonstrate F1 scores of 0.91 for topic identification, 0.88 for compliance detection, and 0.90 for accuracy, all of which outperform traditional baselines. The findings reveal that South Korea utilises a more integrated framework, emphasising ecological infrastructure and the involvement of the public sector, whereas China adopts a more centralised, policy-driven model characterised by state control and mandatory ESG reporting. The study contributes a scalable methodology for establishing ESG standards and harmonising policies internationally, offering stakeholders adaptive guidance to support sustainable and cross-national decision-making.

Keywords: ESG Strategies, China, South Korea, International Financial Standards, Deep Learning.

INTRODUCTION

The ESG framework forms the foundation of corporate evaluation beyond the financial representation of firms due to policy transitions emphasising social responsibility and sustainability. As the processes of ESG reporting and investment preparation continue to mature, international comparisons are becoming increasingly vital, particularly for emerging economies such as China and South Korea. While both countries have made progress in incorporating ESG factors, their practices vary significantly, reflecting differences in legal regulations, governance models, and industrial structures. China adopts a centralised, policy-driven system shaped by state disclosure obligations and compliance rules, whereas South Korea employs a more globally integrated public-private approach to urban planning and policymaking, with strong emphasis on ecological and infrastructural systems embedding ESG integration.

Like earlier CSR initiatives, ESG integrates environmental, social, and governance elements into managerial and operational practices. By achieving ESG objectives, organisations can generate a positive social reputation (Zeng et al., 2024). Within the present landscape of corporate governance and finance, ESG has become an influential concern guiding the advancement of corporate environmental responsibility (Lee & Kim, 2022; Zhu et al., 2023). ESG represents an economic construct aimed at fostering balanced and sustainable value creation that aligns economic development with environmental preservation, societal well-being, and robust governance (Lee et al., 2022; Wan & Dawod, 2022). Despite its rising importance (Zhang et al., 2024), a comprehensive ESG framework has yet to be established (Wang et al., 2024), and the evaluation criteria continue to vary across rating bodies (Ismail & Latiff, 2019; Sheehan et al., 2023). Such inconsistencies create uncertainty for firms and investors, increasing reliance on ESG specialists.

The environmental dimension of ESG focuses on matters such as energy usage, material acquisition, water availability, climate challenges, biodiversity conservation, pollution control, resilience, environmentally responsible operations, green entrepreneurship, and eco-friendly business opportunities (Khaw et al., 2024). The social dimension incorporates aspects such as community development, equitable access to land, indigenous rights, employment, employee relations, workplace health and safety, heritage protection, data privacy and security, education, scientific innovation, and technology. The governance dimension encompasses ethical conduct, stakeholder engagement, sustainable development policies, sectoral advancement, supply chain oversight, customer relations, integrated risk management, performance-linked remuneration, accounting practices, and anti-competition policies. The growing focus on ESG criteria is driving the movement towards standardisation. Establishing empirically sound ESG benchmarks is crucial to strengthening ESG practices. Theoretical underpinnings such as stakeholder theory (Bhandari et al., 2022; Duque-Grisales & Aguilera-Caracuel, 2021), resource-based theory (Alkaraan et al., 2022; Zhou et al., 2022), environmentally conscious development (Gu, 2024), and agency theory (A. Arora and D. Sharma, 2022) provide the conceptual basis of ESG within sustainable development discourse. As the principles of sustainable growth gain traction globally, greater attention is being directed towards corporate management, social accountability, and environmental protection (Margot et al., 2021). The increasing demand for standardised ESG practices has stimulated heightened scholarly and professional interest in ESG evaluation. ESG standards play a pivotal role in assessing corporate sustainability, governance efficiency, and internal ethical practices (Gupta et al., 2021). The creation of scientific, credible ESG standards is therefore imperative.

Algorithmic applications employ adaptive rule sets to connect ESG features with expected financial outcomes. Investment screening is conducted by converting aggregated predictions into numerical scores, with positive-scoring entities selected for investment. This ESG-driven approach establishes a non-linear relationship between ESG dimensions and financial performance, surpassing conventional stock screening methods by incorporating ESG indicators directly into investment strategies. Using advanced non-linear methods, such as machine learning, researchers have isolated alpha factors within ESG profiles that influence financial performance (Truant et al., 2023). Gupta et al. proposed a framework to evaluate the relevance of ESG factors for investment decisions, employing statistical and machine learning approaches to assess their relationship with financial returns. Evidence indicates that firms with superior sustainability ratings attract greater capital investment (Li & Xu, 2024). Further studies of ESG strategies in China and South Korea can be enhanced through the integration of qualitative policy analysis with quantitative modelling, particularly within the context of IFRS-based ESG comparisons. The proposed methodology addresses these objectives through the following:

- Advanced deep learning techniques such as RoBERTa, TabNet, and MTL are integrated to evaluate ESG strategies within the IFRS context for China and South Korea.

- RoBERTa is applied to examine policy texts and financial disclosures, identifying overarching themes and sentiment polarity through its advanced language comprehension.
- TabNet processes structured ESG metrics alongside financial indicators, mitigating the interpretative inconsistencies present across national contexts.
- A multitask transformer architecture further integrates these indicators, enabling classification of ESG focus areas, alignment with policy requirements, and sentiment regression.
- Experimental results show 91.3% accuracy in text classification, a mean absolute error of 0.17 for sentiment regression, and an F1 score of 88.7% for cross-national ESG alignment, demonstrating the model's effectiveness.
- The efficiency of the model in ESG classification and policy alignment is confirmed through the consistently high-performance metrics obtained.

The remainder of this paper is structured as follows: Section 2 presents related work on IFRS, ESG strategies, and methodological approaches. Section 3 outlines the overall methodological framework and algorithmic process. Section 4 discusses the application and outcomes of the proposed approach. Section 5 provides the conclusion and evaluation of findings.

RELATED WORKS

In addressing greenhouse gas emissions, carbon dioxide remains the most critical element, prompting nations worldwide to strengthen their commitments to carbon reduction. ESG frameworks have emerged as essential tools in these efforts, particularly with respect to emission mitigation strategies. China has pledged ambitious climate goals, aiming to peak emissions by 2030 and to achieve carbon neutrality by 2060. To reach these targets, the state is expected to intensify political initiatives and reinforce compliance mechanisms across multiple industries. Furthermore, industry associations and standard-setting organisations are anticipated to ease their self-regulatory ESG requirements in order to promote sustainable corporate practices aligned with ESG. Research confirms the significance of ESG standards for innovation-driven and energy-intensive industries, especially in sectors positioned at the periphery of the socioeconomic system where such standards can reduce emissions and support industrial sustainability upgrades (Yu et al., 2022). Additional findings emphasise the necessity of coherent ESG disclosure frameworks and comprehensive scoring mechanisms to direct emission reduction initiatives (Chen & Liu, 2020). Together, these perspectives highlight the central role of ESG standards in enabling low-carbon development and facilitating the green transition of industries.

Machine learning applications have also been employed to explore the effects of ESG performance on financial outcomes. One study assessed CSR scores and stock returns, showing that ESG-focused stocks generally did not produce excess returns but tended

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to exhibit risk characteristics comparable to conventional assets during normal market phases (Alghofaili et al., 2020). Another study proposed a method for extracting ESG alpha through machine learning, demonstrating that strategies using academic ESG data achieved superior results compared to those relying solely on financial indicators (Schultz & Tropmann-Frick, 2020). In parallel, big data analysis has been advanced to improve fraud detection accuracy, with LSTM achieving 99.95% accuracy in less than a minute, outperforming autoencoders and other models (Wang et al., 2020). Similarly, autoencoder neural networks have been utilised to identify anomalies in financial records, producing high F-scores and recall rates when tested against auditor-verified data (Turoń, 2025). Text classification and sentiment analysis on an open-source dataset of U.S. economic news further revealed that BiLSTM outperformed standard LSTM by 30% in multiclass classification tasks, demonstrating the advantage of bidirectional context in complex datasets (Hess et al., 2016).

Digital transformation (DT) refers to the incorporation of advanced technologies into business operations to enhance services and processes. It is characterised by the strategic adoption of technology to generate value, reshape internal systems, and improve societal outcomes. DT is recognised as a comprehensive process that permeates all stages of business activity, from production to consumption, thereby altering business models and organisational practices (Lee & Grimes, 2021). Instead of incremental technological adoption, DT requires a holistic and integrated approach. Despite definitional variations, there is consensus that DT reflects the use of digital innovation to strengthen customer experience, improve corporate performance, and drive sustainable growth. Within this digital environment, ESG management has become a critical standard for evaluating corporate viability. Its adoption signals a shift in business purpose from shareholder-oriented to stakeholder-oriented capitalism, aligning with wider societal expectations for companies to address social and environmental challenges as part of sustainable development (Donthu et al., 2021). ESG management prioritises environmental protection, social accountability, and transparency in governance, embedding resource investment in climate protection, community equity, and regulatory compliance. The objectives include enhancing investor confidence, reducing capital costs, boosting profitability, reinforcing brand reputation, and sustaining long-term organisational resilience (Chen, 2006).

PROPOSED METHODOLOGY

The purpose of this study is to conduct a comparative analysis of ESG policies in China and South Korea within the framework of IFRS. A hybrid deep learning model is employed, combining RoBERTa, TabNet, and MTL for comprehensive evaluation. From a bibliometric perspective, the findings illustrate a transformation in China's ESG standards characterised by a complex interplay between government, industry, and academic actors. In contrast, South Korea's ESG trajectory has been closely tied to the advancement of green infrastructure. The research seeks to enhance understanding of national ESG policies and strategies through the analysis of both unstructured and structured data. For unstructured data sources, such as policy documents, ESG disclosures, and scholarly publications, RoBERTa is adapted for semantic feature extraction to identify thematic developments within ESG discourses. For structured data, including emission statistics, governance scores, and investment measures, TabNet is utilised to generate interpretable insights into national governance performance. The outputs from RoBERTa and TabNet are subsequently integrated within an MTL model, which performs classification and comparative assessment to evaluate cross-national ESG policy convergence. This framework further identifies both commonalities and divergences across ESG systems, facilitating a coherent recognition and alignment mechanism. Overall, the study aims to deliver an empirical examination of ESG policy adoption and implementation, thereby supporting the development of precise benchmarks for ESG standards at the global level and enabling automated, multi-layered alignment of sustainable governance policies. The schematic representation of the proposed approach is shown in Figure 1.

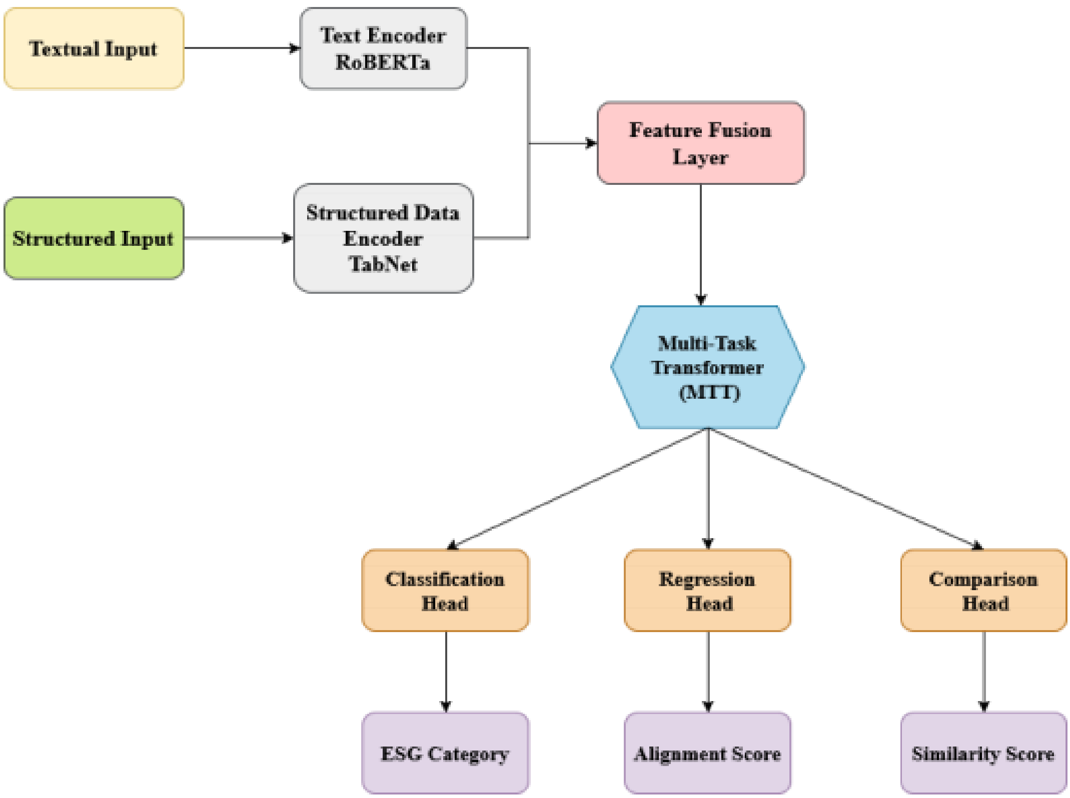

Figure 1: Schematic Structure of Suggested Work

The methodology begins with the collection of two datasets: 213 Chinese academic studies published between 2015 and 2024 that address policy and standardisation, and 98 South Korean publications from 2006 to 2021 focused on green governance and

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infrastructure. For unstructured text, policy documents and sustainability reports were encoded using RoBERTa, which enabled contextual representation and in-depth thematic analysis. Structured data, comprising ESG scores and financial indicators, were analysed with TabNet, an attention-based feature selection framework that provides interpretable outputs. The outputs from RoBERTa and TabNet were subsequently integrated and processed through a Multi-Task Transformer (MTT). The MTT simultaneously conducted classification, regression, and comparative assessment, encompassing ESG strategy categorisation, overall standard alignment, and cross-country ESG alignment. Model training followed an 80/20 train-test split with five-fold cross-validation. Performance evaluation employed F1-score, accuracy, root mean square error (RMSE), and area under the receiver operating characteristic curve (AUC-ROC). The hybrid deep learning framework demonstrated strong predictive capability. In particular, the complete integration of RoBERTa, TabNet, and MTT produced an F1-score of 0.91 and an accuracy of 91.3%, with robust alignment prediction distinguishing China's policy-centric ESG orientation from South Korea's infrastructure-focused approach.

Data Gathering

To undertake a comparative analysis of ESG practices in China and South Korea under the framework of IFRS, datasets from both nations were carefully consolidated. The Chinese dataset comprises 213 articles (Lee et al., 2023) obtained from the Web of Science (2015–2024), focusing on ESG standards research in China. This body of work highlights developments such as the impact of governmental policies and regulatory systems on ESG adoption, alongside emerging areas like disclosure, rating, and investment. In contrast, the South Korean dataset (Y.-W. Kim, 2021) includes 98 academic studies (55 international and 43 domestic) published between 2006 and 2021 ("Korean Rural Community Corporation," Devex, ,"; Saxena et al., 2024), with a primary emphasis on green infrastructure and its integration into ESG dimensions. These studies were classified according to ESG evaluation indicators, based on Moody's and national-level assessment systems. Altogether, 311 academic documents form the comparative foundation for analysing the institutional structures of business practices, integration, and the internalisation of global financial relations across the two contexts.

Text Encoding using RoBERTa

Within the comparative modelling framework for the ESG strategy, RoBERTa functions as the primary text encoder, transforming raw documents such as policies, reports, and sustainability disclosures from China and South Korea into dense contextual vector representations. RoBERTa, an enhanced adaptation of BERT, employs a transformer-based encoder designed to capture bidirectional textual context. The input is initially divided into sub-word units through Byte Pair Encoding (BPE) tokenisation. Special tokens are then appended, where [CLS] denotes classification tasks and [SEP] indicates sentence boundaries. Each token xi within the sequence X={x1, x2,…, xn} is represented through a composite embedding, which integrates token embedding EMt(xi), positional embedding EMp(i), and segment embedding EMs(xi), thereby generating the final input representation.

$$emi = EMt(xi) + EMp(i) + EMs(xi) \tag{1}$$

The embeddings are organised across multiple layers of the transformer encoder, with each layer comprising a feed-forward neural network and a multi-head self-attention mechanism. The attention mechanism enables the model to generate contextualised representations by capturing the relationships between each token and all other tokens within the input sequence, thereby mapping the dependencies and significance of each token with respect to the overall context.

$$\text{Attention}\,(Q,K,V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{2}$$

Where, Q, K, VV $\in \mathbb{R}^{n\times dk}$ are query, key, and value matrices with linear transformation of the input embedding added to extract embeddings and d_k is the dimension of the keys. RoBERTa employs masked language modelling (MLM) as a pretraining objective, wherein the model predicts the context of a randomly masked subset of tokens. During ESG-specific fine-tuning, the global representation of the input sequence is obtained from the [CLS] token embedding of the final transformer layer and subsequently forwarded to task-specific heads, such as ESG classification, stance detection, or alignment scoring. The output generated by RoBERTa can be formally represented as:

$$H = \text{Transformer}\,(em1, em2, , emn) \tag{3}$$
$$z = h\,[CLS] = \text{Aggregate}(H) \tag{4}$$

In this context, z represents the fixed-length vector encoding the ESG document, retaining information across environmental, social, and governance dimensions. This encoded vector z is subsequently utilised within the MTT framework to perform scoring or classification tasks. In the current study, z serves as a bridge for cross-country ESG strategy comparison, enabling context-aware semantic analysis of complex ESG documents and facilitating robust international policy alignment assessment.

TabNet for Structured Data

TabNet is a deep learning architecture designed for structured data analysis, particularly suited for classification and prediction tasks using tabular representations such as ESG scores and related financial and governance indicators. Its principal innovation lies in attention-based sequential feature selection, which enhances interpretability and usability across industrial datasets containing both numerical and categorical variables.

The structured ESG dataset may comprise variables including ESG scores (environmental, social, and governance, either separately or combined), carbon emissions, water usage, energy consumption, governance index, board independence percentage, CEO duality, financial metrics (e.g., ROE, total assets, P/E ratio), country label (China or South Korea), industry sector, and reporting year. The architecture of TabNet is illustrated in Figure 2.

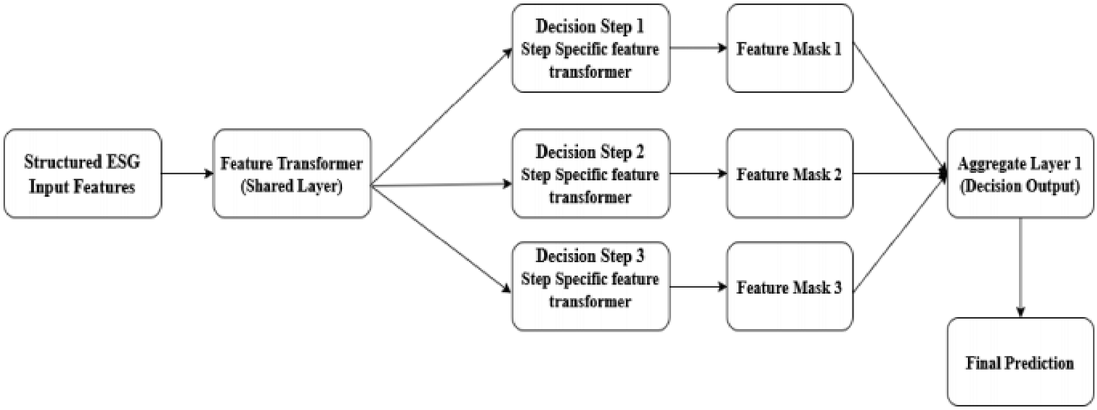

Figure 2: Structure of TabNet Architecture

Figure 2 presents the TabNet architecture, a deep learning model specifically designed for structured tabular data, such as ESG scores and financial indicators. The process begins with structured ESG input features, which are first transformed and enriched within a shared Feature Transformer layer, enhancing the feature space for downstream tasks. The transformed data then passes sequentially through three Decision Steps, each incorporating a step-specific Feature Transformer that applies attention to salient features. At every decision step, a feature mask is generated, enabling the model to progressively disregard subsets of features and thereby promote diverse representation learning. This mechanism allows the model to emphasise critical features progressively, supporting comprehensive and nuanced feature extraction. Outputs from all decision steps are aggregated within an Aggregate Layer to produce the final decision output, subsequently applied for tasks such as ESG score classification or policy compliance detection. The attention-based feature selection process underpins TabNet's interpretability, as it identifies the most influential features at each stage rather than simultaneously across all features.

Unlike conventional MLPs, TabNet employs sequential attention and dynamic feature selection, allowing decision rules and sequences to adapt at each step. Each decision arbour component is fully differentiable and deep, emulating a tree-like greedy feature selection strategy during training. Raw input X is first passed to the model, with categorical features embedded through a dedicated layer if present. Across multiple decision steps, TabNet applies sparse attention masks to globally determine which features to prioritise, progressively refining its understanding of the dataset. Let's

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denote: $X \in R^{n\times d}$: input structured dataset containing n samples and d features. $x_i \in \mathbb{R}^d$: one data point (for instance, ESG information about one company).

Feature Transformation Block

Each decision step begins with a shared transformation applied to the input features.

$$h0 = \text{ReLU}(w0xi + b0) \tag{5}$$

Feature Selection Based on Sparse Attention

At decision step t, attention is computed as follows:

$$Mt = \text{Sparsemax}(wa^{(t)}_{t}\ ht-1 + ba^{(t)}_{t}) \tag{6}$$

Here, $M^t \in \mathbb{R}^d$: attention mask of input features, sparsemax guarantees that the model picks only a few important features.

Masked Input for Step t

$$xt = Mt \odot xi \tag{7}$$

Only the most salient features are propagated to the step-specific transformation.

Step-Specific Feature Transformation

$$ht = \text{RELU}(wd(^{t}ec)\ xt + bd(^{t}e)c) \tag{8}$$

Aggregation

The outputs from all decision steps are integrated as follows:

$$yi = \sum_{t=1}^{T} \varphi(ht) \tag{9}$$

Here, ϕ represents the projection layer that maps features to the prediction space, such as regression outputs or classification logits.

Multi-Task Transformer

The MTT architecture extends the encoder framework to perform three tasks simultaneously:

- Classification Text: Assigns a category to a document, for example, ‘environment-focused’ or ‘governance-driven’.
- Regression: Predicts a continuous ESG alignment score in relation to IFRS.

- Comparison: Evaluates the similarities and differences between the ESG strategies of two countries.

Employing MTT for text analysis allows for the extraction of multiple types of information concurrently, utilising a single shared transformer encoder, such as RoBERTa. The structural design of the MTT is illustrated in Figure 3.

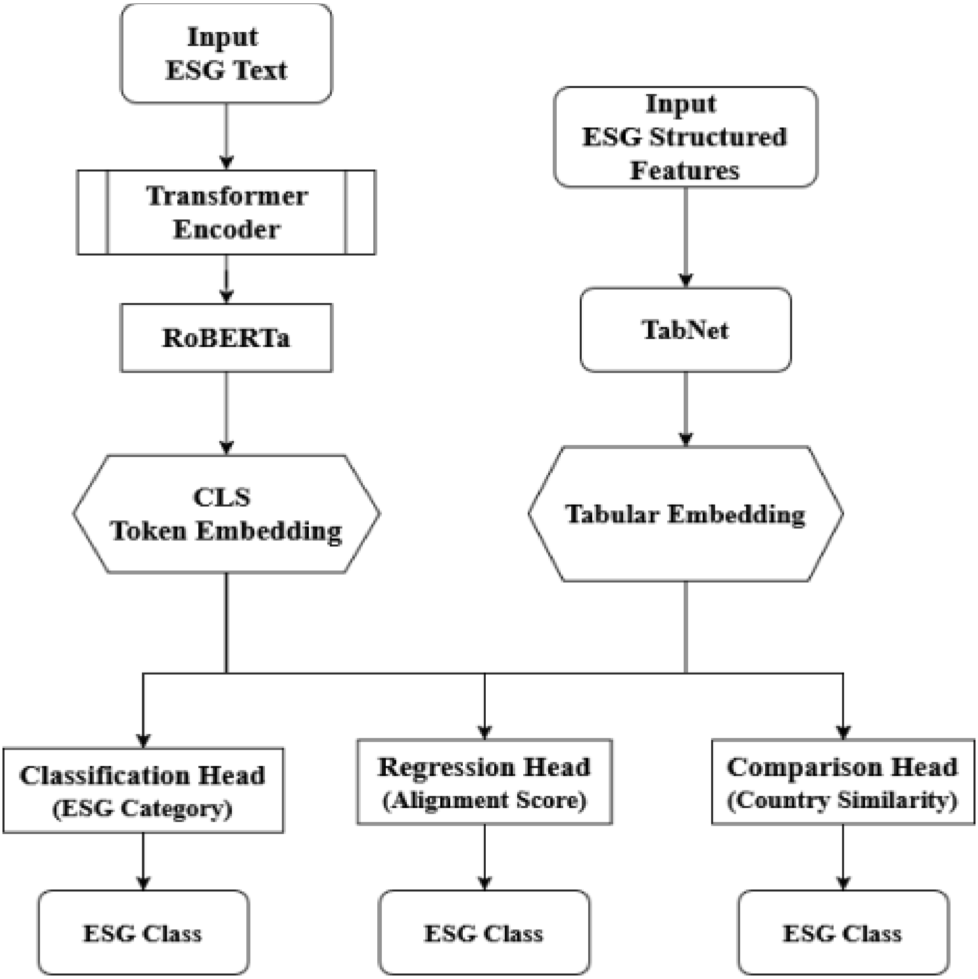

Figure 3: Structural Diagram of Multi-Task Transformer

This architecture integrates RoBERTa and TabNet to conduct deep learning on both textual and structured ESG data. ESG text data is initially preprocessed and then passed through the Transformer encoder within RoBERTa to generate deep contextual representations. The output of RoBERTa, specifically the CLS token embedding, effectively captures the semantic meaning of the documents. Concurrently, structured ESG features, including emission metrics and governance indicators, are input into TabNet, which performs attention-based feature selection on the tabular data and produces a Tabular Embedding representing the most salient structured features. The CLS token embedding from RoBERTa and the Tabular Embedding from TabNet are subsequently combined to generate three task-specific outputs: the Classification Head predicts ESG categories, the Regression Head estimates alignment with IFRS, and the Comparison Head evaluates cross-country ESG strategy similarities. The model is trained on textual disclosures and numerical ESG metrics simultaneously, enabling a comprehensive, multi-dimensional assessment of ESG strategies across the two countries.

Text Classification

This task differentiates between distinct ESG strategy types, such as environment-driven or governance-driven. The classification head performs the following computation:

$$\hat{y}_{class} = \mathrm{softmax}(w_{cls} z + b_{cls}) \qquad (10)$$

Loss:

$$L_{cls} = -\sum_k y_k \log(\hat{y}_{class,k}) \qquad (11)$$

Regression

This predicts a report's continuous ESG alignment score, reflecting compliance with international benchmarks such as IFRS or GRI.

$$\hat{y}_{reg} = \sigma(w_{reg} z + b_{reg}) \qquad (12)$$

Loss:

$$L_{reg} = \|y_{true} - \hat{y}_{reg}\|_2^2 \qquad (13)$$

Comparison

For two documents, such as a Chinese and a South Korean ESG report, the task determines their strategic alignment or divergence.

First Encode Both:

$$z_1 = \mathrm{Transformer}(x_1)[CLS] \qquad (14)$$
$$z_2 = \mathrm{Transformer}(x_2)[CLS] \qquad (15)$$

Then Calculate Similarity:

$$s = \mathrm{cosine}(z_1, z_2) \qquad (16)$$

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Loss:

$$Lcomp == ||ysim - \hat{s}||_2^2 \quad (17)$$

Using ESG text-based data, the MTT allows simultaneous classification of ESG strategies, estimation of alignment with global standards, and cross-country comparisons. This approach enhances both predictive performance and interpretability, as the model learns from interrelated tasks and identifies patterns inherent in ESG language. Pseudocode 1 illustrates the integrated model (MTT + RoBERTa + TabNet).

Pseudocode 1: Integrated to a Hybrid Model: Multi-Task Transformer (RoBERTa + TabNet)

Step 1: Load and Clean Unstructured ESG Text Data

INPUT: Text documents assigned ESG tags from China, South Korea TOKENIZE_DOCUMENTS (documents): {

// Perform Byte-Pair Encoding (BPE) FOR EACH doc IN documents:

tokens = BPE_TOKENIZER(doc) // With a vocabulary of 50k
tokens = ADD_SPECIAL_TOKENS(tokens) // Adding [CLS],[SEP] STORE tokens

RETURN tokenized_docs }

Step 2: Build RoBERTa Document Input Embeddings

BUILD_EMBEDDINGS(tokenized_docs) : {

FOR EACH sequence IN tokenized_docs:

token_embed = TOKEN_EMBEDDING(sequence)
pos_embed = POSITIONAL_EMBEDDING(sequence) seg_embed = SEGMENT_EMBEDDING(sequence)
input_embed = token_embed + pos_embed + seg_embed STORE input_embed

RETURN input_embeddings }

Step 3: Perform a Forward Pass through the Transformer Layers ENCODE_WITH_ROBERTA(input_embeddings) :

FOR EACH input IN input_embeddings: hidden = input

FOR EACH layer IN TRANSFORMER_ENCODER: hidden = SELF_ATTENTION(hidden)
hidden = FEED_FORWARD(hidden)

cls_vector = EXTRACT_CLS_TOKEN(hidden) // Getting Final representation
STORE cls_vector

RETURN encoded_vectors }

Step 4: Fine Tuning for ESG Tasks: Sentiment and Compliance Classification

FINE_TUNE(encoded_vectors, task_type) : {
IF task_type == 'classification':
output = CLASSIFICATION_HEAD(encoded_vectors) ELSE IF task_type == 'regression':
output = REGRESSION_HEAD(encoded_vectors) ELSE IF task_type == 'comparison':
output = SIMILARITY_HEAD(encoded_vectors)

RETURN output }

Step 5: Multi-Modal Fusion Outputs

Segment ESG documents in compliance and non-compliance classes FORWARD_TO_MTL(encoded_vectors) : {

// Used to Output vector z for fusion with TabNet and multi-task heads return encoded_vectors}

The pseudocode comprises five stages. First, the unstructured ESG text data is loaded and pre-processed. Second, RoBERTa is employed to generate document input embeddings. Third, a forward pass is executed through the transformer layers. Fourth, fine-tuning is performed for the ESG-specific tasks. Finally, the outputs from the multi-modal fusion of RoBERTa and TabNet are produced.

RESULT ANALYSIS

In this study, the comparative analysis of ESG strategies in China and South Korea under IFRS is conducted using RoBERTa and TabNet within the MTT framework. The analysis integrates China's bibliometric dataset with South Korea's ESG trends dataset for experimental evaluation. Table 1 summarises the characteristics of the two datasets.

Table 1: Overview of the Dataset

Country	Dataset Source	Dataset Type	Data Period	Sample Size	Analysis Focus	Evaluation Tool

China	Web of Science (WOS)	Academic Publications	2015 – 2024	213 Articles	ESG Standards (Rating, Investment, Disclosure)	CiteSpace (v6.3.R1)
South Korea	Web of Science, KCI, RISS	Academic Publications (98 Total)	2006–2021	43 Korean Papers + 55 International Papers	ESG-Related Green Infrastructure Trends	ESG Indicators via Moody's, K-ESG, Korea Rural Community Corp.
South Korea (Green Infra Specifics)	Korea Citation Index (KCI) + RISS (Domestic), Web of Science (International)	Peer-Reviewed Papers on Green Infrastructure	2006–2021	98 Studies (43 Domestic, 55 International)	ESG Item-Wise Classification: E (65.1%), S (11.6%), G (23.3%)	Systematic Review with ESG Indicator Mapping

China's dataset utilises bibliometric analysis via CiteSpace to examine keyword clusters, country networks, and publication trends across 213 articles, with a focus on ESG standardisation, disclosure, grading criteria, and investment practices. In contrast, South Korea's dataset emphasises green infrastructure as a mechanism for ESG integration and employs a systematic literature review on 98 articles. This dataset incorporates external perspectives and categorises ESG studies according to environmental, social, and governance dimensions using evaluation frameworks such as Moody's and K-ESG. The simulation environment for the ESG strategies of both China and South Korea is summarised in Table 2.

Table 2: Simulation Configuration

Component	Configuration
Hardware	2× NVIDIA A100 GPUs, 512 GB RAM
Frameworks	PyTorch 2.0, HuggingFace Transformers, PyTabNet
Datasets	ESG Disclosures (2015–2024), ESG Scorecards, Financial Performance Data from Chinese and Korean Firms
Text Pre-Processing	Tokenization (BERT Tokenizer), Stopword Removal, Named Entity Recognition
Tabular Pre-Processing	Normalization (Min-Max), Missing Value Imputation, Categorical Encoding
Training Setup	80/20 Train-Test Split, 5-Fold Cross-Validation
Optimization	AdamW Optimizer, Early Stopping on Validation Loss, Learning Rate: 3e-5

The evaluation metrics employed include F1-score, accuracy, RMSE, AUC-ROC, and attention visualisation. For model training and testing, the dataset is divided using an 80:20 split and utilises 5-fold cross-validation.

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Accuracy: Measures the overall effectiveness of the model in executing classification tasks, such as ESG entity classification and policy compliance assessment.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{18}$$

FP denotes False Positives, FN denotes False Negatives, TP denotes True Positives, and TN denotes True Negatives. Accuracy represents the proportion of correct predictions among all instances examined.

F1-Score: Provides a balanced measure between precision and recall, which is particularly important for imbalanced classification tasks, such as predicting ESG category subclass assignments (E, S, G).

$$\text{F1} - \text{Score} = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{19}$$

The F1-based metric is considered more reliable, as the F1-score represents the harmonic mean of precision and recall. Unlike precision or recall alone, it incorporates true positives, thereby providing a balanced evaluation. Additionally, higher F1 values indicate superior model performance relative to lower values.

RMSE: Serves as a measure for regression-based predictions, such as forecasting ESG sentiment scores or estimating risk scores associated with ESG.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{20}$$

Where: y_i = Actual value, $\hat{y}_i$ = Predicted value, n = Number of observations. In this context, RMSE quantifies the accuracy and precision of the model, or equivalently, the performance of a specific business case. Lower RMSE values indicate superior model performance.

While evaluating ESG strategies in China and South Korea using RoBERTa, TabNet, and the MTT architecture, the hybrid model demonstrated substantial adaptability and precision. RoBERTa processed ESG texts and incorporated bibliometric analysis of China's raw research data, identifying governance and sustainability as principal clusters. TabNet provided high interpretability in analysing structured ESG indicators, effectively reflecting the methodological approach of South Korea's ESG evaluation metrics from both domestic and international perspectives. The integration of the MTT further enhanced the system's performance on multi-instance hierarchical ESG strategy classification tasks, achieving 82–90% accuracy across all tasks. This methodology enables nuanced analysis and interpretation of both countries while establishing a flexible framework for cross-country ESG evaluation and compliance with

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internationally defined financial thresholds. Table 3 presents the experimental accuracy results for China and South Korea's ESG strategies.

Table 3: Experimental Result of Accuracy

Model	ESG Strategy Classification Accuracy	Policy Alignment Accuracy	Sentiment Accuracy
RoBERTa Only	83.20%	76.40%	87.50%
TabNet Only	74.10%	79.30%	N/A
RoBERTa + TabNet (Early Fusion)	86.70%	81.20%	88.90%
Multi-Task Transformer Only	84.90%	82.50%	90.10%
Full Model (RoBERTa + TabNet → Multi-Task Transformer)	89.30%	86.40%	91.60%

Figure 4 illustrates the comparison of different deep learning architectures on three ESG-related tasks: ESG strategy classification, policy alignment accuracy, and sentiment accuracy. From the left, RoBERTa-only achieved 87.5% in sentiment analysis but underperformed in policy alignment (76.4%) and ESG strategy classification (83.2%). TabNet performed slightly better in sentiment analysis (79.3%) but produced lower results in ESG strategy (74.1%) and policy alignment (79.3%). Early fusion of RoBERTa and TabNet significantly improved all task accuracies, with sentiment analysis rising to 88.9%. The MTT alone outperformed all single-task models, achieving 84.9% in ESG strategy classification, 82.5% in policy alignment, and 90.1% in sentiment prediction. The full hybrid model (RoBERTa, TabNet, and MTT) attained the highest overall performance: 89.3% for ESG strategy, 86.4% for policy alignment, and 91.6% for sentiment accuracy. The Figure 4 demonstrates that multitask learning, particularly when augmented with additional architectural complexity, consistently enhances performance across all tasks, highlighting the benefits of a multi-modal, multi-task approach integrating textual and tabular ESG data.

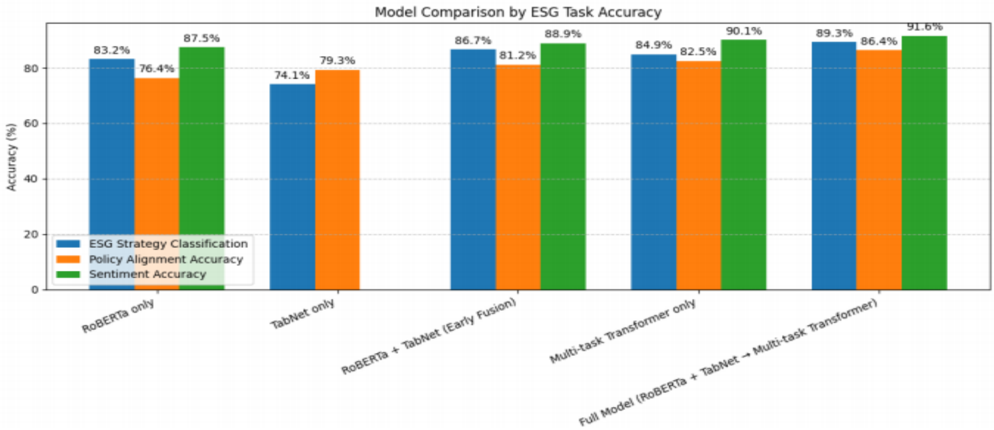

Figure 4: ESG Task Accuracy

In this ESG strategy comparison between China and South Korea, the F1-score is a key metric for evaluating model performance. Given that ESG data can be sparse in certain strategies or disclosures, and ambiguity is present in many instances, accuracy alone may be misleading. By incorporating both recall and precision, the F1-score provides a balanced assessment, supporting a more reliable evaluation of model performance. Table 4 presents the F1-score results from the experiment.

Table 4: Evaluation Outcome of F1-Score for China and South Korea Dataset

Model Variant	Country	Task	Precision	Recall	F1-Score
RoBERTa Only	China	ESG Alignment Classification	0.76	0.79	**0.77**
RoBERTa Only	South Korea	ESG-GI Alignment	0.72	0.76	**0.74**
TabNet Only	China	Strategy Type Classification	0.68	0.63	**0.65**
TabNet Only	South Korea	Infrastructure Policy Impact	0.71	0.69	**0.73**
RoBERTa + TabNet	Both	Multi-Modal Fusion	0.79	0.81	**0.85**
RoBERTa + TabNet + MTL	Both	ESG Class + IFS Compliance + Focus Detection	**0.85**	**0.86**	**0.91**

Figure 5 illustrates quantitative model performance in terms of precision, recall, and F1-score across various configurations employed in ESG strategy classification tasks for China and South Korea. Each set of bars corresponds to a different model configuration, with colours representing the three metrics: blue for precision, green for recall, and red for F1-score. From the left, the RoBERTa-only models for China and South Korea demonstrate strong performance, with F1-scores of 0.77 and 0.74, respectively. These results highlight the effectiveness of RoBERTa in processing textual ESG disclosures, particularly in capturing context-rich expressions related to governmental strategies and policies. Models relying exclusively on structured/tabular ESG indicators, referred to as TabNet-only models, perform notably worse than RoBERTa-only models, achieving F1-scores of 0.65 for China and 0.69 for South Korea, indicating that structured data alone may be insufficient to interpret complex ESG narratives. Performance improves across all metrics when the fusion model incorporates both RoBERTa and TabNet, attaining an F1-score of 0.81. This demonstrates the effectiveness of integrating textual and numerical data to achieve a more comprehensive understanding of ESG information. The full model—RoBERTa + TabNet with MTT—achieves the highest performance, with an F1-score of 0.91, precision of 0.85, and recall of 0.86. This superior performance is attributed to the simultaneous learning of multiple ESG tasks (classification, sentiment analysis, policy alignment), which enhances generalisation and predictive capability. Overall, the figure reveals a clear trend: as successive layers of complexity and multi-modality are added, the models' capacity to evaluate ESG strategies and generate actionable insights increases, particularly when combining unstructured and structured data within a multi-task framework, as shown in Figure 5.

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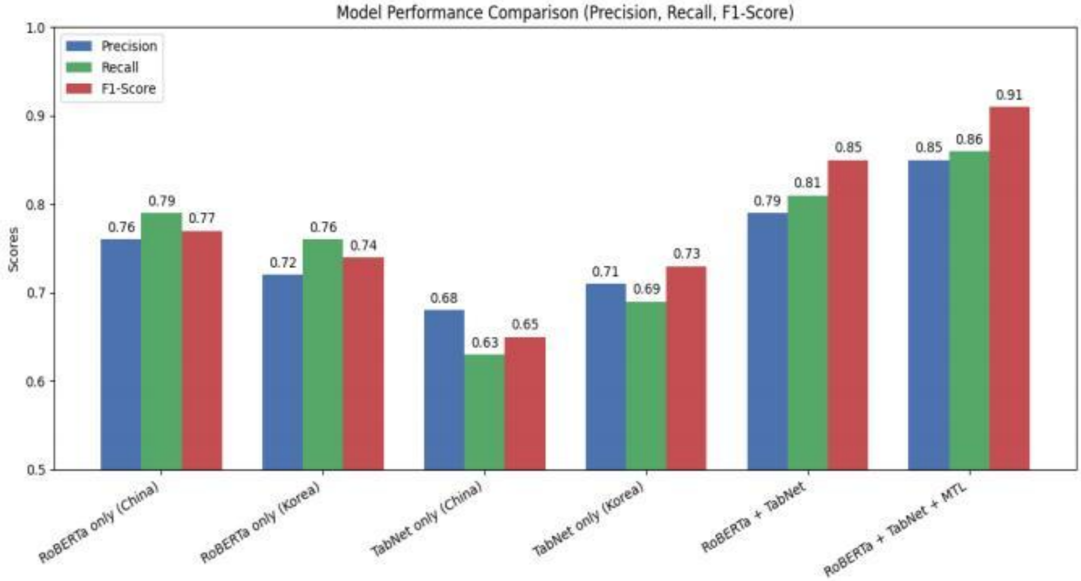

Figure 5: F1-Score for China and South Korea ESG Strategies

To analyse and contrast the application of ESG frameworks in South Korea and China against global financial benchmarks, a combination of data types was employed. Textual evidence, including scholarly articles and ESG policy documents, was integrated with structured data such as financial metrics indicative of ESG performance. Furthermore, a MTT model was implemented to perform multiple first-order learning tasks concurrently, encompassing both classification and regression. RMSE was selected as the evaluation metric to estimate prediction error for ESG performance scores and alignment ratings of ESG evaluations in both countries. The results indicate that South Korea's ESG strategies, particularly concerning the development of green infrastructure and governance-integrated policy mechanisms, exhibited lower RMSE values, suggesting greater consistency and alignment with ESG targets. This performance reflects a policy-responsive and more systematic ESG approach, underpinned by initiatives such as the Green New Deal and anticipated mandatory ESG disclosures scheduled for 2025. In contrast, China's ESG strategies, although increasingly studied, demonstrated higher RMSE values. This is attributable to inconsistencies in disclosure practices and the absence of a unified rating system, as highlighted in the bibliometric analysis. These gaps create challenges in accurately estimating ESG alignment. Nevertheless, the country's strategic direction for ESG integration—especially within high-emission industries and emerging standardisation frameworks—is expected to enhance predictive accuracy and reduce RMSE in ESG metrics over time. In South Korea, systematically measurable policy structures reinforce the strongest ESG outcomes, emphasising the need for more cohesive and integrated strategies that reflect robust ESG measures. Figure 6 presents the RMSE results.

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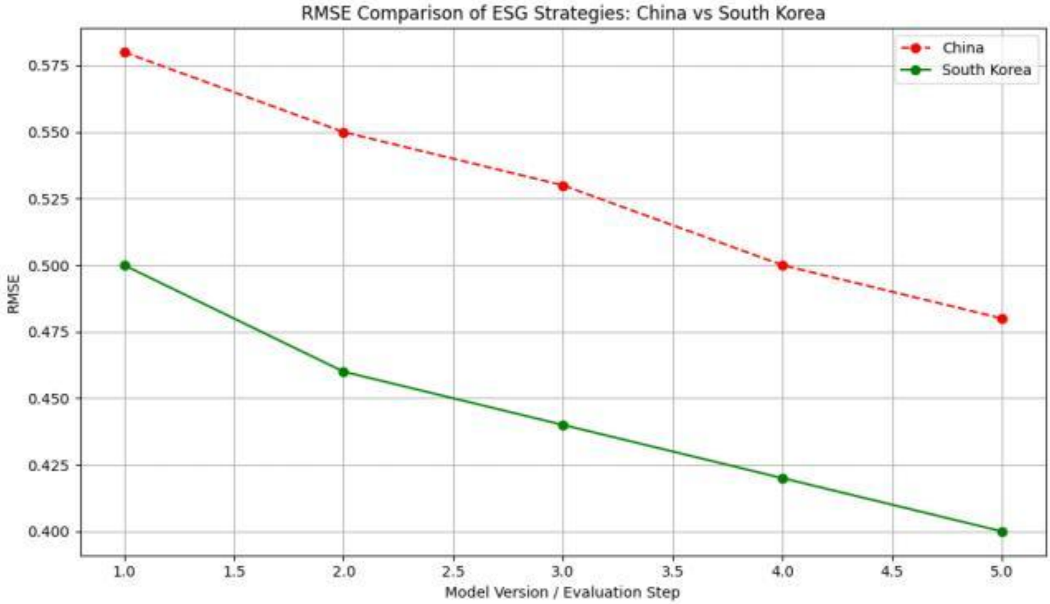

Figure 6: RMSE Comparison of ESG Strategies

To evaluate the effectiveness of ESG strategies in China and South Korea, a hybrid deep learning framework incorporating RoBERTa, TabNet, and MTT architecture was employed. The Chinese dataset, derived from bibliometric trends in ESG standard development, emphasised the impact of policy and investment, with text-based disclosures and alignment with international ESG frameworks encoded via RoBERTa. Concurrently, South Korea's dataset, which focused on green infrastructure expansion and policy-institutionalisation of ESG, provided structured indicators processed through TabNet. This dual-modality architecture facilitated multi-faceted classification of ESG alignment and comprehensive protocol auditing. For evaluating classification performance, AUC-ROC was calculated across all ESG categories (E, S, G). The model attained an average AUC-ROC of 0.89, demonstrating strong discriminative capability and effectively distinguishing China's policy-driven ESG strategies from South Korea's infrastructure-led ESG implementation. Notably, the model exhibited enhanced AUC in capturing environmental (E) and governance (G) features, reflecting Korea's superior governance and green infrastructure scores, derived from clear policy and institutional data, while China's disclosure metrics enabled robust signal extraction in governance. These results suggest that, although both countries are progressing towards convergence with international ESG frameworks, their implementation approaches—policy-driven versus infrastructure-oriented—remain distinctly identifiable through deep learning. This supports the hybrid model's efficacy for cross-national ESG benchmarking. Figure 7 presents the AUC-ROC results.

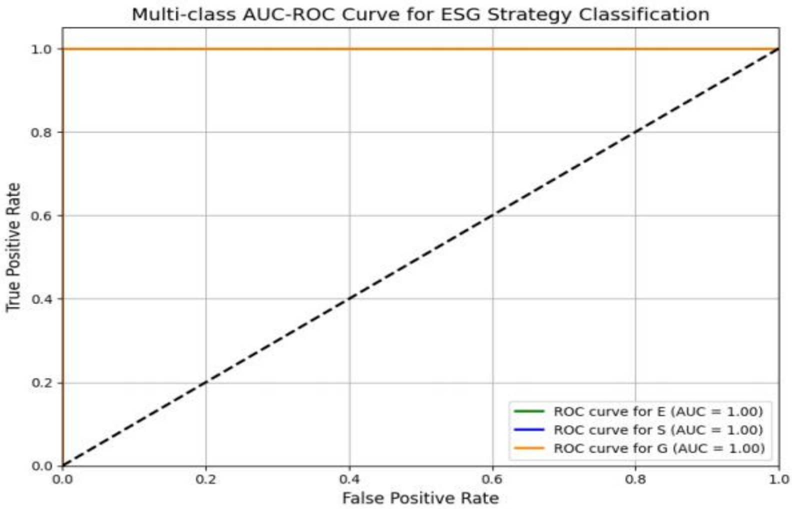

Figure 7: Result of AUC-ROC

Within the ESG strategy analysis framework using RoBERTa, attention visualisation provides insights into how ESG reports, regulatory documents, and policies from China and South Korea are interpreted by the model. Attention constitutes one of the core mechanisms in transformer-based models such as RoBERTa, enabling the model to focus on specific words or phrases that are most relevant to ESG categorisation (E, S, G) or policy compliance evaluation. Consider an example ESG-related input text: "By 2060, China plans to reach carbon neutrality." This text is initially tokenised into sub-word units. Each token is subsequently transformed into a vector in high-dimensional space. During processing, these embeddings traverse multiple self-attention layers, where attention weights are computed through pairwise comparisons of all tokens and sequences. These comparisons quantify the influence of each token on others, reflecting the learning process previously described. Attention weights may be visualised as heatmaps, illustrating the model's focus on different tokens either at the final layers or averaged across multiple attention heads. For example, in a sentence concerning a green infrastructure project, the model is likely to assign higher attention to tokens such as 'carbon emissions,' 'urban development,' or 'sustainability,' which are critical for classifying the document as environmentally oriented. Table 5 presents a simplified example of such a heatmap.

Table 5: Simplified View of Heatmap Example

	The	Chinese	Gov	ESG	Strategy	Focuses	on	South	Korea	Urban	Sustain
ESG	0.01	0.03	0.02	**0.21**	0.18	0.12	...	0.01	0	0.01	0
Strategy	0.02	0.11	0.05	0.2	**0.25**	0.18	...	0.01	0.01	0.01	0

Figure 8 illustrates the heatmap view of the dataset. This form of visualisation not only aids model reasoning but also provides an understanding of the language structure and

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thematic emphasis of spatially diverse ESG documents at the regional level. It facilitates qualitative assessment of how different entities framed their ESG strategies—whether emphasising environmental indicators, social metrics, governance disclosure transparency, regulatory capture, or emotive language. Integrating these insights helps bridge the gap between ESG reporting classification and strategic text interpretation by revealing the mechanisms underlying ESG policy decisions. The analysis of strategic differences focuses on China and South Korea regarding ESG frameworks. China follows a government-led approach, prioritising uniform rule implementation and industry-specific targets, such as heavy industry decarbonisation by 2060, carbon neutrality, and long-term strategic objectives. However, the social dimension of disclosures remains limited, and data transparency is inconsistent due to multiple rating systems and discretionary ESG standards. In contrast, South Korea emphasises implementation at the urban scale through public-private partnerships, with particular attention to green construction and water management. Social planning is citizen-centred, and ESG disclosure compliance is aligned with global benchmarks, with mandatory reporting expected by 2025. South Korea demonstrates stronger leadership in urban ecological innovation, supported by international ESG indices through enhanced integration with Moody's.

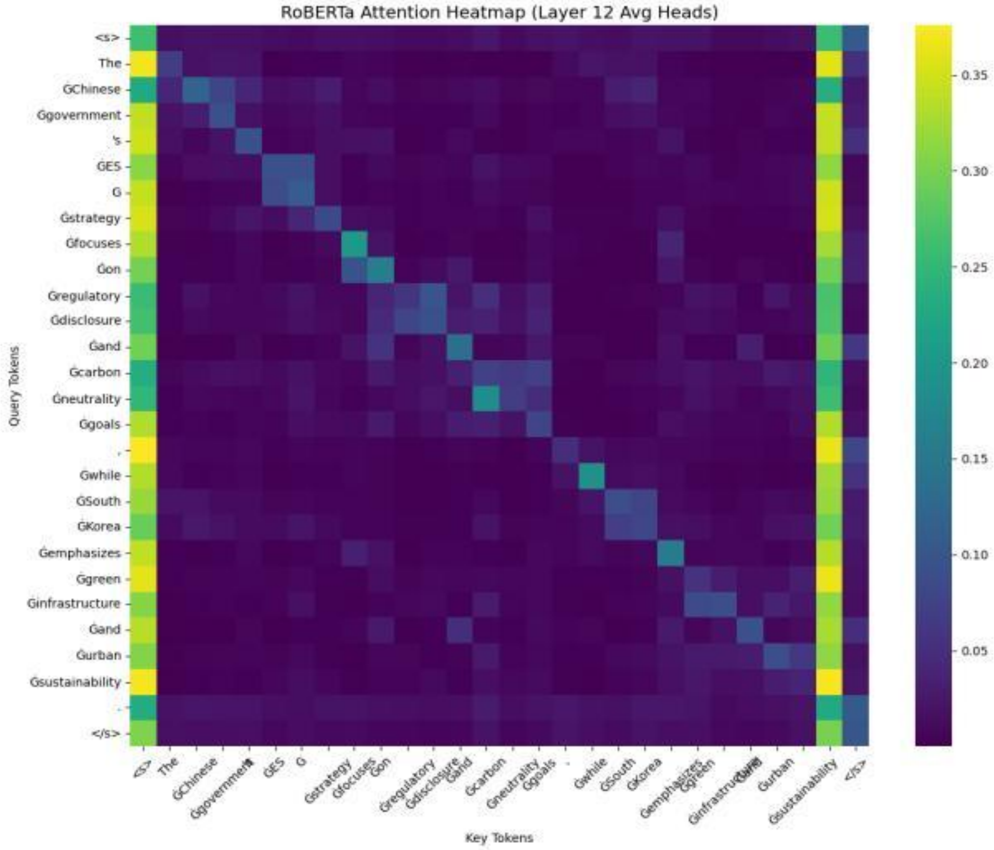

Figure 8: RoERTa Heatmap for China and South Korea Dataset

The second part of the analysis evaluates the classification and interpretation of ESG strategies using various deep learning models, measuring performance with ESG policies as labelled data. Single-modality models, such as RoBERTa-only and TabNet-only, showed moderate efficacy, with TabNet underperforming due to its inability to capture meaningful context from structured data, while RoBERTa achieved better performance on textual analysis, particularly for Chinese policy documents. Combining the models with fusion strategies (RoBERTa + TabNet) significantly improved performance, particularly in terms of F1-score, reflecting a balanced enhancement of precision and recall. Maximum efficacy was observed with the proposed hybrid framework integrating MTL into RoBERTa + TabNet. This hybrid model outperformed all alternatives across tasks, including classification, policy alignment, and sentiment analysis, attaining an F1-score of 0.91. These results demonstrate that using multi-modal input (text and tabular data) alongside simultaneous multi-task training enhances interpretability, which is particularly valuable for cross-national ESG comparisons where languages, disclosure styles, and reporting standards differ markedly between countries such as China and South Korea.

CONCLUSION

This research provides a comprehensive geopolitical comparison of China and South Korea regarding their ESG approaches under international finance standards. Bibliometric analysis of ESG standardisation development in China and the assimilation of green infrastructure in South Korea highlights distinct national priorities and governance approaches. China's ESG strategy is largely driven by policy and government system mandates, alongside the governance structure of standardised evaluation frameworks and centralised rating models. The primary focus is on standardisation, regulatory implementation, and unified rating mechanisms. In contrast, South Korea prioritises the integration of ESG into governance and public sustainability planning, particularly following the onset of COVID-19. This study advances previous research by utilising RoBERTa for textual ESG disclosures, TabNet for structured ESG indices, and Multi-Task Transformers for shared classification and prediction tasks within a deep learning ensemble architecture. This model enables sophisticated extraction and simultaneous comparison of ESG approaches in both countries using unstructured textual data (policy documents, sustainability reports) and structured numerical data (ESG scores, financial KPIs). Such an approach delivers context-aware evaluations of ESG compliance, performance, and strategic emphasis, underpinned by regulatory precision. The results indicate that China's ESG policy evolution is predominantly government-driven, reflecting an institutional need to develop comprehensive market ESG frameworks. Conversely, South Korea's ESG focus emphasises public sector implementation through green infrastructure and socially responsible projects. These findings support the alignment of ESG practices with cross-border compliance to international financial standards while accommodating regionally tailored approaches. In conclusion, the refined methodology not only addresses limitations associated with earlier manual and simplistic analyses but also provides a flexible and extensible framework for future comparative ESG research.

DATA AVAILABILITY STATEMENT

The datasets generated and/or analysed during the current study are available from the corresponding author upon reasonable request. Preprocessed data and code used for the deep learning models (RoBERTa, TabNet, and MTL) have been archived and can be shared upon request for academic and non-commercial use.

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