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ARTICLE

COMPETITIVE INTELLIGENCE-DRIVEN ESG ANALYTICS: A STRATEGIC FRAMEWORK FOR ESG DISCLOSURE INTELLIGENCE AND SUSTAINABLE DECISION SUPPORT

ANALYTICS ESG ORIENTADO POR INTELIGÊNCIA COMPETITIVA: UM FRAMEWORK ESTRATÉGICO PARA INTELIGÊNCIA DE DISCLOSURE ESG E SUPORTE SUSTENTÁVEL À DECISÃO

[1] **Tian Yang**: Fuculty of Management, Multimedia University, Persiaran Multimedia, Cyberjaya, Selangor, Malasia. ORCID: https://orcid.org/0009-0003-1209-0517

[2] **Teh Boon Heng**: Fuculty of Economics and Management, Jining Normal Collage, Ulanqab City, China. ORCID: https://orcid.org/0000-0003-0215-484X

[3]**Kwan Jing Hu**: Discipline Inspection Department, Ulanqab Vocational College, Ulanqab City, China. ORCID: https://orcid.org/0000-0002-7447-3228

[4]**Zhang Tao**: Discipline Inspection Department, Ulanqab Vocational College, Ulanqab City, China. ORCID: https://orcid.org/0009-0003-3857-9433

Corresponding Author:
Teh Boon Heng
E-mail: 1221400005@student.mmu.edu.my

Editor in chief
Altieres De Oliveira Silva
Alumni.In Editors

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ABSTRACT

Purpose: This study aims to establish and validate a Competitive Intelligence (CI)-driven ESG analytics framework capable of transforming ESG disclosure analysis from a purely computational classification exercise into a strategic intelligence mechanism for sustainable decision-making and competitive advantage.

Methodology/approach: The research adopts a strategic-intelligence approach integrating the Competitive Intelligence cycle, dynamic capabilities perspective, and natural language processing (NLP). Using a publicly available dataset containing 8,471 ESG disclosure sentences from Chinese listed companies, the study applies preprocessing, feature engineering, TF-IDF vectorization, and supervised machine learning models, including logistic regression, complement naïve Bayes, and linear support vector machines. A Competitive Intelligence Score was developed to evaluate disclosure maturity and strategic relevance.

Originality/Relevance: The study contributes by reframing ESG analytics as an organizational intelligence capability embedded within intelligence governance and strategic foresight processes. It introduces a maturity-aware CI framework linking ESG disclosure quality to sustainable competitive intelligence and decision-support systems.

Key findings: The proposed models achieved strong classification performance, with disclosure-quality classification reaching 0.882 accuracy and macro-F1 of 0.799. The Competitive Intelligence Score effectively differentiated quantitative, qualitative, and irrelevant disclosures, revealing significant evidence gaps across ESG pillars and supporting managerial benchmarking and strategic responsiveness.

Theoretical/methodological contributions: The article advances the literature by integrating Competitive Intelligence, dynamic capabilities, ESG intelligence governance, and NLP-based analytics into a unified strategic framework. Methodologically, it operationalizes ESG disclosure maturity through a reproducible intelligence-oriented analytical pipeline.

Keywords: Sustainable Competitive Intelligence. ESG disclosure intelligence. Intelligence cycle. Dynamic capabilities. Strategic decision-making. Sustainable competitive advantage. Natural language processing. Chinese listed companies.

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RESUMO

Objetivo: Este estudo tem como objetivo estabelecer e validar um framework de analytics ESG orientado por Competitive Intelligence (CI), capaz de transformar a análise de disclosure ESG de um exercício puramente computacional em um mecanismo estratégico de inteligência para suporte à decisão sustentável e vantagem competitiva.

Metodologia/abordagem: A pesquisa adota uma abordagem de inteligência estratégica integrando o ciclo de Competitive Intelligence, a perspectiva de capacidades dinâmicas e técnicas de processamento de linguagem natural (NLP). Utilizando um dataset público contendo 8.471 sentenças ESG de empresas chinesas listadas, o estudo aplica pré-processamento, engenharia de atributos, vetorização TF-IDF e modelos supervisionados de machine learning, incluindo regressão logística, complement naïve Bayes e máquinas de vetor de suporte lineares. Foi desenvolvido um Competitive Intelligence Score para avaliar maturidade e relevância estratégica dos disclosures.

Originalidade/Relevância: O estudo contribui ao reposicionar ESG analytics como capability organizacional de inteligência integrada à governança da inteligência e aos processos de strategic foresight. O framework proposto conecta qualidade de disclosure ESG à inteligência competitiva sustentável e aos sistemas de suporte à decisão.

Principais resultados: Os modelos apresentaram desempenho robusto, alcançando acurácia de 0.882 e macro-F1 de 0.799 na classificação da qualidade dos disclosures. O Competitive Intelligence Score diferenciou efetivamente disclosures quantitativos, qualitativos e irrelevantes, evidenciando gaps de maturidade informacional entre os pilares ESG.

Contribuições teóricas/metodológicas: O artigo integra Competitive Intelligence, capacidades dinâmicas, governança da inteligência ESG e analytics baseados em NLP em um framework estratégico unificado. Metodologicamente, operacionaliza a maturidade dos disclosures ESG por meio de um pipeline analítico reproduzível orientado ao ciclo de inteligência.

Palavras-chave: Inteligência Competitiva Sustentável. Inteligência de disclosure ESG. Ciclo de inteligência. Capacidades dinâmicas. Tomada de decisão estratégica. Vantagem competitiva sustentável. Processamento de linguagem natural. Empresas chinesas listadas.

1. INTRODUCTION

In the era of stakeholder capitalism, the importance of having sustainable competitive advantage has become more dependent on how organizations sense, interpret, and respond to the ESG signals that are being conveyed through the narrative disclosures of organizations in their own and others (Schimanski et al., 2024; Maluleka & Chummun, 2023; Oehler & Neuss, 2025). Under the regulatory and market uncertainty, Strategic Competitive Intelligence (CI) equips the organizational capability needed to transform this semantically rich, yet fragmented information into decision-ready knowledge for strategic foresight, risk intelligence, and managerial choice (Maluleka & Chummun, 2023; Calof, 2025). Although the field of finance and accounting has experienced an explosion of ESG analytics, the analytical linkage between the ESG narrative and the CI cycle has not yet been theorized and operationalized (Seow, 2025; Sneideriene & Legenzova, 2025).

In this context, ESG disclosure is not just a compliance product, it is a communication tool that can be used to convey a firm's long-term legitimacy, to communicate its dynamic capabilities, and to influence stakeholder expectations (Oehler & Neuss, 2025; Huang et al., 2024). But the diversity of ESG 'ESG' language, quantitative evidence and boilerplate language results in a comparability challenge that normal rating systems are unable to completely address (Oehler & Neuss, 2025; Fabijanska et al., 2025). CI is the perfect way to tackle the challenges of unstructured, weak-signal environments with systematic intelligence cycles of planning, collection, analysis, dissemination, and feedback (Maluleka &

Chummun, 2023; Calof, 2025).

The Chinese ESG context is an empirical context that is quite challenging for CI-driven ESG analytics. The Chinese listed firms must deal with the changing regulatory requirements, the increasing pressure from investors and the different ratings from various domestic and international rating agencies (Huang et al., 2024; David et al., 2024; Liu, 2025). Strategic intelligence is not a luxury that can be used in such settings, but rather a dynamic capability that enables the firm to reshape its disclosure practice, sustainability initiative and stakeholder engagement toward evolving institutional logics (Maluleka & Chummun, 2023; David et al., 2024; Sneideriene & Legenzova, 2025). However, current analytics pipelines only focus on the accuracy of classification and do not offer the strategic and governance layer which is required by CI (Seow, 2025; Calof, 2025).

Previous studies have demonstrated the potential of natural language processing (NLP) and machine learning to significantly enhance ESG measurement tasks, such as identifying subdomain categories, assessing disclosure quality, and identifying greenwashing risk (Schimanski et al., 2024; Lagasio, 2024; Sneideriene & Legenzova, 2025; Zeng et al., 2025). However, many of these studies focus on the technical aspects of performance and financial gains, and neglect to consider the broader intelligence cycle from the disclosure text to managerial decisions, strategic foresight, and long-term competitive advantage (Seow, 2025; Calof, 2025; Lee, Raschke, et al., 2023). This creates an ESG-intelligence gap at the discipline level, with a growing number of increasingly sophisticated classifiers emerging from the ESG analytics, and a lack of organizational guidance on how to incorporate these outputs into strategic intelligence routines, intelligence governance, and dynamic capability renewal.

A second gap is in the use of evidence maturity for strategic intelligence. While most ESG analytics studies are based on a binary or multiclass classification problem, they pay little heed to the fact that ESG performance information has a “maturity trajectory,” in which companies first commit to, then narrate, and finally quantify their actions on ESG (Huang et al., 2024; Davidescu et al., 2026; Sneideriene & Legenzova, 2025). The concept of trajectory-based perspectives, which has been a common issue in the literature on staged-competence research (Liu, 2025) can readily be extended to the dynamic capabilities’ perspective, because they refer to the gradual development of the firm's routine of sensing, seizing, and reconfiguring, which forms the basis of sustainable competitive advantage (Maluleka & Chummun, 2023; Sneideriene & Legenzova, 2025; Hao et al., 2025). With this trajectory logic being built into a CI framework, it provides a richer interpretive layer, so that disclosure quality is no longer a classification result, but a measurable measure of the maturity of an organization's ESG intelligence.

The present work aims to overcome these limitations by applying ESG analytics as a Strategic Competitive Intelligence problem and by introducing a framework for ESG based on the CI cycle, dynamic capabilities, and a maturity-aware scoring. Three research questions are explored. In the first place, what is the analytical pipeline that can convert ESG sentence data from Chinese to structured intelligence for business and decision making? Second, what evidence-maturity patterns are observed when the data is interpreted using the CI cycle and the dynamic capabilities lens across the ESG pillars? Third, how can a Competitive Intelligence Score be developed to be able to transform the classification outputs and evidence-based features into pillar-level benchmarks that will help in strategic decisions and in obtaining a sustainable competitive edge?

The paper offers three contributions. Theoretically, it reframes ESG performance analysis as an intelligence cycle integrated with dynamic capabilities and intelligence governance, thereby connecting ESG analytics to sustainable competitive advantage (Maluleka & Chummun, 2023; Calof, 2025; Sneideriene & Legenzova, 2025). Methodologically, it operationalizes this CI framework through a reproducible pipeline that links sentence-level NLP outputs to pillar-level intelligence scoring, with weight choices justified through the CI literature rather than treated as arbitrary (Seow, 2025; Lee, Raschke, et al., 2023). Managerially, it provides a CI-driven decision-support logic for managers, investors, and regulators who must benchmark ESG maturity in environments characterized by rating inconsistency and disclosure asymmetry (Oehler & Neuss, 2025; David et al., 2024; Fabijanska et al., 2025).

2. THEORETICAL FRAMEWORK

The theoretical scaffolding of the study is developed by sequentially introducing five conceptual blocks: (i) Competitive Intelligence as a strategic organizational capability embedded in the intelligence cycle; (ii) dynamic capabilities and their connection between ESG intelligence and sustainable competitive advantage; (iii) ESG disclosure as a stream of strategic intelligence, such as greenwashing risk and intelligence governance; (iv) NLP and machine learning as enabling technologies for the operation of ESG intelligence; and (v) the context of Chinese listed firms as strategic-intelligence environment. The section is concluded with a comparative synthesis.

2.1 Competitive Intelligence as a Strategic Organizational Capability

According to (Maluleka & Chummun, 2023; Calof, 2025), the Strategic Competitive Intelligence is the ability of the organization to strategically plan, collect, analyze, disseminate, and act on information about the external and internal environment of the organization to support strategic decisions and competitive positioning in the strategic process. CI is not just a classification tool, it is a perpetual intelligence cycle that is built into organizational routines, governance frameworks and managerial activities (Maluleka & Chummun, 2023). The value of CI depends on the extent to which its products are made use of and are clearly tied to the strategy implementation process through governance structures and management action, as argued by Maluleka and Chummun (2023). Calof suggests that CI and strategic foresight share epistemic foundations and are complementary techniques of intelligence that enable the conversion of weak signals into strategic insight (2025).

ESG's application of the CI concept shifts the analysis focus from "How well do we categorize a sentence?" to "How can ESG narrative be converted into organizational knowledge that can be used for decision making, risk management, and engagement with stakeholders? (Seow, 2025; Lee, Raschke, et al., 2023; Sneideriene & Legenzova, 2025). This reframing is consequential as it demands that the analyst needs to create intelligence products, such as dashboards, maturity scores, pillar-level benchmarks, which are easily consumed by managers and which are incorporated into the intelligence cycle as part of an ESG intelligence governance routine (Calof, 2025; Sneideriene & Legenzova, 2025). The CI cycle thus offers a coherent, structured model for the organization and sensemaking of the preprocessing, NLP, and scoring steps as sequential parts of a process, instead of as separate computational components.

2.2 Dynamic Capabilities and Sustainable Competitive Advantage

Sustainable competitive advantage in the ESG domain is increasingly attributed to dynamic capabilities, that is, the firm's capacity to sense external signals, seize opportunities, and reconfigure resources in response to environmental change (Sneideriene & Legenzova, 2025; Hao et al., 2025). ESG intelligence is, in this view, a specific class of dynamic capability concerned with sensing sustainability-relevant signals, seizing them through strategic decisions on disclosure, investment, and stakeholder engagement, and reconfiguring organizational practices to maintain legitimacy and performance (Huang et al., 2024; Sneideriene & Legenzova, 2025; An et al., 2025). Hao and colleagues show that ESG ratings are positively associated with digital technology innovation, suggesting that ESG-related dynamic capabilities translate into innovation outcomes (2025). An, Ran, and Gao further indicate that high-quality ESG disclosure can relax financing constraints and increase firm value in China, illustrating a direct route from ESG intelligence to competitive advantage (2025).

CI in the context of dynamic capabilities framework directly highlights the strategic importance of ESG analytics in this sense: CI cycles represent the routines of sense making and seizing, and CI scores represent the measurable ability of a firm to reconfigure its disclosure architecture toward sustainable competitive advantage (Maluleka & Chummun, 2023; Sneideriene & Legenzova, 2025; Hao et al., 2025). This linkage also explains that accuracy based ESG classifiers alone are not enough as they are only able to recognize patterns but not the organizational learning loop that accumulates and renews dynamic capabilities (Seow, 2025; Calof, 2025).

2.3 ESG Disclosure as a Source of Strategic Intelligence and Intelligence Governance

ESG disclosure, from a CI point of view, is a channel of high-density information in which firms disclose their strategic priorities but also the level of their sustainability practices (Oehler & Neuss, 2025; Huang et al., 2024). In the context of ESG-washing detection, Lagasio's research demonstrates that disclosure can be systematically and significantly different from practice, and, therefore, evidence-quality checks can be added to the CI systems, not only based on disclosure volume (Lagasio, 2024). Sentiment analysis and topic modeling are used by Davidescu et al. to measure the severity of greenwashing in Central and Eastern European companies (2026). They show how information provided in ESG disclosures varies between rating agencies, which reflects a governance issue that CI can help solve (Oehler & Neuss, 2025). Huang et al. demonstrate that the length, readability, redundancy, and completeness of sustainability reports in Chinese have varying impacts on the ESG ratings issued by domestic and foreign agencies (2024). In China's experience, when the pressure of social media becomes too strong corporate hypocrisy and ESG greenwashing have been documented by Long, Wang, and Zhang (2025) and it is more important to have risk-aware intelligence governance.

The results suggest that CI needs to be coordinated with a clear ESG intelligence governance process defining the process for validation, weighting, and sharing of disclosure signals with the managers, boards, and regulators. Intelligence governance, in turn, enables strategic foresight by preventing anomalies (boilerplate language, abrupt tone change, rare, but material topics) from being averaged or lost (Calof, 2025; Sneideriene & Legenzova, 2025). This paper proposes a framework that incorporates this 'governance logic' by introducing features of evidence-specificity and a rarity-based scoring system that can keep strategically significant, low-frequency, topics visible in the CI cycle.

2.4 NLP and Machine Learning as Enabling Technologies for ESG Intelligence

Computational ESG measurement has matured rapidly. Schimanski and colleagues show that transformer-based models trained on large corpora distinguish environmental, social, and governance discourse and meaningfully explain variance in ESG ratings (2024). Yang and colleagues use machine learning with governance covariates to predict ESG disclosure quality, while Cini and Ferrari estimate ESG ratings from balance-sheet ratios (Yang et al., 2025; Cini & Ferrari, 2025). Ferjancic and colleagues link the textual content of corporate sustainability reports to ESG scores through topic modeling and lexical analysis (2024). Dakle and colleagues apply transformer-based models to news-level ESG impact identification (2024), and Lee and colleagues propose generative LLM-based ESG issue identification frameworks (Lee, Choi, et al., 2023). Wu and colleagues introduce SusGen-GPT as a data-centric LLM for financial NLP and sustainability report generation (2024), while Aldridge and Martin examine ESG signals in corporate filings from an AI perspective (2022). More recent contributions by Ding and colleagues (EulerESG) and Zou and colleagues (ESGReveal) demonstrate that LLMs can automate ESG disclosure extraction and structuring (Ding et al., 2025; Zou et al., 2025).

While imbalanced learning is one of the most recurring issues in ESG NLP, Chen and colleagues review the imbalanced learning advances (Chen, Yang, et al., 2024) and Sneideriene and Legenzova give a bibliometric synthesis of greenwashing prevention in ESG disclosures (2025). Ong et al. suggest aspect-action analysis and cross-category generalization to enable a strong ESG analysis against greenwashing risk (2025). Others, particularly in the field of ESG reporting, present E-BERT models for ESG reporting (Zhang et al., 2025) or measure the intention to sustain ESG funds using few-shot learning (Singh et al., 2024). These contributions validate that NLP can serve as the technical framework of ESG intelligence, but they do not address the organizational framework that supports NLP outputs with CI cycles, ESG intelligence governance, and managerial decisions. The current research falls right in the middle of this crossroad.

2.5 Machine Learning for ESG Prediction and Scoring

A complementary stream uses machine learning to predict ESG scores, identify ESG-related price effects, and forecast sustainability performance (Yang et al., 2025; Ghallabi et al., 2025). Ghallabi and colleagues integrate ESG and clean-energy signals for stock-price prediction (2025). Hao and colleagues link ESG ratings to digital technology innovation (2025), while Khan provides a bibliometric and meta-analytic view of ESG-firm performance research (2022). Chen and colleagues study analyst recommendations and ESG performance in the Chinese market (Chen, Cheng, et al., 2024), and Mashayekhi and colleagues develop a two-step machine learning and analytical framework for the relative importance of ESG pillars (2024). Zeng, Wang, and Zeng propose an optimized machine learning framework for predicting and interpreting corporate ESG greenwashing behavior (2025). These works strongly motivate a CI-driven synthesis: ESG analytics is producing increasingly powerful predictive signals, but their strategic deployment requires the intelligence-cycle architecture proposed here.

2.6 ESG in Chinese Listed Firms as a Strategic-Intelligence Environment

Chinese ESG disclosure constitutes an exceptionally information-rich setting for CI-driven analytics. David and colleagues build a China-focused ESG scorecard using predictive machine learning (2024); Liu evaluates Chinese ESG policy texts through policy instruments, themes, and subjects (2025); Huang and colleagues analyze the textual properties of Chinese sustainability reports (2024); and Yin, Yin, and Wen use double machine learning to study artificial intelligence and climate risk (2025). An, Ran, and Gao show that ESG disclosure interacts with financing constraints to raise firm value in China (2025). Together, these contributions describe an environment characterized by regulatory acceleration, heterogeneous rating signals, and meaningful within-country variation in ESG practice—precisely the conditions under which CI delivers the highest strategic value (Maluleka & Chummun, 2023; Calof, 2025; David et al., 2024; Sneideriene & Legenzova, 2025).

2.7 Comparative Synthesis

Table 1 compares recent ESG analytics studies with the present study along four dimensions: scope, method, contribution, and the research gap addressed. The synthesis shows that the field has advanced on technical fronts—subdomain classification, greenwashing detection, rating prediction—while devoting limited attention to the strategic-intelligence layer. Few papers explicitly connect sentence-level evidence maturity to the CI cycle, dynamic capabilities, and intelligence governance (Schimanski et al., 2024; Seow, 2025; Sneideriene & Legenzova, 2025).

Table 1. Comparison of recent ESG analytics studies and the present study.

Study	Focus	Method	Contribution	Gap addressed
Schimanski et al. (2024)	ESG subdomain NLP	Transformer fine-tuning	Domain-specific ESG language models	Does not frame results as a CI cycle
Ferjancic et al. (2024)	Sustainability text and ESG scores	Topic modeling and lexical analysis	Connects narrative content with ESG scores	Limited sentence-level quality labels
Huang et al. (2024)	Chinese sustainability reports	Computational linguistics	Effects of length, tone, and completeness	Report level rather than sentence level
Lagasio (2024)	ESG-washing detection	Sentiment and content scoring	ESG-washing severity index	Requires external validation data
Oehler and Neuss (2025)	Disclosure vs rating consistency	Textual analysis	Information value gap with ratings	Limited Chinese coverage
David et al. (2024)	China ESG scoring	Predictive machine learning	China-focused ESG scorecard	Uses proprietary financial data
Yang et al. (2025)	Disclosure quality predictors	ML with governance covariates	Links disclosure quality to organizational roles	Does not classify sentence evidence
Cini and Ferrari (2025)	ESG rating estimation	ML with balance sheet ratios	Predictive power of structured firm data	Limited textual granularity
Seow (2025)	ESG analytics and ML	Systematic literature review	Mapping of ESG analytics applications	No raw-data preprocessing pipeline
Davidescu et al. (2026)	Greenwashing in CEE firms	NLP and severity index	Cross-firm greenwashing measurement	Limited integration with CI framework
This study	CI-driven ESG intelligence framework	CI cycle + NLP + maturity scoring + governance	Connects raw ESG text to strategic decision support and sustainable competitive advantage	Integrates dynamic capabilities and intelligence governance with sentence-level evidence maturity

3. METHODOLOGY

The study adopts a strategic-intelligence design that combines a reproducible quantitative text-analytics pipeline with an explicit Competitive Intelligence cycle, ensuring that each computational step has a clear role within the broader intelligence architecture (Schimanski et al., 2024; Maluleka & Chummun, 2023; Calof, 2025). The workflow is organized as a seven-stage pipeline, raw data loading, exploratory audit, cleaning, feature engineering and encoding, vectorization, classification, and ESG intelligence interpretation mapped onto the planning, collection, processing, analysis, dissemination, and feedback phases of the CI cycle (Ferjancic et al., 2024; Seow, 2025; Maluleka & Chummun, 2023). Figure 1 visualizes the integrated pipeline.

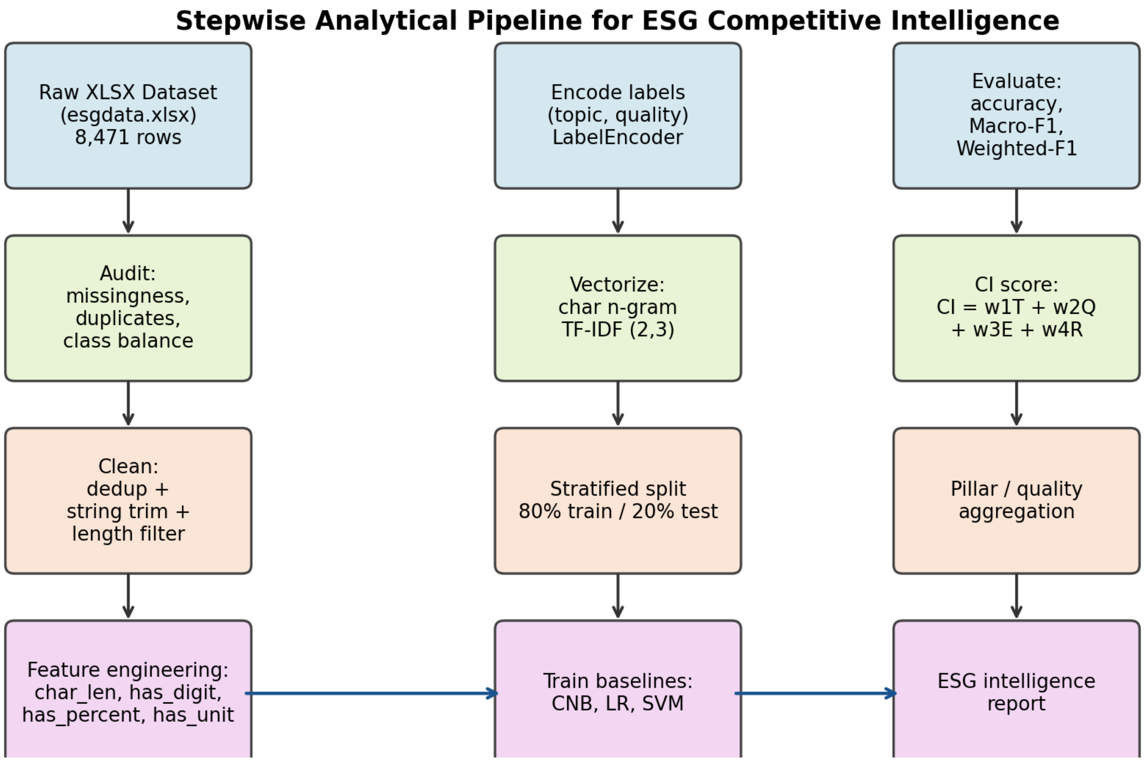

Figure 1. Stepwise analytical pipeline for ESG competitive intelligence.

3.1 Dataset and Variables

The empirical material consists of a publicly available labeled ESG dataset extracted from the sustainability reports of Chinese listed companies, supplied as a raw XLSX file inside a ZIP archive (Li, 2025; Huang et al., 2024). The core file contains three variables: the original Chinese ESG sentence, a topic label drawn from a 37-class taxonomy, and a quality label drawn from a three-class scheme of qualitative text, quantitative text, and irrelevant text (Yang et al., 2025; Liu, 2025). Table 2 summarizes the variables and the analytical role each plays in the CI cycle.

Table 2. Dataset variables and analytical roles.

Variable	Type	Definition	Role in study
sentences	Text	Chinese ESG report sentence	Primary textual evidence input to classifiers
label	Categorical (37 classes)	ESG topic label or irrelevant class	Topic indicator of ESG disclosure coverage
quality	Categorical (3 classes)	Qualitative, quantitative, or irrelevant text	Evidence-maturity indicator for disclosure quality
char_len	Numeric engineered	Chinese character count of the sentence	Proxy for disclosure detail and verbosity
has_digit	Binary engineered	Presence of Arabic numerals	Proxy for quantitative reporting evidence
has_percent	Binary engineered	Presence of percentage or rate expression	Proxy for measurable ESG performance
has_unit	Binary engineered	Presence of monetary or physical units	Proxy for measurement specificity
pillar	Categorical engineered	Mapping of topic label to E, S, or G pillar	Aggregated dimension for CI scoring
label_code, quality_code	Encoded categorical	Integer codes for topic and quality labels	Machine-learning target representations

3.2 Data Preprocessing within the CI Collection and Processing Phases

The preprocessing pipeline was designed for Kaggle notebooks using Python 3, pandas, NumPy, scikit-learn, matplotlib, seaborn, and openpyxl (Schimanski et al., 2024; Ghallabi et al., 2025). GPU acceleration is considered optional because the baseline character n-gram TF-IDF features with logistic regression, complement naive Bayes, and linear support vector classifiers are CPU-efficient and produce strong interpretable baselines (Seow, 2025; Zhang et al., 2025). The same dataframe can be used to train a Chinese transformer-based language model through a Kaggle GPU instance without modifying the preprocessing procedures (Ong et al., 2025; Aldridge & Martin, 2022). In CI terms, this stage operationalizes the collection and processing phases of the intelligence cycle: raw narrative is acquired, audited, and prepared for analytical use (Maluleka & Chummun, 2023; Calof, 2025).

The uncleaned dataset comprised 8,471 rows with no missing values in the sentence, label, and quality fields (Li, 2025; Huang et al., 2024). Fifteen duplicate rows were dropped using an equality operator across the three core fields, yielding 8,456 observations after cleaning (Lagasio, 2024; Yang et al., 2025). Whitespace was trimmed and zero-length sentences were removed to preserve the integrity of the character n-gram representation (Zhang et al., 2025; Aldridge & Martin, 2022).

Feature engineering produced four interpretable sentence-level evidence features (Schimanski et al., 2024; Huang et al., 2024): char_len for narrative detail; has_digit for the presence of Arabic numerals; has_percent for percentages or rates; and has_unit for monetary and physical units used in Chinese ESG reports (Li, 2025; Fabijanska et al., 2025). Topic and quality annotations were integer-encoded with scikit-learn's LabelEncoder, while char_len was normalized to zero mean and unit standard deviation via StandardScaler (Ghallabi et al., 2025; Chen, Yang, et al., 2024). Table 3 summarizes the preprocessing pipeline and its CI-cycle alignment.

Table 3. Preprocessing pipeline and final dataset preparation.

Step	Implementation	Purpose
Data loading	pandas read_excel with openpyxl engine	Read raw XLSX dataset and confirm shape
Missingness audit	isna and isnull diagnostics	Verified zero missing values in core fields
Duplicate removal	drop_duplicates across three core fields	Eliminated 15 duplicate sentences
Text cleaning	astype(str) and string strip with length filter	Removed whitespace artefacts while preserving Chinese characters
Feature engineering	Regular expressions for digit, percent, unit markers	Constructed interpretable evidence features
Encoding	LabelEncoder for topic and quality	Prepared categorical targets for modeling
Normalization	StandardScaler on char_len	Made numeric metadata comparable across models
Vectorization	Character n-gram TF-IDF with min_df and max_features	Reduced sparse feature noise for short sentences
Splitting	Stratified train/test split, 80 vs 20	Preserved class proportions across folds
Final dataset	Exported clean_esg_dataset.xlsx	Reproducible analysis-ready file for CI cycle

3.3 Mathematical Formulation

Five equations formalize the analytical framework. Equation (1) defines the standardization rule used for the engineered numeric features (Ghallabi et al., 2025; Chen, Yang, et al., 2024).

$$z_{ij} = (x_{ij} - \mu_j) / \sigma_j \qquad (1)$$

In Equation (1), x_{ij} is the value of feature j for sentence i, μ_j is the feature mean computed on the training data, and σ_j is the corresponding standard deviation, so that all engineered numeric features share a common scale before they enter dense classifiers (Ghallabi et al., 2025).

Equation (2) defines the character n-gram TF-IDF representation used as the primary sentence encoder; character n-grams are appropriate for Chinese ESG text because they do not depend on a single word segmentation dictionary (Schimanski et al., 2024; Aldridge & Martin, 2022).

$$\mathrm{tfidf}(t, d) = \mathrm{tf}(t, d) \times \log(N / (1 + \mathrm{df}(t))) \qquad (2)$$

In Equation (2), tf(t, d) is the raw frequency of character n-gram t in sentence d, N is the total number of cleaned sentences in the training set, and df(t) is the document frequency of t (Schimanski et al., 2024; Seow, 2025). The min_df threshold filters out idiosyncratic n-grams and the max_features parameter bounds the vocabulary size (Ghallabi et al., 2025; Chen, Yang, et al., 2024).

Equation (3) expresses the decision rule used by the complement naive Bayes classifier, which is well suited to imbalanced ESG text (Ghallabi et al., 2025; Chen, Yang, et al., 2024).

$$\hat{y}(d) = \mathrm{argmax}^c \; [\log \mathrm{P}(c) + \Sigma_t \, x_t \cdot \log \mathrm{P}(t \mid c)] \qquad (3)$$

In Equation (3), c indexes the candidate class label, x_t is the TF-IDF weight of n-gram t in sentence d, and P(t | c) is the smoothed class-conditional probability estimate (Ghallabi et al., 2025). The same decision rule generalizes to other linear classifiers used in this study, namely logistic regression with class weighting and the linear support vector classifier with a hinge loss (Seow, 2025; Sneideriene & Legenzova, 2025).

Equation (4) defines the proposed Competitive Intelligence Score for sentence i, which aggregates topic relevance, disclosure-quality maturity, evidence specificity, and rarity-adjusted salience into a single bounded indicator (Maluleka & Chummun, 2023; Calof, 2025).

$$\mathrm{CI}_i = w_1 \cdot T_i + w_2 \cdot Q_i + w_3 \cdot E_i + w_4 \cdot R_i \qquad (4)$$

$T_i = 1$ if sentence i contains a non-irrelevant ESG issue and 0 otherwise; Q_i equals 0, 0.5, and 1 for irrelevant, qualitative, and quantitative quality levels respectively, reflecting the staged-maturity approach grounded in the dynamic capabilities and trajectory literatures (Sneideriene & Legenzova, 2025; Liu, 2025). The evidence-specificity term E_i is the average of the four binary evidence markers for digit, percent, unit, and year, which jointly proxy the presence of measurable content (Li, 2025; Huang et al., 2024). The rarity term R_i equals one minus the normalized topic frequency, ensuring that strategically important but infrequent ESG issues receive non-trivial weight in the aggregated score (Lagasio, 2024; Lee, Raschke, et al., 2023).

Critically, the weights w_k is not arbitrary. Their structure reflects CI-cycle priorities documented in the strategic intelligence literature: topic relevance and disclosure-quality maturity are the primary drivers of decision usefulness in CI products and therefore receive the highest weights ($w_1 = 0.30$ and $w_2 = 0.30$) (Maluleka & Chummun, 2023; Calof, 2025; Sneideriene & Legenzova, 2025); evidence specificity acts as a verification mechanism for managerial trust in the signal ($w_3 = 0.25$) (Oehler & Neuss, 2025; Huang et al., 2024); and rarity captures strategic salience for low-frequency but material issues ($w_4 = 0.15$), consistent with risk-intelligence and foresight rationales (Calof, 2025; Lee, Raschke, et al., 2023). Sensitivity analyses are recommended for organizational deployment and are discussed in Section 5 as a route to data-driven recalibration against expert ratings and intelligence governance feedback (Maluleka & Chummun, 2023; Oehler & Neuss, 2025).

Equation (5) defines the macro-F1 score that supplements accuracy when evaluating class imbalanced ESG models (Chen, Yang, et al., 2024; Sneideriene & Legenzova, 2025).

$$\text{MacroF1} = (1 / C) \cdot \Sigma^c [2 \cdot \text{Precision}^c \cdot \text{Recall}^c / (\text{Precision}^c + \text{Recall}^c)] \qquad (5)$$

In Equation (5), C denotes the number of classes, and macro-F1 averages the harmonic mean of precision and recall across classes with equal weight (Chen, Yang, et al., 2024). This metric is essential for ESG analytics because raw accuracy can mask weak performance on rare but strategically important categories such as responsible investment and environmental penalties (Lagasio, 2024; Davidescu et al., 2026).

3.4 Algorithm Description

Table 4 lists the stepwise algorithm. It is intentionally transparent so that any practitioner can reproduce the workflow on the supplied dataset using only the scikit-learn ecosystem, and so that each step has a clear correspondence to a CI-cycle phase (Seow, 2025; Maluleka & Chummun, 2023; Ghallabi et al., 2025).

Table 4. Algorithmic pipeline for ESG Competitive Intelligence analysis.

Component	Description
Input	Raw ESG XLSX file with sentences, topic labels, and quality labels
Step 1 (Collection)	Load the workbook with the openpyxl engine and select the populated sheet
Step 2 (Audit)	Audit missingness, duplicates, class distribution, and character length
Step 3 (Processing)	Remove duplicates and blank strings while preserving Chinese characters
Step 4 (Feature)	Engineer evidence features for length, digit, percent, unit, and year markers
Step 5 (Encoding)	Encode topic and quality labels and map topics to E, S, or G pillars
Step 6 (Vectorize)	Build the character n-gram TF-IDF matrix with min_df and max_features
Step 7 (Split)	Perform stratified 80/20 train and test split for both targets
Step 8 (Analysis)	Fit complement naive Bayes, logistic regression, and linear SVM classifiers
Step 9 (Evaluation)	Evaluate models using accuracy, macro-F1, weighted-F1, and confusion matrices
Step 10 (CI Synthesis)	Aggregate sentence-level outputs into the Competitive Intelligence Score from Equation (4)
Output (Dissemination)	Cleaned dataset, model metrics, visual diagnostics, and ESG intelligence interpretation

3.5 Managerial Validation Logic and Intelligence Governance

Although the present study uses a single public dataset and does not survey individual managers, the framework is designed for organizational deployment and incorporates an explicit managerial validation logic. First, every output of the pipeline class probability, evidence flag, pillar score—is interpretable, which is a prerequisite for CI products to be trusted and acted upon by decision-makers (Maluleka & Chummun, 2023; Sneideriene & Legenzova, 2025). Second, the CI score is structured as a managerial dashboard input: it answers the strategic questions "How comprehensively are ESG topics covered?", "How mature is the evidence?", "How specific are the disclosures?", and "How salient are the rare risk categories?" (Calof, 2025; Lee, Raschke, et al., 2023). Third, the intelligence governance layer prescribes who owns, reviews, and acts on each CI output: corporate sustainability and strategy team's own topic coverage; internal audit and assurance own evidence specificity; investor relations and risk committees own pillar-level CI scores and rarity-adjusted alerts (Oehler & Neuss, 2025; Sneideriene & Legenzova, 2025). Future deployments can refine weights against expert ESG ratings within this governance architecture, as discussed in Section 5.

4 RESULTS AND DISCUSSIONS

4.1 Dataset Description and Exploratory Findings

The cleaned dataset contains 8,456 sentences distributed across 37 topic labels and three disclosure-quality classes (Li, 2025; Huang et al., 2024). Figure 2 shows the twenty most frequent topic labels after cleaning and confirms that employee-related, organization-related, technology-innovation, customer, charity, product-quality, waste-management, and supply-chain topics dominate the corpus (Ferjancic et al., 2024; Huang et al., 2024).

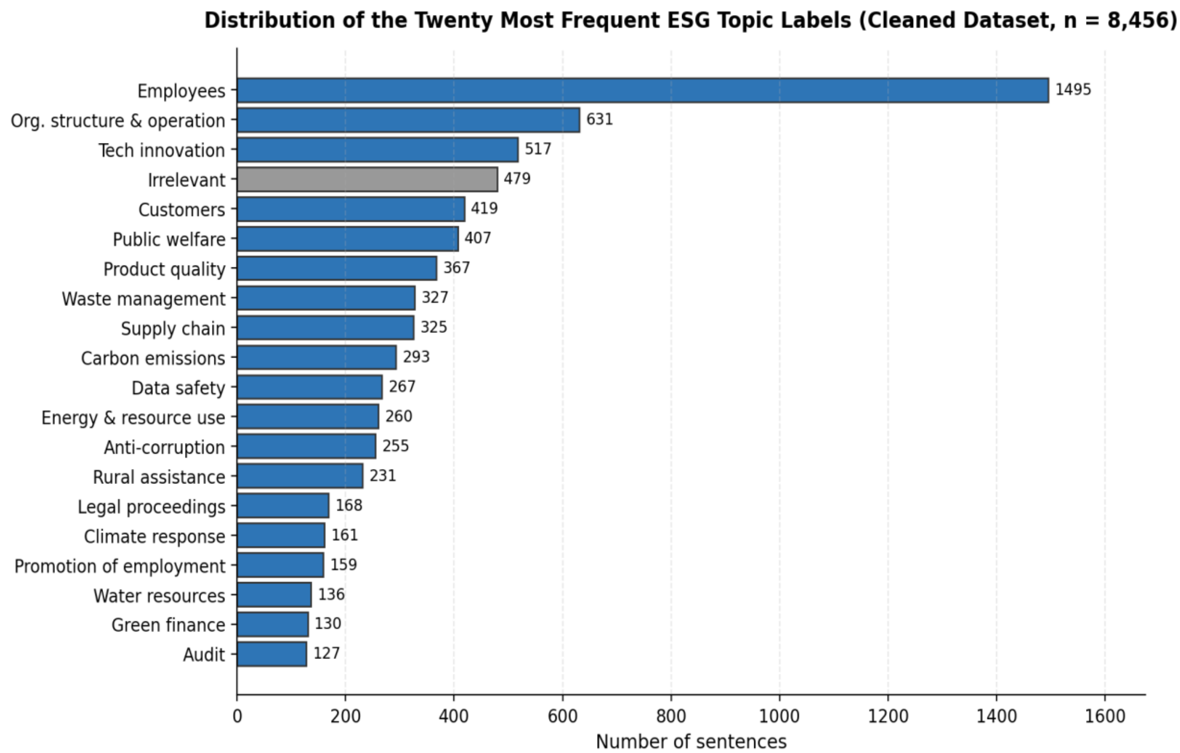

Figure 2. Distribution of the twenty most frequent ESG topic labels in the cleaned dataset.

The prevalence of social and operational pillar topics suggests that Chinese ESG disclosures in the corpus emphasize stakeholder dialogue and corporate governance practices, while strategically material but low-frequency disclosures—such as responsible investment, environmental sanctions, and chemicals safety—are less common (Huang et al., 2024; Davidescu et al., 2026). This imbalance is itself a strategic signal: CI systems must balance the apparent importance of high-volume topics with the latent risk profile of low-volume but material categories, which is precisely the role of the rarity-adjusted term R_i in Equation (4) (Lagasio, 2024; Lee, Raschke, et al., 2023).

The quality and pillar-wise distribution of ESG disclosures is shown in Figure 3 (Li, 2025; Huang et al., 2024). Qualitative text accounts for 69.5 percent of sentences, quantitative text for 24.8 percent, and irrelevant text for 5.7 percent (Lagasio, 2024; Davidescu et al., 2026). Social disclosures contribute 3,854 sentences, governance disclosures 2,210, environmental disclosures 1,913, and the remaining 479 fall under the irrelevant category (Huang et al., 2024; David et al., 2024). From an intelligence governance perspective, this composition signals an evidence deficit: more than two-thirds of disclosure is qualitative, which restricts the comparability and verifiability that managers and investors expect from CI products (Maluleka & Chummun, 2023; Oehler & Neuss, 2025).

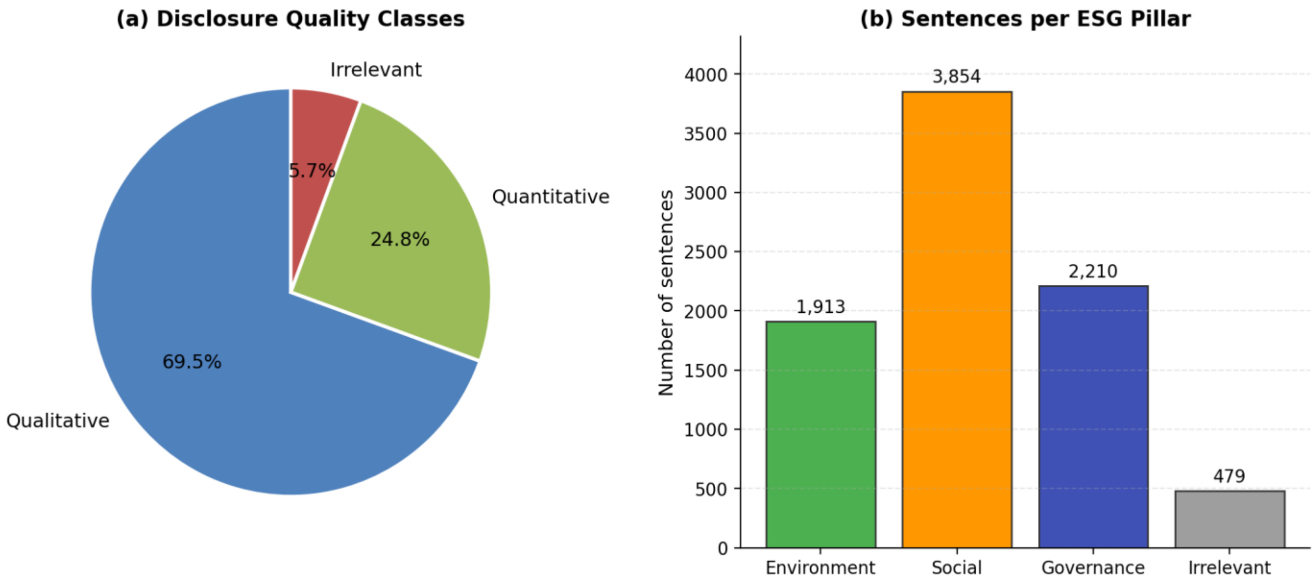

Figure 3. Disclosure-quality classes and sentence counts per ESG pillar in the cleaned dataset.

Table 5 presents the disclosure-quality distribution after cleaning, while Table 6 lists the ten most frequent ESG topic labels (Schimanski et al., 2024; Huang et al., 2024).

Table 5. Disclosure-quality distribution after cleaning.

Quality class (Chinese)	Number of sentences	Share of corpus
定性文本 (Qualitative)	5,879	69.52 percent
定量文本 (Quantitative)	2,098	24.81 percent
无关文本 (Irrelevant)	479	5.67 percent

Table 6. Ten most frequent ESG topic labels after cleaning.

Topic label (English translation)	Number of sentences	Share of corpus
Employees (员工)	1,495	17.68 percent
Organization structure and operation (组织架构与运作)	631	7.46 percent
Technology innovation (科技创新)	517	6.11 percent
Irrelevant text (无关文本)	479	5.66 percent
Customers and consumers (客户与消费者)	419	4.95 percent
Public welfare and volunteer service (公益和志愿服务)	407	4.81 percent
Product quality (产品质量)	367	4.34 percent
Waste management (废弃物管理)	327	3.87 percent
Supply chain management (供应链管理)	325	3.84 percent
Carbon emissions (碳排放)	293	3.47 percent

Figure 4 illustrates the distribution of sentence lengths for different quality levels using a violin chart (Schimanski et al., 2024; Huang et al., 2024). Then comes the range of quantitative statements, which are longer than qualitative statements, since they often include not only narrative information but also numerical performance measures, while there are irrelevant statements in the shortest range (Li, 2025; Huang et al., 2024). The median lengths of the Chinese characters in qualitative and quantitative statements are 80 and 87, respectively, which is approximately two times the length of the Chinese characters in the irrelevant statements (40) (Lagasio, 2024; Davidescu et al., 2026).

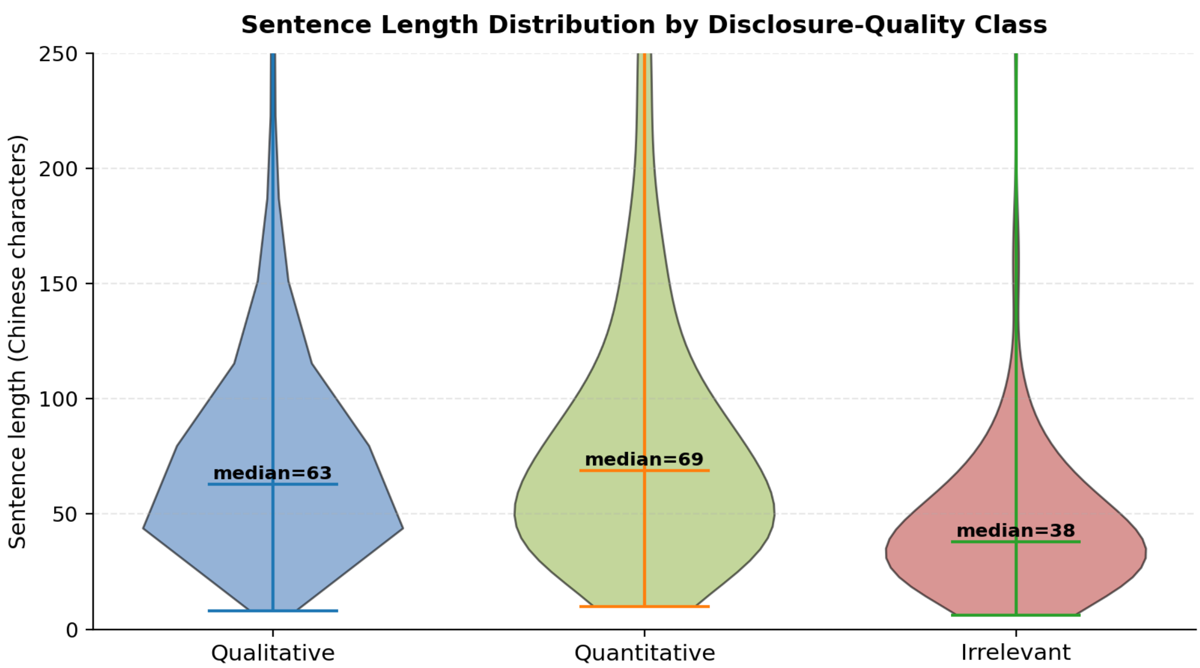

Figure 4. Sentence-length distribution by disclosure-quality class.

The results for the pillar level further confirm the trajectory and dynamic capabilities reading (Sneideriene & Legenzova, 2025; Liu, 2025). There are fewer numbers of measurement units in environmental sentences, with 13.2 percent of these sentences having one or more units of measurement, and 48.8 percent having Arabic numerals; social sentences have 47.5 percent with one or more units of measurement and 42.9 percent with Arabic numerals; governance sentences have 44.9 percent Arabic numerals and 42.9 percent have one or more units of measurement. This pattern is consistent with the fact that environmental disclosures are the most evidence rich pillar, while governance disclosures are mostly narrative, a structural characteristic that any CI system must consider when interpreting pillar-level scores as pointed out in (Huang et al., 2024; Sneideriene & Legenzova, 2025).

4.2 Model Development and Classification Performance

Three base classifiers were trained for both the disclosure-quality and topic-classification tasks: complement naive Bayes, logistic regression with class weighting, and a linear support vector machine (Seow, 2025; Ghallabi et al., 2025). All three classifiers have the same TF-IDF feature space, where n-gram features are used to represent the character segments, with min_df=2 and max_features set to 15,000, 20,000, depending on the task (Schimanski et al., 2024; Aldridge & Martin, 2022). A stratified 80/20 split with random seed 42 has been used to ensure the same class proportions are maintained between the training and evaluation (Chen, Yang, et al., 2024; Sneideriene & Legenzova, 2025).

Table 7 summarizes the headline performance of each classifier on the held-out test set (Schimanski et al., 2024; Sneideriene & Legenzova, 2025). The best disclosure-quality model is logistic regression with balanced class weighting, achieving 0.874 accuracy and 0.799 macro-F1, while the best topic model is the linear support vector classifier, achieving 0.795 accuracy and 0.743 macro-F1 (Chen, Yang, et al., 2024; Ong et al., 2025). From a CI standpoint, these performance levels are sufficient to operationalize the analysis phase of the intelligence cycle, while leaving headroom for transformer-based extensions to strengthen rare-class recall (Zhang et al., 2025; Ong et al., 2025).

Table 7. Model performance summary on the held-out test set.

Task and model	Accuracy	Macro-F1	Weighted-F1
Quality classification (Complement NB)	0.864	0.771	0.864
Quality classification (Logistic Regression, balanced)	0.874	0.799	0.875
Quality classification (Linear SVM)	0.882	0.772	0.877
Topic classification (Complement NB)	0.774	0.712	0.765
Topic classification (Linear SVM)	0.795	0.743	0.791

Table 8 reports per-class metrics for the complement naive Bayes baseline on the disclosure-quality task. The dominant qualitative class achieves precision 0.918 and recall 0.889; the quantitative class achieves precision 0.765 and recall 0.855; and the rare irrelevant class achieves precision 0.627 and recall 0.542 (Chen, Yang, et al., 2024; Sneideriene & Legenzova, 2025). These numbers confirm that the baseline performs strongly on the majority class but is weaker on the rare irrelevant class, the expected behavior under sentence-level class imbalance (Lagasio, 2024; Chen, Yang, et al., 2024).

Table 8. Quality classification metrics by class (Complement NB).

Class	Precision	Recall	F1-score
Qualitative	0.918	0.889	0.903
Quantitative	0.765	0.855	0.808
Irrelevant	0.627	0.542	0.581

Figure 5 visualizes the normalized confusion matrix of the best disclosure-quality model, logistic regression with class weighting (Chen, Yang, et al., 2024). The diagonal entries reach 0.908 for qualitative, 0.819 for quantitative, and 0.698 for irrelevant, indicating that the model can recover all three quality classes with useful accuracy despite the imbalance (Lagasio, 2024; Chen, Yang, et al., 2024). In organizational terms, these levels are compatible with the kind of decision support CI products provide, where directional reliability matters more than perfect classification (Maluleka & Chummun, 2023; Sneideriene & Legenzova, 2025).

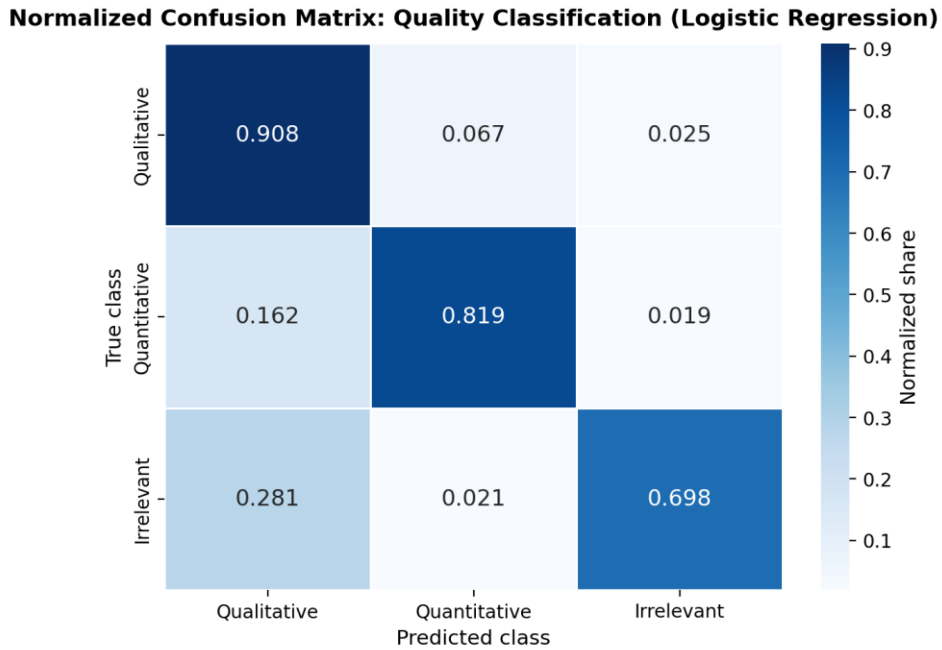

Figure 5. Normalized confusion matrix for quality classification (Logistic Regression with balanced weighting).

These findings indicate that Chinese ESG texts at the sentence level exhibit lexical stability for various ESG issues, and basic linear models based on character n-grams can facilitate ESG intelligence at a functional baseline level (Schimanski et al., 2024; Ong et al., 2025). However, the current limitations in predicting rare categories call for further research in hierarchical classification, data augmentation, and fine-tuning transformers on a GPU runtime (Zhang et al., 2025; Aldridge & Martin, 2022).

Overall, these findings indicate that Chinese ESG texts at the sentence level exhibit lexical stability for various ESG issues, and that basic linear models based on character n-grams can support ESG intelligence at a functional baseline level (Schimanski et al., 2024; Ong et al., 2025). The remaining ceiling on rare class recall points to a clear extension path: hierarchical classification, targeted data augmentation, and fine-tuning of Chinese transformers on a GPU runtime (Zhang et al., 2025; Aldridge & Martin, 2022). Within an intelligence governance routine, these technical gaps are themselves CI signals that must be communicated transparently to decision-makers.

4.3 Competitive Intelligence Scoring and Disclosure Trajectories

Figure 6 illustrates the distribution of the Competitive Intelligence Score from Equation (4) by ESG pillar and disclosure-quality class (Maluleka & Chummun, 2023; Calof, 2025). The environmental pillar attains the highest mean score of 0.701, while social and governance pillars reach 0.680 and 0.677 respectively, and irrelevant content reaches 0.169 (Huang et al., 2024; Lee, Raschke, et al., 2023). The mean score for quantitative disclosures is 0.854, compared with 0.624 for qualitative disclosures and 0.169 for irrelevant text (Lagasio, 2024; Sneideriene & Legenzova, 2025). The score therefore translates the analytical insights from sections 4.1–4.2 into a single, decision-ready intelligence indicator suitable for managerial dashboards and intelligence governance reviews (Maluleka & Chummun, 2023; Calof, 2025).

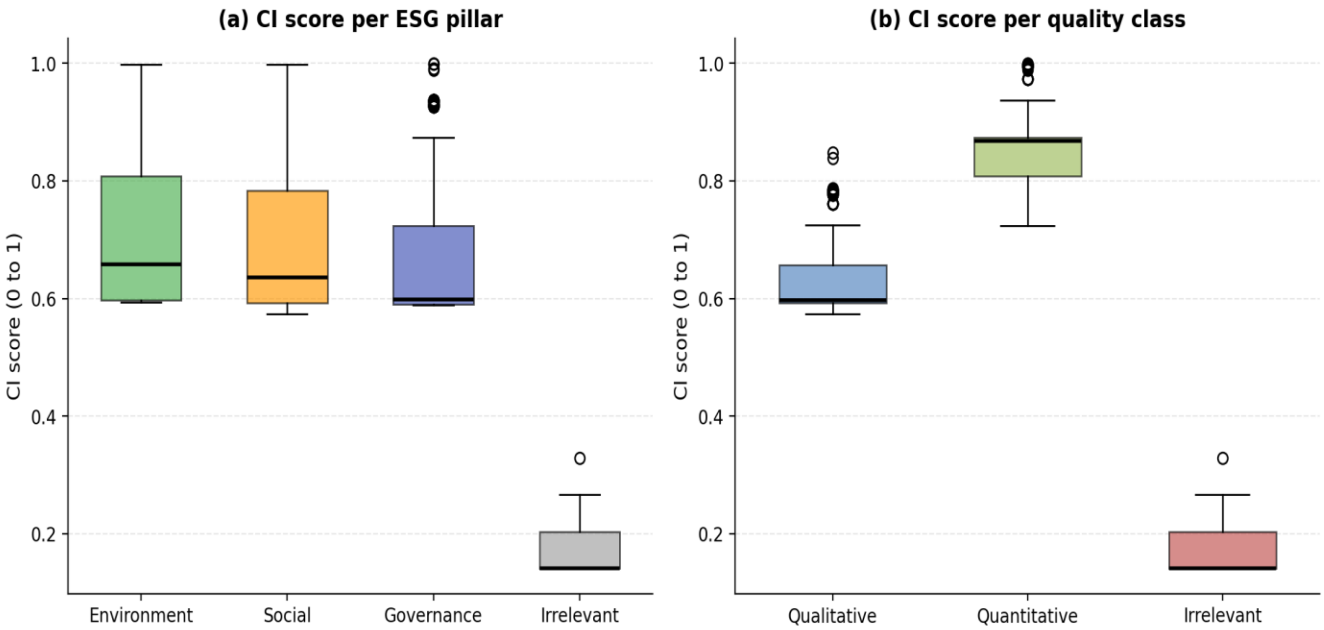

Figure 6. Competitive intelligence score per ESG pillar and per disclosure-quality class.

The trajectory in figure 7 is similar to that of a disclosure-quality trajectory that progresses from irrelevant content to a qualitative commitment, to quantitative evidence (Sneideriene & Legenzova, 2025; Liu, 2025). This is a staged progression in keeping with cognitive and skill-based learning models where competence is developed over time and the dynamic capabilities view, where strategic intelligence routines develop over time (Sneideriene & Legenzova, 2025; Liu, 2025; Hao et al., 2025). The path applied to ESG suggests that disclosure sophistication is a quantifiable organizational characteristic: beginning at the irrelevant level, the mean CI score increases by approximately a factor of five across the two other stages, intelligence cycles (Lagasio, 2024) and quantitative (Davidescu et al., 2026).

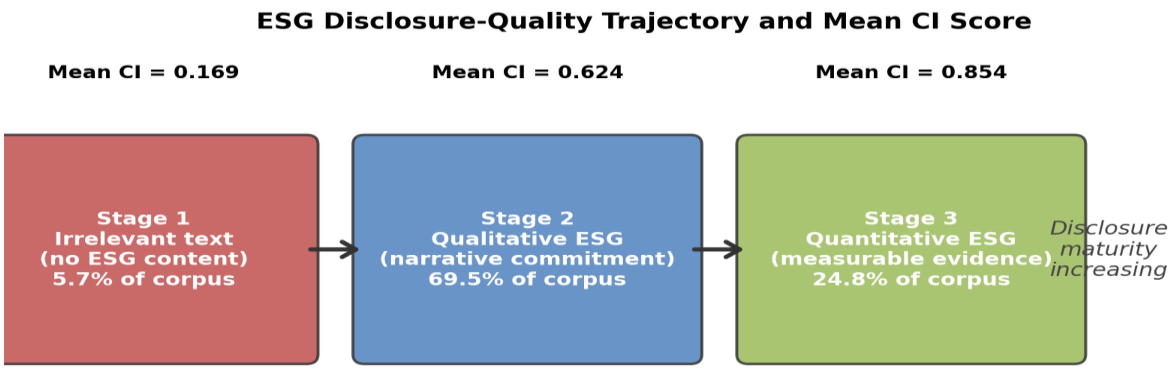

Figure 7. ESG disclosure-quality trajectory with mean competitive intelligence score per stage.

4.4 Evidence Maturity, Strategic Decision-Making, and Sustainable Competitive Advantage

The empirical results suggest the need for a separation between the simple mention of an ESG topic and the quality of evidence provided, which is the main difference behind strategic decision making in the context of ESG-related topics (Huang et al., 2024; Davidescu et al., 2026). Many of the Chinese ESG reports make statements about intent, policy, and actions, rather than measurable performance metrics, given the predominance of qualitative, non-numerical sentences in the corpus. This evidence asymmetry is a strategic problem for investors and analysts seeking comparable performance signals

(Lagasio, 2024; Oehler & Neuss, 2025), and through the lens of dynamic capabilities, it reveals where firms must strengthen their sensing and reconfiguring routines if they wish to convert ESG disclosure into sustainable competitive advantage (Sneideriene & Legenzova, 2025; Hao et al., 2025; An et al., 2025).

Pillar-level evidence diagnostics reinforce this conclusion (Li, 2025; Huang et al., 2024). Environmental sentences carry the highest density of numerical and unit markers, suggesting that Chinese environmental disclosures are more measurable than governance disclosures (Huang et al., 2024; David et al., 2024). Governance disclosures often consist of process-oriented narrative that is harder to quantify but critical for risk-based competitive intelligence and intelligence governance (Maluleka & Chummun, 2023; Lee, Raschke, et al., 2023). For boards and strategy teams, this finding indicates where governance disclosure architecture should be redesigned to produce more verifiable, machine-readable evidence that can support strategic foresight and ESG ratings convergence (Oehler & Neuss, 2025; Fabijanska et al., 2025; Sneideriene & Legenzova, 2025).

4.5 Topic Concentration and Strategic Blind Spots

The frequency distribution of topic labels shows the issues that companies put in the spotlight in their public ESG communication (Ferjancic et al., 2024; Huang et al., 2024). The issues of employee welfare, corporate structure, technology, service quality and product quality are frequently cited with others like responsible investment, environment sanctions, and chemical safety appearing scarcely (Huang et al., 2024; Davidescu et al., 2026). This concentration is analytical in nature, as rare topics in ESG can also have strategic significance that far exceeds their incidence (Lagasio, 2024; Lee, Raschke, et al., 2023). So, the rarity term, R_i, in Equation (4) is not an addendum to the model, but a strategic mechanism: it prevents CI systems from amplifying topical bias, and signals low-frequency, high-stakes problems to managerial attention (Maluleka & Chummun, 2023; Lee, Raschke, et al., 2023).

4.6 Competitive Intelligence Interpretation and Managerial Implications

The framework aligns ESG disclosures to four layers of decisions compliant with classic CI architectures (Maluleka & Chummun, 2023; Calof, 2025). The first layer involves identifying the topics on ESG covered in the layer. In the second, they consider the disclosure as irrelevant, qualitative, or quantitative. In the third, evidence is gathered via numbers and units. The fourth level organizes topics by strategic level and the maturity of the evidence, using the CI score (Lee, Raschke, et al., 2023; Sneideriene & Legenzova, 2025). Managers can use the same database for four decision support functions: comparative firm analysis, benchmarking of evidence maturity, reporting gap diagnosis, and detection of greenwashing risk, which are tightly coupled to the planning, collection, analysis, dissemination, and feedback steps of the intelligence cycle (Lagasio, 2024; Oehler & Neuss, 2025; Davidescu et al., 2026).

For corporate managers, the framework identifies parts of ESG reports where there is little evidence to support the section and parts where quantitative targets need to be added to make year-on-year and cross-firm comparisons (Huang et al., 2024; Fabijanska et al., 2025). The reason is that it allows a set of investors to screen for evidence-specificity, not just headline ESG ratings, which is particularly important in China, where the opinion of various rating firm may differ (Oehler & Neuss, 2025; David et al., 2024). Regulators and standard setters are pleased that their results have validated the benefits of more transparent disclosure regulation and machine-readable signals, given that automated ESG intelligence works best when the underlying disclosure architecture is structured (Davidescu et al., 2026; Sneideriene & Legenzova, 2025). In both audiences and in all three, the CI score acts as a unified metric that bridges sentence-level analytics and enterprise-level strategic decision-making and sustainable competitive advantage (Maluleka & Chummun, 2023; Calof, 2025; Hao et al., 2025).

4.7 Novelty and Theoretical Contribution

This paper is not about using TF-IDF or linear classifiers but the use of NLP outputs within a Strategic Competitive Intelligence system based on the intelligence cycle, dynamic capabilities, and governance of intelligence (Maluleka & Chummun, 2023; Calof, 2025; Sneideriene & Legenzova, 2025). The trajectory perspective takes the view that ESG analytics is a journey from irrelevant or boilerplate statements to qualitative commitment to quantitative data, like the evolution of strategic intelligence routines into dynamic capabilities in (Sneideriene & Legenzova, 2025; Liu, 2025; Hao et al., 2025). In this way, the framework distinguishes ESG communication from ESG performance and introduces a CI-inspired way of quantifying communication and performance ESG gaps (Oehler & Neuss, 2025; Huang et al., 2024; Fabijanska et al., 2025).

5 FINAL CONSIDERATIONS

This study repositioned ESG analytics as a Strategic Competitive Intelligence problem and developed a CI-driven framework that integrates the intelligence cycle, dynamic capabilities, and intelligence governance with a reproducible empirical pipeline. The preprocessing pipeline cleaned 8,471 raw rows into 8,456 usable observations, encoded topic and quality labels, engineered four interpretable evidence features, and produced reproducible model outputs that can be regenerated by other researchers (Li, 2025; Ghallabi et al., 2025).

The empirical results show that ESG text carries useful signals for both quality and topic classification (Schimanski et al., 2024; Sneideriene & Legenzova, 2025). The disclosure-quality classifier reached 0.882 accuracy and 0.772 macro-F1 with a linear support vector model, and 0.874 accuracy and 0.799 macro-F1 with logistic regression and class weighting, while the topic classifier reached 0.795 accuracy and 0.743 macro-F1 with a linear support vector model (Chen, Yang, et al., 2024; Sneideriene & Legenzova, 2025). The proposed CI Score expressed by Equation (4) effectively distinguished the quantitative disclosure (0.854), qualitative commitment (0.624) and irrelevant text (0.169), which further validated that the disclosure maturity of sentences in Chinese ESG reports is a measurable attribute, and that sentence-level disclosure maturity is a useful input to strategic decision-making (Lagasio, 2024; Davidescu et al., 2026).

Three implications of theory and management are presented. First, the volume of disclosure is not sufficient for the performance review of ESG to be conducted; there are three key factors that are essential, namely the maturity, specificity, and strategic relevance of the underlying evidence (Huang et al., 2024; Davidescu et al., 2026). Second, Competitive Intelligence (CI) for ESG needs to be connected to four dimensions of communication: topicality, quality of the evidence, measurability, and strategic salience, in a transparent manner in the context of an explicit routine of intelligence governance (Maluleka & Chummun, 2023; Lee, Raschke, et al., 2023; Sneideriene & Legenzova, 2025). Third, the trajectory perspective, based on dynamic capabilities, offers an integrating explanatory layer in which these pillars are stages of organizational ESG intelligence maturity, closely connected to the process of achieving sustainable competitive advantage (Sneideriene & Legenzova, 2025; Liu, 2025; Hao et al., 2025).

The study has some restrictions, which also outline the directions for future research (Seow, 2025; Sneideriene & Legenzova, 2025). One, the dataset is a sentence level one, and lacks firm identifiers, reporting periods, industry classification and external ESG rating, so direct linkages between the CI scores and firm level outcomes is not possible. An extension to this is to add to the data firm metadata and then connect the sentence level intelligence to the firm level to the outcome variables using panel regressions and causal modeling and establishing the framework into real organizational intelligence governance processes (David et al., 2024; Davidescu et al., 2026). Second, the baseline classifiers have good accuracy for the majority classes but low accuracy for the minority classes; future work can combine the Chinese transformers, ESG topic classification, explainable AI, and aspect-action analysis to improve the recall of strategically material low-frequency topics (Zhang et al., 2025; Ong et al., 2025). Third, there needs to be a managerially validated ESG intelligence dashboard to monitor evidence specificity and topical salience and maturity of the ESG over time – ideally with policy and regulatory texts relevant to the Chinese context – to make it a living intelligence product for investors, regulators, and corporate strategy teams (Fabijanska et al., 2025; Sneideriene & Legenzova, 2025; Liu, 2025). Lastly, the CI weights used in Equation (4) are theoretically based but should be empirically calculated based on expert ESG ratings or external sustainability indicators in future studies, allowing the analyst-anchored weighting to be tailored to external and changing ESG regulatory environments in China (Maluleka & Chummun, 2023; Oehler & Neuss, 2025; David et al., 2024; Liu, 2025).

Combined, the framework shows that the strategic value of ESG analytics is at its greatest when grounded in the CI cycle, interpreted by dynamic capabilities, and built into a clear architecture of intelligence governance. With this setup, ESG disclosure intelligence is a legitimate basis for sustainable decision support and sustainable competitive advantage. Brief disclosures. The labeled Chinese ESG sentences data is available in public, the same steps as described in Section 3 are followed for the clean data and preprocessing code, and the modeling notebook can be reproduced. This was a public, anonymised text dataset which did not require ethical review. The authors have no specific funding for this work and have no conflicts of interest to declare. AI tools have been used only for grammar and copy-editing assistance, rendering equations and figures, but all the scientific content, analytical design, code, results, and conclusions are the responsibility of the authors.

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