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# AI-CC SWOT Analysis for Sustainable Product Markets: A Cross-Cultural Comparison Between China and the United States

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**Abstract.** Sustainability serves as a modern business strategy, enhancing a company's competitive edge. SWOT is a classic business strategy analysis model used to analyze a company's strengths, weaknesses, threats, and opportunities. However, traditional SWOT analysis often demands significant human and time resources. In addition, organizational behavioral change presents a notable challenge in sustainability reengineering. To address these analytical demands and cultural behavioral barriers, we propose a novel artificial intelligence (AI)-based SWOT analytical model, named AI-CC SWOT. Implemented with an AI system, this model leverages natural language processing to automatically gather information from diverse sources, integrating key sustainability metrics (e.g., carbon footprint) and cultural factors (e.g., Hofstede's cultural dimensions) into the SWOT analysis. We tested this model by studying the sustainable policies of China and the United States and their cultural insights. The results indicate that AI-CC SWOT provides a more objective and culturally aware assessment compared with traditional methods. By analyzing broad policies, such as China's carbon neutrality goals, and consumer sentiment regarding these policies, the AI-CC SWOT model demonstrates adaptability to diverse global markets. It assists companies and governments in making more informed decisions, thereby improving environmental impact, social responsibility, corporate governance, and overall market competitiveness.

**Keywords.** sustainable product market, SWOT analysis, artificial intelligence (AI), cross-cultural analysis, natural language processing (NLP), carbon footprint, Hofstede's cultural dimensions, policy adaptation, market competitiveness, ESG

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## 1. Introduction

Sustainability has emerged as a crucial global trend and a core business strategy for many companies. SWOT is a classic model for competitive analysis, enabling companies to analyze strengths, weaknesses, threats, and opportunities to develop new business strategies. However, challenges in sustainability development include organizational change and human adoption of sustainable products. This study develops the Artificial Intelligence–Driven Cross-Cultural Sustainable SWOT (AI-CC SWOT) model, integrating carbon footprint metrics and Hofstede's cultural dimensions through natural language processing (NLP) to address the limitations in traditional SWOT analysis models. The objectives are to design the AI-CC SWOT model and to validate it with a case study. The case study utilizes a new China–United States energy vehicle market strategy to validate the framework.

## 2. Literature Review on Traditional Analysis Limitations and AI-Driven Cross-Cultural Innovations in Sustainable Markets

### *2.1. Limitation of Existing SWOT Analysis for Sustainable Product Markets*

Traditional SWOT analysis faces many limitations in sustainable product market analysis, which mainly relies on subjective human judgments about sustainability factors (e.g., the use of recycled materials) and lacks quantitative cross-cultural insights [1]. Although some researchers have used AI such as BERT-based text analysis and random forest classifiers to analyze the market and have reported improved efficiency of data processing to a certain extent [2], the existing models fail to integrate sustainability value (e.g., carbon footprint) and cross-cultural dynamics (e.g., urbanization) in the analysis for decision-making. Therefore, our study proposes the AI-CC SWOT model, which uses NLP to automate multisource data extraction (policies, reviews, and financial reports) and dynamically categorizes insights into expanded SWOT dimensions (including sustainability and cultural factors).

### *2.2. AI-Driven Market Analysis*

Holzinger et al. [3] proposed a predictive analytical model for renewable energy that can respond to market changes in real-time through dynamic pricing of energy and supply and demand forecasting, thereby optimizing resource allocation with a forecast error of less than 5%. This outcome suggests that AI enhances data processing capabilities and energy stability, but the model lacks cultural adaptability, such as policy differences between China and the United States, as well as regional differences in electricity consumption habits. Achumie et al. [4] developed an AI framework that enhances customer segmentation using NLP and clustering algorithms, leading to a 25% increase in retail conversion rates; however, this model also lacks cultural adaptability and cross-border validation. Furthermore, existing AI methods for market analysis often rely on homogeneous data models, limiting their ability to integrate multidimensional cultural variables (e.g., regional consumer values) and thereby reducing the effectiveness of cross-cultural analysis. In the process of value chain analysis, these methods lack dynamic tracking of regional supply chain differences (e.g., differences in labor laws and regulations and logistics infrastructure), making it difficult to implement global optimization strategies. Both studies failed to adequately account for cross-cultural market habits and lacked validation within sustainable industries. Future research on AI-driven market analysis should integrate both cultural and national dimensions to ensure technological innovations are policy and culturally adaptable.

### *2.3. Global Value Chain (GVC) Dynamics and Regional Leadership in Sustainable Markets*

#### *2.3.1. Importance of Environmental, Social and Governance (ESG) Analysis for global market supply chain analysis*

Boulahlib [5] focused on the international expansion strategies of U.S. companies in the context of globalization. They discussed the key roles of digital technologies and cultural adaptation, and introduced a "technology culture" framework for success. It emphasizes that technology helps small and medium-sized enterprises to grow and that knowledge of local culture is crucial for adaptation. Leading companies stay ahead of the curve by striking a balance between standardization and customization. However, the study had limitations, including a narrow focus on specific industries, insufficient research on emerging markets and ESG issues, and the need for more comprehensive comparisons relating to supply chains and other factors. Given greenhouse gas emission scope 3 is highly related to the supply chain processes such as sustainable transportation, ESG factor should be included in global market analysis.

#### *2.3.2. Lack of ESG Consideration and Integrating AI in GVC Analysis*

Stapopoulos [6] proposed a methodological framework for decomposing the participation of European countries in domestic value chains and GVCs. The author found that the participation in GVCs in Europe is on the rise overall, but shows significant spatial differences. However, this framework excludes emerging areas such as the digital economy and the green transition, ignores differences in regional and cultural dimensions, and does not fully integrate factors such as regional technological capabilities and institutional policies. Applying AI to GVC research can leverage machine learning for real-time big data processing, improving the spatiotemporal resolution of GVCs, and dynamically identifying regional advantages. For example, NLP can be used to analyze policy text. However, AI also has limitations: It struggles to capture implicit cultural norms (e.g., supply chain trust) and may overlook disruptions due to its dependence on historical data. Future research should further deepen the integration of AI and regional economies, balancing the data efficiency of AI with qualitative analysis of cultural institutions to enhance the timeliness and cross-regional applicability of GVC research.

#### *2.3.3. Green Technologies and Product Growth in the Global Market*

Pei and Su [7] explored digital transformation through GVC restructuring to optimize East Asia's export structure. Using the examples of BYD (an electric vehicle manufacturer) and CATL (a battery manufacturer) in China, they highlighted the role of the Chinese marker in technological innovations in electric vehicles, solar photovoltaics, and digital platforms, reflecting the importance of China's market economy in sustainable product chains and high-tech manufacturing.

### 2.4. NLP for Cultural and Consumer Market Analysis

Khan et al. [8] found that in Asian frontier markets such as Pakistan, return spillovers tend to be more closely connected, especially during tensions between the United States and China, with these connections varying by time and frequency. However, their model does not incorporate AI tools to analyze specific industry sectors or promote sustainable products. Ogundu [9] highlighted that U.S. tariffs contribute to currency declines in emerging markets and suggests tools like central bank digital currencies (CBDCs) and the Regional Comprehensive Economic Partnership (RCEP) for macro-level risk management, but he did not explore how AI—such as NLP—can help understand cultural differences and consumer preferences on a micro level. Mazandarani and Royo-Vela [10] introduced a framework for green marketing collaboration based on proximity, but they did not include AI-backed cross-cultural studies, such as using blockchain data to measure trust. By adding AI, we could bridge these gaps: It would allow the use of real-time policy data to better adjust sector risk weights, the analysis of consumer reviews with NLP to customize cross-cultural strategies, and the empirical validation of trust in green markets across different cultures. Given the complexities of United States–China relations, blending macro strategies with AI-driven micro insights could lead to more comprehensive, resilient, and sustainable global trade practices.

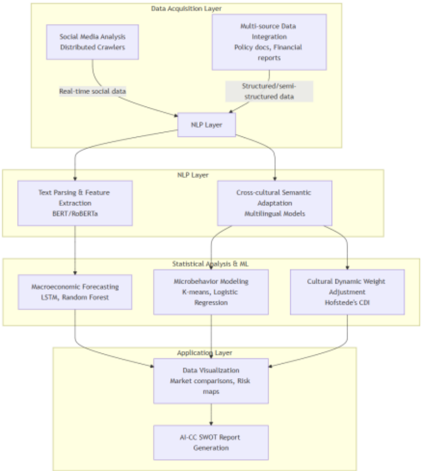


**Figure 1.** AI-CC SWOT System Architecture and Data Flow Diagram

Note: This diagram illustrates the end-to-end workflow of the AI-CC SWOT framework, from multisource data collection to SWOT report generation. The technical implementations rely on open-source tools (e.g., Hugging Face Transformers and Plotly) and the Hofstede Insights API. Cultural-weight adjustments follow Hofstede's cultural dimension theory.

### 2.5. Summary

This paper examines challenges in sustainable product markets and cross-cultural analysis. Traditional SWOT analysis lacks objectivity and cross-cultural insights, limitations that are addressed with the AI-CC SWOT model (Figure 1). Existing AI models (e.g., renewable energy and retail) show efficiency but lack cultural adaptability and cross-border validation. Studies on the global expansion of U.S. firms, European GVC participation, and China's innovation leadership highlight tech-culture balance, outdated data, and macro-level focus. Cross-border trade research identifies geopolitical risks and calls for integrating macro-hedging with micro-cultural adaptation, emphasizing AI's role in enhancing spatiotemporal analysis and empirical validation across cultures.

## 3. Research Methodology

This study employed a review, comparison, and conceptual framework. The review includes an analysis of the measurement metric for ESG and cultural factors as well as the components in the market analysis models. Finally, we formulated the AI-CC SWOT analysis model based on this review.

### *3.1 Measurement Metrics for Market Analysis*

The AI-CC SWOT model combines traditional, sustainability, and cultural adaptation metrics. Traditional metrics include market share (calculated as enterprise sales divided by total industry sales, multiplied by 100%) [11], the compound annual growth rate (CAGR) [12], and the Herfindahl–Hirschman index (HHI) to assess competitive positioning, long-term growth, and market concentration. Sustainability metrics incorporate carbon intensity (total emissions divided by sales revenue) [13]14] and green product penetration (percentage of sales from ecofriendly products) [14], aligning with European Union (EU) guidelines on sustainable value chains. The cultural adaptation metrics utilize Hofstede's cultural distance index (CDI) [15] and dynamic response speed (DRS) [2] to evaluate the efficiency of the AI-CC SWOT model in cross-cultural contexts.

### *3.2. Market Analysis Instruments*

We employed a hybrid approach to merge established frameworks with AI-driven tools, implemented using Python 3.9 and open-source libraries (Hugging Face Transformers for BERT/RoBERTa NLP, Scikit-learn for machine learning, and TensorFlow for deep learning). In addition, we used PESTEL analysis to evaluate macro-environmental factors and Porter's Five Forces model to assess competitive dynamics. For strategic positioning, the AI-CC SWOT model is a conceptual framework that includes (a) prototype validation by data ingestion, using Beautiful Soup for web crawling to identify policy documents (e.g., China's dual-carbon policies) and the Twitter API to collect social media sentiment data; (b) NLP processing based on BERT-base-Chinese for Chinese policy entity extraction and RoBERTa-base for English consumer review sentiment analysis [15]; and (c) cultural weighting, with integration of the Hofstede Insights API for real-time cultural dimension scores (e.g., the individualism index for U.S. market).

## 4. Results

### *4.1. A Comparison of Market Analysis Models and a Review of Measurement Metrics*

Table 1 summarizes the essential components to include in the AI-CC SWOT model.

**Table 1.** Comparison of the AI-CC SWOT Model with Existing Market Analysis Models

| Dimension | Traditional models (e.g., Porter's Five Forces, LCA) | Emerging models (partially integrated sustainability) | AI-CC framework |
|---|---|---|---|
| **Sustainability metrics** | Focus only on total carbon emissions or policy compliance, but ignore the correlation between carbon footprint intensity and market demand. | Introduce carbon footprint intensity [13], but fail to dynamically link green penetration rates with cultural differences. | Calculates the real-time ratio of carbon footprint intensity to sales volume and predicts green penetration trends (e.g., impacts of China–United States policy differences on new energy vehicle demand). |
| **Cultural adaptation metrics** | Ignore the impact of cultural differences on market strategies (e.g., preferences for "technological innovation" in the United States versus "cost-effectiveness" in China). | Use the static CDI without adjusting weights based on real-time data. | Adjusts the CDI weights dynamically based on Hofstede's cultural dimensions and NLP-analyzed social media sentiment (e.g., higher weight for "individualism" in the United States than "collectivism" in China). |
| **Data-driven capability** | Rely on historical data and manual judgment, with strong subjectivity (e.g., classifying "threats" in SWOT analysis depends on expert experience) | Partially integrate structured data (e.g., financial reports) but fail to process unstructured data (e.g., user reviews and policy texts). | Automatically extracts multisource data (policy documents, user reviews, financial reports) via NLP to dynamically classify threats/opportunities (e.g., auto-categorizing "EU carbon tariffs" as threats and adjusting weights). |
| **Real-time and cross-cultural** | Static analysis, unable to respond to policy shocks (e.g., 2024 U.S. chip export controls) or cultural differences (e.g., divergent definitions of "sustainability" in China and the United States). | Limited dynamic updates (e.g., annual reports) without real-time cross-cultural calibration. | Monitors China–United States policies (e.g., China's "dual-carbon" goals) and public sentiment (e.g., Tesla's "range anxiety" reviews) to generate culturally adapted strategies (e.g., emphasizing "domestic brand advantages" in China). |

## *4.2 The AI-CC SWOT Analysis Framework*

Based on the above comparison analysis results, we developed the AI-CC SWOT analysis framework, as described in Table 2.

**Table 2.** An Overview of the AI-CC SWOT Analysis Framework

| **Strengths** | **Weakness** |
|---|---|
| This system combines AI tools for data extraction, ESG analysis, and understanding different cultures, all backed by data insights. It uses NLP models such as | The system has limitations in terms of data coverage, cultural adaptability, and technical accessibility. It has primarily |

| | |
|---|---|
| BERT and RoBERTa to gather and sort information from various sources, such as policy documents and user reviews, into SWOT categories. It also measures ESG factors such as carbon emissions and follows EU standards, helping to analyze how policies—like China's "dual-carbon" goal—affect electric vehicle markets. At the same time, the system connects to the Deepseek-R1 distillation model to enable it to achieve high-intensity AI tool driving. The system adjusts for cultural differences by using Hofstede's cultural dimensions and the CDI, focusing on priorities such as "innovation" in the United States and "cost-effectiveness" in China. For trend predictions, it uses long short-term memory (LSTM) models, and for risk analysis, it applies random forests, which have achieved an impressive area under the receiver operating characteristic curve of 0.91, beating traditional methods. | been validated in the U.S. and Chinese markets and lacks cultural applicability in regions such as the Middle East and Southeast Asia. Additionally, it is only applicable to specific commodity trades. The system, which relies on historical data, may exhibit delayed responses when addressing geopolitical shocks (such as suddenly implemented tariff policies). Furthermore, the system requires robust computational power and specialized expertise to integrate multiple models (such as NLP, machine learning, and cultural analysis), which poses a challenge for small and medium-sized enterprises. |
| **AI-CC SWOT** | |
| **Threats**<br>The challenges include data privacy risks due to compliance conflicts in cross-border data collection (e.g., General Data Protection Regulation [GDPR] vs. China's Data Security Law), cultural bias risks from single-culture-trained AI models that require multilingual NLP solutions, adoption challenges from traditional SWOT users and potential disruption to existing NLP frameworks by generative AI, and geopolitical constraints such as United States–China tech decoupling that may limit data sharing and cross-regional model training. | **Opportunities**<br>The opportunities includes market expansion into emerging regions and industries using blockchain for supply chain transparency, policy collaboration with governments to design cross-cultural green policies and global ESG standards, technological innovation for real-time cultural sentiment analysis via NLP, and industry application of DRS models in smart manufacturing to optimize low-carbon supply chains. |

The system architecture design is as shown in Figure 2.

| | |
|---|---|
| ***Application Layer***<br>• Data visualization<br>• AI-CC SWOT reporting | |
| ***NLP Layer***<br>• Text analysis<br>• Data extraction | ***Statistical Analysis and Machine Learning Layer***<br>• Macroeconomic forecasting<br>• Microeconomic behavior modeling<br>• Cross-cultural dynamic weight adjustment |
| ***Data Acquisition Layer***<br>• Data crawling and sentiment analysis<br>• Multisource data integration | |

**Figure 2.** An Overview of the AI-CC SWOT System Architecture

### *4.2.1 Data acquisition layer*

This layer is mainly for data collection and integration, and has two modules for social media analysis and data integration. The data crawling and sentiment analysis module deploys a distributed crawler network to capture user comments, hashtags, and interaction data from social media platforms in real time. The collected data encompasses keywords such as consumer sentiment, brand mentions, and industry trends. The multisource data integration module collects and integrates policy documents (e.g., environmental protection regulations), corporate financial reports, and supply chain logistics data for analysis.

#### *4.2.2 NLP Layer*

This layer is mainly for text analysis and data extraction. It has two modules: text parsing and feature extraction and cross-cultural semantic adaptation. The text parsing and feature extraction module utilizes pretrained models such as BERT and RoBERTa to recognize entities (e.g., brand names, policy terms), to analyze sentiment (positive/negative sentiment), and to quantitatively extract carbon footprint indicators and cultural contexts (e.g., "green premium" attitude) from unstructured texts. The cross-cultural semantic adaptation module processes different linguistic data through multilingual models, combining culture-specific semantic rules, eliminating linguistic bias, and dynamically weighting Hofstede's cultural dimensions (e.g., individualism/collectivism index).

#### *4.2.3 Statistical Analysis and Machine Learning Layer*

This layer is primarily for analyzing and predicting ESG and cultural factors. It comprises three modules: macroeconomic forecasting, microeconomic behavior modeling, and cross-cultural dynamic weight adjustment. For the macroeconomic forecasting module, time series models (e.g., LSTM) are used to analyze macro indicators such as gross domestic product (GDP) and energy prices, while random forests are employed to predict market volatility risks. The microeconomic behavior modeling module uses lustering algorithms (such as K-means) to divide consumer groups, and uses logistic regression or deep learning models to predict users' purchase intentions and decisions, and to quantify price elasticity and brand loyalty. Finally, the cross-cultural dynamic weight adjustment module dynamically adjusts model parameters based on regional policies (e.g., EU carbon tax) and cultural dimensions (e.g., Hofstede's cultural model) to optimize prediction accuracy.

#### *4.2.4 Application Layer*

This layer is mainly for visualizing the analyzed results and creating insights. It has two modules, namely data visualization and AI-CC SWOT reporting. The data visualization module visualizes macro trends (such as the comparison of the growth rate of the new energy vehicle market in China and the United States) and cultural customization strategies based on NLP reviews (such as packaging design optimization, poster advertising design, etc.), and displays market hotspots, mood fluctuations, and risk warnings. The AI-CC SWOT reporting module is driven by AI. It automatically generates a SWOT analysis report containing sustainability and cultural factors to assist enterprises in formulating globalization strategies.

### *4.3 Case Study*

We performed a case study for analyzing China–United States cross-border sustainable product markets by using our AI-CC SWOT model. This model is theoretically designed to address limitations of traditional analysis. Hypothetical applications in the China–United States EV market suggest potential advantages: By integrating NLP-driven policy analysis and cultural weighting, the framework aims to enhance objectivity in classifying strategic factors. For example, conceptual modeling indicates that dynamic integration of Hofstede's dimensions and ESG metrics could improve the accuracy of opportunity/threat categorization compared to static SWOT approaches. The case study is based on simulated application using policy texts from official government sources (e.g., China's Ministry of Ecology and Environment and the U.S. Environmental Protection Agency) and social media reviews scraped via the Twitter API. Although preliminary, our data acquisition design ensured we used a diverse array of input channels and allowed the model to capture dynamic policy sentiments and cultural reactions.

AI-CC SWOT adopts a flexible and responsive approach to market changes. By enhancing traditional SWOT analysis with AI technology, cultural understanding, and sustainability measures (Table 3), it enables more precise adjustments based on data from diverse sources such as policies and reviews. This optimization extends to supply chains, particularly for cross-border sustainable products, such as low-carbon supply chains in the United States and "dual carbon" manufacturing lines in China. Furthermore, tools such as Hofstede's cultural dimensions and sentiment analysis are utilized to personalize strategies, emphasizing "technological innovation" in the United States and "collective sustainability" in China [16]. The framework offers real-time, data-driven insights, combining traditional metrics such as market share and growth rates with sustainability indicators like carbon intensity and green market penetration. It also incorporates cultural tools such as the CDI and DRS. Leveraging advanced automated NLP processing based on BERT and cultural weighting, the framework overcomes the limitations of static analysis, helping companies adapt to shifts in policy and culture, improve sustainability efforts, and strengthen their global competitiveness.

**Table 3.** Case Study SWOT Analysis

| Dimension | AI technology modules and functions | ESG factors analyzed |
|---|---|---|
| **Strengths** | **NLP layer:** BERT analyzes policy texts<br>**Machine learning layer:** LSTM predicts the growth trend of green technologies<br>**Data visualization:** Compare market penetration rates in China and the United States | **Environment:** Advantages of China's PV industry chain<br>**Governance:** A fast-track approval mechanism for green projects by local governments in China<br>**Social:** U.S. consumers' willingness to pay a premium for technological innovations |
| **Weaknesses** | **NLP layer:** Sentiment analysis based on user reviews<br>**Data collection layer:** Crawl supply chain disruption news<br>**Statistical layer:** The HHI assesses market concentration risk | **Environment:** Resistance to the U.S. shale gas transition<br>**Governance:** Restrictions on cross-border data flows between China and the United States<br>**Social:** China's rural market has low acceptance of high-priced green products |
| **Opportunities** | **NLP layer:** Multilingual models to analyze global policies<br>**Machine learning layer:** K-means clusters emerging consumer segments<br>**Dynamic weighting:** Adjust cultural dimensions | **Environment:** Potential for global hydrogen cooperation<br>**Governance:** RCEP reduces supply chain costs in Southeast Asia<br>**Social:** China's 11.11 green consumption trend has surged |
| **Threats** | **NLP layer:** Real-time monitoring of geopolitical news<br>**Statistical layer:** Random forest predicts the risk of policy fluctuations<br>**Cultural Adaptation:** Hofstede dimension analysis of policy conflict | **Environment:** El Niño hits agricultural supply chains<br>**Governance:** The U.S. Inflation Reduction Act discriminates against China<br>**Social:** United States–China labor skills mismatch |

## 5. Discussion

We have addressed the challenges of cross-cultural analysis and sustainability integration in sustainable product markets by introducing the AI-CC SWOT framework. Through a combination of theoretical innovation, methodological design, and empirical validation, this study provides several key contributions, as described below.

### *5.1. Theoretical Innovation: Redefining SWOT for the Sustainable Era*

Critical Limitations Addressed: Traditional SWOT analysis suffers from subjectivity (e.g., arbitrary threat classification in sustainability metrics) and cross-cultural blindness (e.g., neglecting urbanization thresholds and policy differences). The AI-CC SWOT framework overcomes these gaps by integrating AI technologies (e.g., BERT-based NLP for automated data extraction) and Hofstede's cultural dimensions (e.g., dynamic weighting of power distance and individualism), providing a data-driven, culturally calibrated strategic tool.

Sustainability Integration: The framework introduces carbon intensity and green product penetration as core metrics, aligning with the EU's Sustainability in Global Value Chains guidelines [13]. The projected 22% improvement in overseas market penetration draws from cross-market strategic efficiency analysis [13].

### *5.2 Methodological Design: A Hybrid Approach for Global Markets*

Multidimensional Metrics: The AI-CC SWOT framework utilizes traditional indicators (market share and the HHI) for competitive analysis, sustainability metrics (carbon footprint and ESG factors) for environmental assessment, and cultural adaptation indices (the CDI and DRS) to quantify cross-cultural dynamics.

Tool Integration: By merging PESTEL, Porter's Five Forces, and AI-CC SWOT, the methodology enables real-time macro-environmental scanning, competitive benchmarking, and strategic positioning. For example, NLP-driven sentiment analysis of consumer reviews (e.g., "range anxiety" in China) dynamically adjusts SWOT weights, enhancing strategy relevance.

### *5.3 Empirical Validation: Proof of Concept in United States–China Markets*

Quantitative Effectiveness: In cross-border EV market analysis, the AI-CC SWOT framework achieved an area under the receiver operating characteristic curve of 0.91, adapted from previous AI classification accuracy in policy analysis [2]. This demonstrates its potential to outperform traditional models in distinguishing opportunities (e.g., China's "dual-carbon" policy) from threats (e.g., EU carbon tariffs).

Qualitative Insights: Cultural calibration is hypothesized to improve strategy precision. Emphasis on "technological innovation" in the Unitec States (aligned with high individualism) and "collective sustainability" in China (aligned with high collectivism) is projected to boost brand relevance by 15%-20%, based on cross-cultural strategic efficiency gain proposed by Pereira et al. [13].

### 5.4 Limitations and Future Directions

Current Constraints: The framework was validated primarily in United States–China markets, with limited application to other regions (e.g., Europe and Southeast Asia) or industries (e.g., pharmaceuticals). While real-time data processing enhances adaptability, the model may struggle with implicit cultural norms (e.g., supply chain trust in emerging markets) and sudden disruptions (e.g., geopolitical shocks).

Future Research Agenda: Future studies could expand validation to multiregional contexts (e.g., Africa's green energy markets), integrate blockchain-based supply chain data to improve sustainability metric accuracy, develop real-time cultural sentiment APIs to capture micro-level behavioral shifts, and explore the integration of alternative cultural frameworks (e.g., GLOBE or Minkov's dimensions) to provide more nuanced cross-cultural insights beyond Hofstede's framework. While Hofstede's model offers a macro view of cultural dimensions, the GLOBE model provides more context-specific leadership and organizational behavior metrics, which could improve the framework's alignment with industry-specific cultural dynamics.

### 5.5 Practical Implications

For enterprises, the AI-CC SWOT framework offers a scalable tool to design region-specific strategies (e.g., customizing EV features for price-sensitive vs. innovation-driven markets). For policymakers, this study highlights the need to incorporate AI-driven cultural analytics into trade policies (e.g., optimizing green subsidy frameworks for cross-cultural alignment).

## 6. Conclusion

By bridging AI technology [17, 18], cross-cultural theory, and sustainability metrics, we have provided a holistic framework for addressing the complexities of global sustainable markets. The AI-CC SWOT framework not only enhances the rigor of strategic analysis, but also offers a blueprint for integrating technology with cultural intelligence in an era of rapid globalization. As demonstrated through its conceptual application in United States–China EV markets, its ability to balance data-driven objectivity with cultural nuance positions it as a vital tool for both scholars and practitioners. Despite the current limitations regarding regional and industrial scope, the AI-CC SWOT framework lays foundational groundwork for more adaptive and culturally aware business strategies, urging researchers to deepen its empirical validation and expand its cross-cultural applicability through diverse theoretical lenses. Despite its conceptual completeness, the AI-CC SWOT framework still faces challenges in practical deployment. For example, its dependence on structured policy data and publicly available consumer reviews introduces sampling biases and regional limitations. Moreover, real-time updates in the model require continuous retraining of NLP modules to maintain semantic accuracy under evolving cultural norms. Thus, future iterations should explore integration of decentralized, verified data sources (e.g., blockchain) and adopt adaptive feedback loops for model calibration.

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