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Green Textile Life Cycle Assessment and Ecological Discourse Configuration Characteristics Analysis Using an Ecological Discourse Analysis Model

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Article

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ABSTRACT

Current life cycle assessments (LCAs) of green textiles often lack a thorough analysis of ecological discourse configuration characteristics, resulting in an incomplete understanding of the correlation between environmental impacts and social cognition. This study employs an integrated ecological life cycle assessment model, coupled with natural language processing (NLP) techniques, to address this gap by analyzing ecological discourse configuration. First, the study applies LCA methodology to quantitatively evaluate the production, use, and recycling stages of green textiles, focusing on resource consumption and environmental impacts. Subsequently, sentiment analysis and topic modeling are utilized to extract ecological discourse features from relevant texts, thereby constructing a comprehensive discourse structure. Experimental results demonstrate that the accuracy of keyword recognition within the ecological discourse analysis reaches 93.4%. This research provides a theoretical basis for optimizing green textile design and social promotion, facilitating the integration of environmental impact assessment and ecological discourse analysis.

KEYWORDS

green textiles, life cycle assessment, ecological discourse, natural language processing

INTRODUCTION

With increasing global awareness of sustainable development, the demand for green textiles continues to rise. The production of green textiles emphasizes not only the environmental friendliness of materials but also the environmental impacts across the entire life cycle [1,2]. Existing LCAs primarily evaluate technical and environmental benefits, often neglecting in-depth analysis of ecological discourse configuration [3,4].

Ecological discourse is intrinsically linked to the design concepts and environmental advocacy of textiles and reflects varying perceptions of green principles among consumers, enterprises, and society [5,6]. Insufficient consideration of ecological discourse impedes effective integration of environmental impact and social cognition, thus limiting further optimization of sustainable development in green textiles [7,8].

Recent scholarship has advanced LCA methodologies for green textiles [9,10]. Traditional LCA approaches are widely applied to assess the environmental impacts of products from raw material extraction to waste management [11,12]. However, these studies predominantly focus on quantitative assessments of environmental impacts and resource utilization, with limited attention to ecological discourse—specifically, the environmental concepts and ideologies conveyed in marketing and consumer contexts. In response, some researchers have introduced ecological discourse analysis methods that integrate social cognition, environmental policy, and product design, highlighting the role of discourse in promoting sustainable consumption and production [13,14]. Nevertheless, most existing work restricts ecological discourse analysis to individual textile products, lacking a systematic integration of LCA and ecological discourse analysis.

To address these limitations, recent studies have begun to combine ecological LCA models with NLP technologies to simultaneously analyze ecological discourse configuration and evaluate the environmental impacts of green products. For example, Zhang et al. [15] innovatively combined ecolinguistics with sentiment analysis and convolutional neural networks to construct a tonal and modality system from an ecological perspective, applying this method to analyze news reports on Sino-US trade frictions. However, such studies primarily demonstrate local applications and do not fully illustrate the deep integration of ecological discourse and LCA. Furthermore, the analysis of correlations between ecological discourse and distinct life cycle stages remains relatively underdeveloped [16,17]. This paper systematically integrates ecological discourse analysis models with LCA to address these gaps [18,19].

This study aims to comprehensively evaluate the life cycle of green textiles using an ecological discourse analysis model and to analyze the configuration characteristics of ecological discourse in conjunction with NLP techniques. The model quantitatively assesses environmental impacts, including resource consumption and pollution emissions, and applies sentiment analysis and topic modeling to extract and structure ecological discourse features at each life cycle stage. Through these methodologies, the research elucidates the intrinsic connections between environmental impact and ecological discourse, providing a theoretical foundation for optimizing green textile design and promotion, and advancing the theoretical and practical development of sustainable green textiles.

METHODS

The ecological discourse analysis model utilized in this study is a composite framework that integrates ecolinguistics and text analysis modules within the conventional LCA structure. This model incorporates quantitative assessment techniques for resource consumption, pollution emissions, and ecological benefits, while leveraging NLP methods to extract and structure discourse features from textual data. The model's core consists of an environmental indicator quantification module and a text semantic parsing module, which collectively model the associations between environmental data and discourse features through correlation analysis. Drawing upon established theoretical frameworks and interdisciplinary methodologies, this model supports collaborative analysis of both environmental performance and discourse expression throughout the green textile life cycle. Here, the “ecological discourse analysis model” refers to the integrated framework combining LCA and NLP, with the “LCA module” responsible for quantitative environmental impact assessment and the “NLP module” dedicated to textual feature extraction and discourse structure construction. The model operates as a unified system, and experimental evaluations apply the full integrated framework to NLP tasks, underscoring its cohesive functionality in discourse analysis.

Ecological Life Cycle Assessment

Environmental impact assessment of green textiles employs standardized LCA methodology, quantifying impacts across production, use, and recycling stages. Input-output analysis is used to quantify resource consumption, while the emission factor method calculates pollution emissions. Carbon footprint and water footprint serve as primary environmental impact indicators. Figure 1 illustrates the input-output analysis approach.

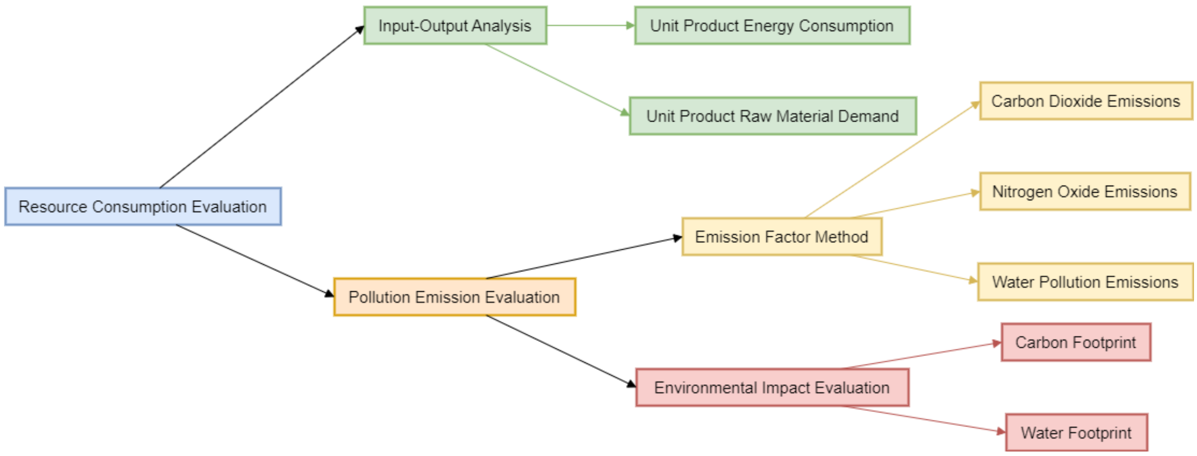

Figure 1. Input-Output Analysis Method

Figure 1 demonstrates the quantification of resource consumption and pollution emissions for green textiles within the ecological discourse analysis model. The ecological footprint method is applied to evaluate environmental benefits at each life cycle stage by assessing the demand and carrying capacity of natural resources—including land, water, and air—from raw material acquisition to waste management. This comprehensive approach determines whether green textiles effectively reduce resource consumption and pollution.

The functional unit for LCA is defined as one kilogram of green textile product, with system boundaries encompassing the entire product life cycle from cradle to grave, including raw material acquisition, production processing, and packaging. Usage phase modeling is based on defined scenarios, considering consumer washing frequency, water temperature, and energy consumption of laundry appliances. Regional power grid emission factors are integrated to account for geographic variation in energy sources during use. The recycling phase is modeled to represent typical end-of-life pathways, including collection, sorting, mechanical processing, and material recovery. Scenario parameters are derived from industry reports and consumer practice studies to ensure the life cycle inventory reflects realistic conditions. All environmental impact data—including resource consumption, pollution emissions, and ecological footprint—are quantified per kilogram of product.

The life cycle inventory is constructed using primary data from field measurements of representative green textile manufacturing processes, supplemented with secondary data from established databases. Energy and material flow data are sourced from the Ecoinvent database (version 3.8), and emission factors for greenhouse gases and other pollutants are obtained from the IPCC Guidelines and the GaBi Professional database. All processes are modeled within system boundaries consistent with the functional unit, in accordance with ISO 14040 and ISO 14044 standards for reproducibility and transparency.

The carbon footprint is calculated using the IPCC 2021 Global Warming Potential (GWP) 100a methodology and integrated into the ReCiPe framework as a distinct impact category under global warming potential. For climate change impact assessment, this study employs the updated GWP values from the IPCC 2021 Sixth Assessment Report, which reflect the latest scientific consensus and methodological advancements. This update does not introduce a new impact category but revises key parameters within the existing “Climate Change” category of ReCiPe 2016. All impact categories are normalized to a common reference scale. The Analytic Hierarchy Process (AHP) is used as an independent decision analysis tool to assign customized weights to ReCiPe midpoint indicators, aggregating standardized assessment results into a single comprehensive environmental impact indicator.

$$E_{total} = \sum_{i=1}^{n} w_i \cdot E_i \quad (1)$$

In formula (1): E_{total} is the comprehensive environmental impact score. E_i is the individual score of the i environmental indicators (such as carbon footprint, water footprint, resource consumption, etc.). w_i is the weight assigned to the i environmental indicator, n is the total number of environmental indicators. Weights are determined using the Analytic Hierarchy Process (AHP), ranking indicators by their relative environmental importance. The assessment method employed is ReCiPe 2016 Midpoint (H), ensuring consistency with standardized product life cycle impact assessment frameworks.

Quantitative results from this LCA provide one data stream for integrated analysis. A separate ecological discourse analysis model, detailed in subsequent sections, is applied in parallel to analyze textual data. Integration of these analytical streams is performed in the correlation analysis described in Section Correlation Analysis between Ecological Discourse and Environmental Impact.

Text Data Collection and Preprocessing

Accurate collection and processing of textual data are critical for ecological discourse analysis. This study compiles text data related to green textiles from diverse sources, including academic literature, marketing materials, consumer reviews, and social media. Web crawler technology is used to automatically retrieve publicly available data, ensuring coverage of perspectives from various audience groups. Academic literature is sourced from databases such as Google Scholar and CNKI (China National Knowledge Infrastructure), while marketing data are obtained from corporate websites, online advertisements, and product descriptions. Consumer reviews are collected from e-commerce platforms (e.g., Taobao, JD.com) and social media (e.g., Weibo, Instagram). The data collection period spans January 2022 to December 2023. The corpus composition is 35% academic literature, 20% corporate marketing materials, 30% social media posts, and 15% e-commerce reviews. Duplicates are removed using a text similarity algorithm with a threshold of 0.85. Only publicly accessible sources are included; no private or restricted content is collected. Variations in discourse attributes across source types are retained as intrinsic features of the ecological discourse ecosystem. The analytical model captures these differences through statistical patterns in topic and sentiment distribution. Ecological discourse is defined as the ensemble of environmental claims, concepts, and sentiments expressed across these heterogeneous sources. To ensure coherence, all textual sources undergo identical preprocessing and feature extraction procedures, treating the corpus as a unified representation of the green textile discourse ecosystem. Potential biases inherent in specific source types, such as promotional tone in marketing materials, are captured as components of the discourse and quantified through statistical analysis of topic prevalence and sentiment distribution. The data collection process accounts for temporal and regional diversity to enhance representativeness. Table 1 presents statistics for ecological discourse characteristics.

Table 1. Statistics of Ecological Discourse Characteristics

Ecological Discourse Feature	Frequency	Proportion
Energy-Saving Design	520	15.40%
Eco-Friendly Materials	430	12.70%
Sustainable Development	350	10.30%
Recycling and Reuse	300	8.80%
Negative Environmental Sentiment	280	8.20%
Positive Environmental Sentiment	500	14.70%

Table 1 summarizes the principal ecological discourse features extracted from texts related to green textiles via ecological discourse analysis, reporting their frequency and proportion among all analyzed texts. The sum of proportions is below 100% due to exclusion of less frequent features. The total frequency presented is 2,380, while the corpus consists of 3,380 documents, indicating that only primary features are included and not all documents contain these specific features.

The corpus comprises 3,380 documents collected over a 24-month period from 2022 to 2023, spanning Asia, Europe, and North America, and encompassing academic, commercial, and public discourse sources. This sample size enables statistically robust analysis across life cycle stages and regional variations. Subsequent experimental sections reference subsets of this corpus for specific analytical tasks, with document counts adjusted according to sampling design.

The original texts contain substantial irrelevant information and noise, necessitating a series of standardization processes. Text segmentation is performed using Jieba for Chinese texts and the NLTK (Natural Language Toolkit) library for English texts to ensure accurate word boundaries and recognition of proper nouns and compound terms. Stop word removal is conducted using a field-specific stop word list for green textiles, eliminating high-frequency, non-informative words and improving the accuracy of subsequent analyses. Field-specific terms and collocations (e.g., “eco-friendly materials,” “sustainable development”) are retained to preserve topic modeling and sentiment analysis integrity.

The ecological discourse analysis model, distinct from quantitative LCA, integrates NLP techniques detailed below to process textual data and extract discourse features. Outputs from LCA and ecological discourse analysis are subsequently integrated for correlation analysis, as described in Section Correlation Analysis between Ecological Discourse and Environmental Impact.

Ecological Discourse Analysis

This study applies sentiment analysis and topic modeling to extract environmental sentiment tendencies and key environmental themes from texts, thereby revealing ecological discourse characteristics in green textile promotion. A domain-specific sentiment dictionary is constructed to enhance sentiment classification accuracy, incorporating environmental protection terminology and related sentiment words commonly used in the green textile sector (e.g., “environmental protection,” “sustainable” for positive sentiment; “pollution,” “waste” for negative sentiment). The sentiment dictionary is employed alongside a support vector machine (SVM) classifier. The dictionary is expanded via synonym discovery and context window analysis from the corpus, with final terms validated by manual review from two domain experts, achieving an inter-annotator agreement coefficient of 0.87. The SVM classifier is trained on a dedicated dataset of 5,000 annotated text segments, partitioned into training, validation, and test sets at a 6:2:2 ratio. Text features are extracted using the term frequency-inverse document frequency (TF-IDF) algorithm to construct feature matrices, which are input into the SVM for sentiment classification.

Topic modeling is performed using the Latent Dirichlet Allocation (LDA) model, configured with batch variational inference and symmetric Dirichlet priors of 0.1 for both document-topic and topic-word distributions. The number of topics is determined by maximizing the topic coherence score, resulting in 15 distinct topics. The LDA model, an unsupervised probabilistic learning method, automatically identifies latent topics by analyzing word frequency distributions. Preprocessed texts are converted to a bag-of-words model and input into the LDA, which iteratively calculates topic distributions for documents and words. Prominent environmental topics identified include "green design," "recyclable materials," and "energy-saving technology."

The SVM employs a radial basis function kernel with penalty parameter C set to 1.0 and gamma set to "scale." The LDA model utilizes batch variational inference with symmetric Dirichlet priors. The BERT-based model is fine-tuned from the bert-base-uncased checkpoint using a learning rate of 2×10^{-5} for four epochs and a batch size of 32. All models are trained on a single NVIDIA V100 GPU with a fixed random seed of 42 for reproducibility. Model performance is compared against a RoBERTa-base classifier, with the fine-tuned BERT model demonstrating superior results across all tasks.

Correlation Analysis between Ecological Discourse and Environmental Impact

Sentiment labels in this analysis reflect public perceptions of each life cycle stage rather than intrinsic stage qualities. Negative sentiment predominates in the production phase due to concerns about pollution and resource use, while the use phase elicits neutral sentiment, and recycling is associated with positive sentiment reflecting circular economy principles. The disconnect between quantified environmental impact and public sentiment is critical for identifying areas of misalignment between technical improvements and communication strategies.

This study integrates LCA and ecological discourse analysis, positing a reflexive relationship between a product's environmental performance and societal perception. Environmental impact data from LCA, including resource consumption, pollution, and ecological footprint, are matched with ecological discourse features derived from sentiment analysis and topic modeling (e.g., sentiment tendencies, topics such as energy saving and green design). Datasets are standardized for comparison across different sources and units. To enhance statistical validity, environmental impact data are disaggregated into process-level nodes, with corresponding ecological discourse features extracted for each node. This extended dataset enables robust correlation and regression analysis, yielding reliable conclusions on relationships between environmental indicators and discourse characteristics. Table 2 presents the revised data structure.

Table 2. Environmental Impact and Ecological Discourse Features at Different Lifecycle Nodes

Lifecycle Node	Resource Consumption (MJ)	Pollution Emissions (kg CO_2-eq)	Ecological Footprint (m^2)	Sentiment
Raw Material Acquisition	1,800	720	540	Negative
Production Processing	2,100	940	720	Negative
Packaging	1,100	340	240	Neutral
Consumer Energy Use	1,600	620	440	Neutral
Maintenance and Washing	1,400	580	360	Neutral
Recycling – Disassembly	700	280	180	Positive
Recycling – Material Reuse	300	120	60	Positive

The quantitative environmental impact data in Table 2 are representative values derived from process-based life cycle inventory modeling, informed by primary manufacturing audits and secondary data from Ecoinvent 3.8 and GaBi 2023 databases. Carbon footprint calculations follow IPCC 2021 GWP 100a methodology, while ecological footprint is quantified using ReCiPe 2016 Midpoint (H) characterization factors. All calculations are normalized per kilogram of textile product. Correlation analysis is conducted on this segmented data, correlating environmental indicators with sentiment polarity and topic distribution at different process stages to create a statistically robust dataset. Pearson correlation coefficients and regression models provide quantitative evidence for the relationship between environmental impact and ecological discourse.

The relationship is quantified using the Pearson correlation coefficient. The calculation formula of the Pearson correlation coefficient is as follows:

$$r=\frac{\sum_{i=1}^{n}(X_i-\overline{X})(Y_i-\overline{Y})}{\sqrt{\sum_{i=1}^{n}(X_i-\overline{X})^2\sum_{i=1}^{n}(Y_i-\overline{Y})^2}} \quad (2)$$

In formula (2): r is the Pearson correlation coefficient, which indicates the linear correlation between two variables, with a range of [-1,1]. Among them, r=1 indicates a perfect positive correlation; r=-1 indicates a perfect negative correlation; r=0 indicates no linear correlation. X_i and Y_i are the values of two variables in the i-th sample (the environmental impact indicator of the life cycle stage and the sentiment score or topic distribution in the ecological discourse characteristics). $\overline{X}$ and $\overline{Y}$ are the means of variables X and Y, respectively. n is the number of samples (the number of life cycle stages or the number of ecological discourse features).

Pearson correlation and linear regression are applied to explore relationships between environmental impact indicators and discourse features, establishing quantifiable links between these domains [20]. While correlation analysis identifies linear relationships, it serves as a first-order approximation and does not capture the full complexity of socio-ecological interactions. The results highlight convergences between material flows and discursive patterns, suggesting the need for more advanced future analyses. Regression modeling treats environmental impact as the dependent variable, with sentiment scores and topic distributions as independent variables, quantifying the predictive power of discourse features on environmental impact.

EXPERIMENTAL EVALUATION

Prediction Performance

A labeled dataset containing keywords, frameworks, and subject-object information is compiled, comprising 500 entries. The data are split into training, validation, and test sets in a 6:2:2 ratio. Text data are preprocessed via word segmentation, stop word removal, and encoding. Two models are evaluated: the ecological discourse analysis model and the bag-of-words model. Model architectures and parameters are tuned according to task characteristics. Both models are trained on the training set, with hyperparameters optimized using the validation set. Predictions are made on three tasks: keyword recognition, frame recognition, and subject-object matching. Test set results are reported for each evaluation metric.

Prediction performance metrics pertain to discrete NLP tasks within ecological discourse analysis. The highest accuracy, 93.4%, is achieved in keyword recognition, specifically for domain-relevant term identification. Performance on frame identification and subject-object matching varies, as illustrated in Figure 2. These results demonstrate the efficacy of the proposed method for specific computational sub-tasks within broader discourse analysis.

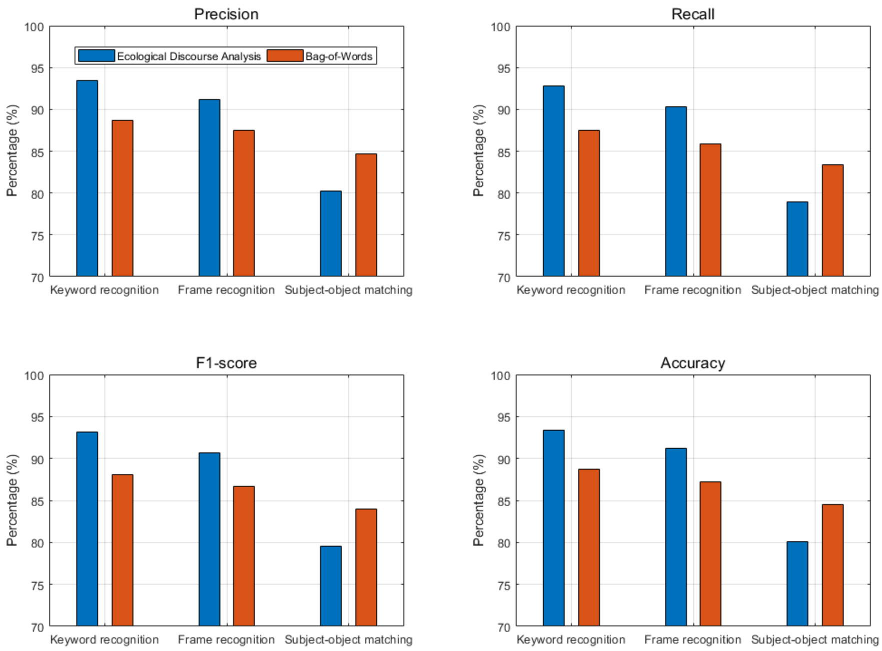

Figure 2. Task Prediction Performance

Figure 2 shows the performance comparison of two models (Ecological Discourse Analysis and Bag-of-Words) across three tasks (keyword identification, frame identification, subject-object matching) using four metrics (precision, recall, F1-score, accuracy). Ecological discourse analysis outperforms Bag-of-Words in keyword and frame recognition, with maximum accuracy reaching 93.4% (keyword recognition) versus 88.7% for Bag-of-Words. The recall rate for ecological discourse analysis is also superior, especially in keyword recognition (92.8%). Overall accuracy for ecological discourse analysis remains above 80%, with the highest approaching 94%, indicating robust prediction performance. Keyword recognition yields the best results, suggesting task simplicity or sufficient data quality.

Semantic Role Labeling Accuracy

Ecological discourse texts are collected in five consecutive four-week batches, each containing approximately 700 documents. The collection period spans January to May 2022, with documents distributed geographically (40% Asia, 30% Europe, 30% North America). Texts are cleaned, segmented, and formatted for automatic labeling. A BERT-based semantic role labeling model is fine-tuned for ecological discourse features using pre-trained corpora and incremental learning. Manually annotated validation sets are used to calculate semantic role labeling accuracy for each batch, analyzing the impact of sample size on performance.

The horizontal axis of Figure 3 represents five sample batches, and the vertical axis represents the accuracy of semantic role labeling. The accuracy of Figure 3 (a) is relatively high and gradually increases, indicating that the quality of automatic labeling is good at this stage. Figure 3 (b) has a slightly lower accuracy but is steadily improving, indicating that the model performs smoothly on the corpus in this time period. Figure 3 (c) has a relatively low accuracy, which may be affected by the complexity of the corpus content or the difficulty of automatic annotation. As the sample batches and sample numbers increase, the accuracy of semantic role annotation improves, indicating that increasing the amount of data helps improve model performance.

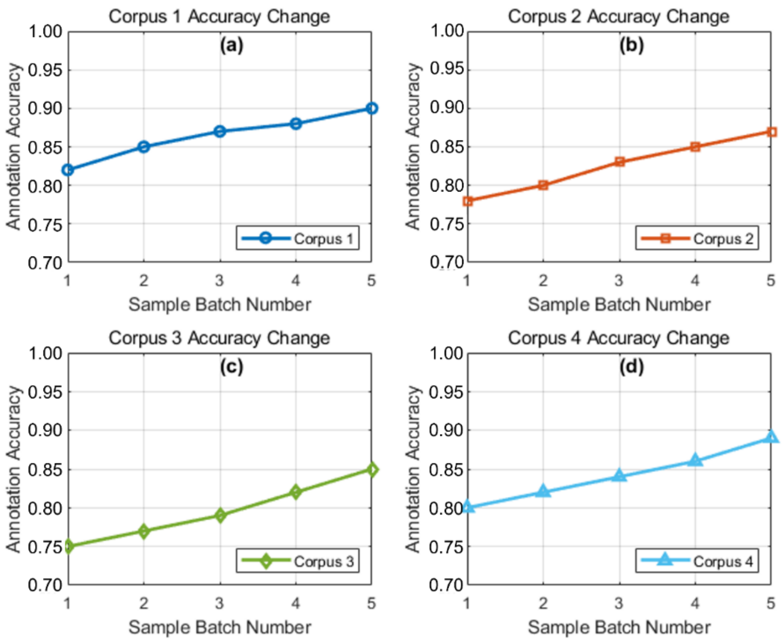

Figure 3. Semantic Role Labeling Accuracy: (a) Corpus 1; (b) Corpus 2; (c) Corpus 3; (d) Corpus 4

Overall Semantic Association Strength

Texts are collected in 10 consecutive two-week batches from June to October 2022, each batch containing at least 350 documents with consistent geographical distribution (40% Asia, 30% Europe, 30% North America).

Preprocessing includes cleaning, segmentation, and stop word removal. Word frequency is calculated in each batch, and high-frequency words are selected for analysis. Co-occurrence frequencies are used to compute semantic association strength via pointwise mutual information (PMI). The average PMI of high-frequency pairs yields the corpus's semantic association index, and the number of ecological keywords is tracked per batch.

The number of keywords identified as ecological core words in each batch is counted. The analysis utilized 10 batches. Each batch contained a minimum of 350 documents. These batches covered consecutive two-week collection windows from June 2022 to October 2022. The geographical distribution for these batches remained consistent at 40% Asia, 30% Europe, and 30% North America.

Figure 4 shows the comparative analysis of the PMI (point mutual information) average value and the number of keywords of the ecological discourse corpus under different sample batches. The horizontal axis represents 10 sample batches, reflecting the different stages of corpus collection. The vertical axis of sub-graph (a) corresponds to the average PMI value, and the vertical axis of sub-graph (b) corresponds to the number of keywords. The average PMI value reflects the overall semantic association strength between word pairs; higher values indicate closer connections. Keyword count reflects corpus richness and diversity. As batches progress, both average PMI and keyword count increase, indicating strengthening semantic networks and enhanced ecological discourse expression.

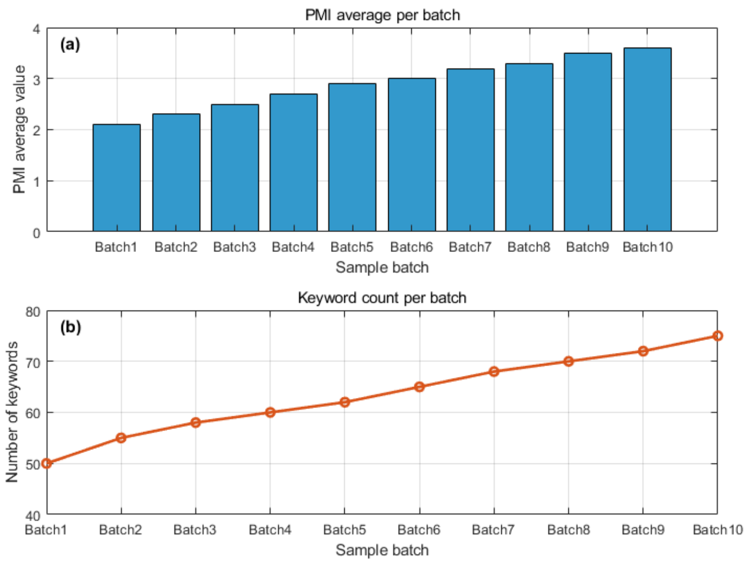

Figure 4. The PMI Average Value and The Number of Keywords of The Ecological Discourse Corpus under Different Sample Batches.

(a) Average PMI of Different Batches; (b) Number of Keywords in Different Batches

Factor Explained Variance Ratio

The ecological discourse corpus is vectorized semantically, and dimensionality reduction is performed using factor analysis or principal component analysis to extract latent configuration dimensions (factors). Explained variance ratios for each factor and cumulative ratios are calculated to determine the optimal number of factors.

The X-axis of the upper subgraph of Figure 5 represents the extracted factor number, and the Y-axis represents the explanatory power of each factor on the overall ecological discourse characteristic variation. The first three factors have a high contribution rate (35.2%, 18.7%, 12.3%), indicating that these three configuration dimensions have the strongest explanatory power on the characteristics of ecological discourse. Starting from the 4th factor, the contribution rate decreases, indicating that the subsequent factors have limited explanatory power and can be considered not to be retained. The X-axis of the sub-graph below is also the factor number, and the Y-axis indicates the percentage of total variation explained by the first n factors. The first 3 factors cumulatively explain 66.2% of the variance, and the first 5 factors cumulatively explain 82.8%, reflecting that most of the ecological discourse configuration information is concentrated in the first few dimensions.

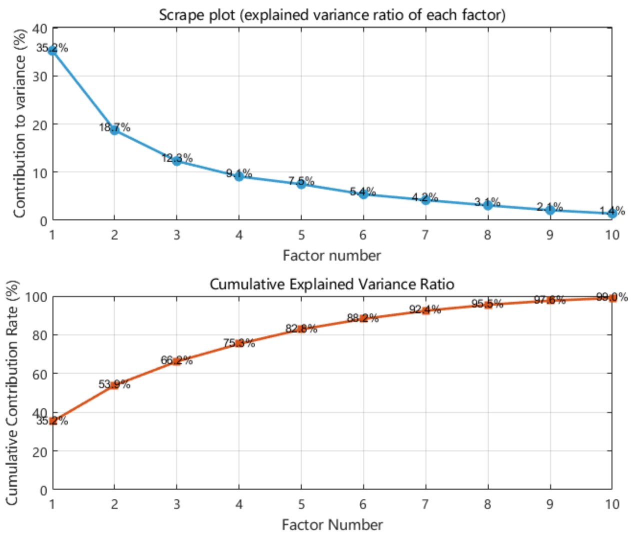

Figure 5. Factor Explained Variance Ratio

Ecological Discourse and Semantic Configuration Semantic Role Labeling Accuracy

A large, balanced corpus covering diverse ecological discourse topics is collected and processed (de-noising, sentence segmentation, batch processing). Discourse is annotated into categories such as green environmental protection, energy conservation and emission reduction, and ecological protection. Sentences are syntactically analyzed and classified into subject-verb-object structure, passive voice structure, parallel structure, and prepositional phrase structure categories. The accuracy of semantic role labeling is calculated for each batch of samples, and the labeling performance of different semantic configurations and ecological discourse categories is counted separately. The labeling test is repeated multiple times to obtain multiple sets of accuracy data to reflect the performance stability and fluctuation range.

The left subfigure in Figure 6 shows the distribution of semantic role labeling accuracy for four major semantic structures: subject-verb-object, passive voice, parallel structure, and prepositional phrase. Semantic role labeling accuracy is calculated for each batch and structure, with repeated tests to assess performance stability.

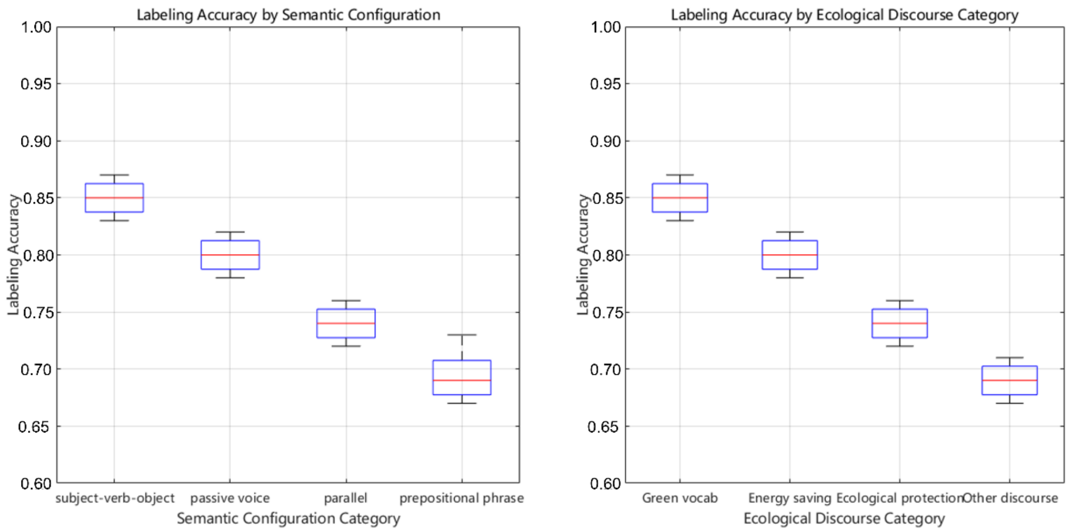

Figure 6. Semantic Role Labeling Accuracy

Subject-verb-object achieves the highest median accuracy (~0.85), followed by passive voice (~0.80), parallel structure (~0.73), and prepositional phrase (~0.69), indicating challenges in labeling complex structures. The right subfigure shows accuracy for ecological discourse categories, all above 0.65. Labeling accuracy for green environmental protection vocabulary is highest, demonstrating the model’s effectiveness in identifying ecological semantics.

Uncertainty and Sensitivity Analysis

Reliability is enhanced through uncertainty and sensitivity analysis using Monte Carlo simulation, as shown in Table 3. Critical parameters—energy consumption, emission factors, resource input coefficients—are assigned probability distributions, with 10,000 iterations generating probability distributions and confidence intervals for key indicators. Results show that input variations cause fluctuations in carbon and water footprints and resource consumption, but distributions remain centered around baseline values, indicating statistical stability. Energy consumption and resource input coefficients follow normal distributions, while emission factors are lognormally distributed, with parameters derived from Ecoinvent, manufacturer data, and literature.

Table 3. Monte Carlo Simulation Results for Environmental Indicators

Indicator	Mean Value	Standard Deviation	95% Confidence Interval	Coefficient of Variation (%)
Carbon Footprint (kg CO_2-eq)	1,850	210	1,440 – 2,260	11.4
Water Footprint (L)	42,600	5.8	31.5 – 54.1	13.6
Resource Consumption (MJ)	4,920	460	3,980 – 5,870	9.3

Sensitivity analysis identifies parameters most influencing environmental impact results. By systematically varying selected parameters and observing impact score changes, relative importance is ranked. Results indicate energy consumption intensity exerts the greatest influence, followed by greenhouse gas emission factors; other parameters have lesser effects. These findings confirm the study's conclusions are robust to data and assumption uncertainties, providing a reliable foundation for sustainable textile development decision-making.

Table 4 demonstrates that energy intensity and greenhouse gas emission factors have the highest influence on the overall impact score, contributing 41.8% and 33.5%, respectively. Energy intensity's significant impact arises from its direct effect on environmental footprint throughout the production lifecycle, especially in energy-intensive industries. Greenhouse gas emissions are closely tied to energy consumption, underscoring their importance in climate change assessments. Material input coefficients have a moderate impact, particularly under resource constraints. Waste recovery efficiency and transport distance assumptions exert minimal influence due to scenario and regional limitations.

Table 4. Sensitivity Ranking of Key Parameters for Comprehensive Impact Score

Parameter	Sensitivity Rank	Relative Influence (%)	Δ Impact Score (Normalized)
Energy Consumption Intensity	1	41.8	0.42
GHG Emission Factors	2	33.5	0.34
Material Input Coefficients	3	15.7	0.16
Waste Recycling Efficiency	4	6.2	−0.06
Transport Distance Assumptions	5	2.8	0.03

Correlation and Regression Results

Correlation and regression analysis results are presented in Table 5. Pearson correlation analysis reveals a statistically significant positive relationship between resource consumption and negative sentiment. Regression analysis indicates that negative sentiment scores are significantly correlated with resource consumption, suggesting common latent drivers such as product type, production technology, or social attention.

Table 5. Correlation and Regression Results between Environmental Impact and Discourse Features

Environmental Impact Indicator	Discourse Feature	Pearson's r	p-value	Regression Coefficient	R2
Resource Consumption (MJ)	Negative Sentiment Score	0.72	< 0.01	185.4	0.52
Pollution Emissions (kg CO_2-eq)	Negative Sentiment Score	0.68	< 0.01	95.2	0.46
Ecological Footprint (m^2)	Topic "Recycling" Prevalence	−0.65	< 0.01	−45.7	0.42

CONCLUSIONS

This study systematically examines the correlation between the life cycle environmental impact of green textiles and the configuration characteristics of ecological discourse by integrating an ecological discourse analysis model with NLP techniques. The proposed model enables detailed assessment of environmental impacts—including resource consumption, pollution emissions, and ecological benefits—across production, use, and recycling stages. Sentiment analysis and topic modeling facilitate extraction of ecological discourse features from a large textual corpus, which are then correlated with quantitative environmental impact data. This research provides a theoretical foundation for optimizing the design and promotion of green textiles, advancing the integration of environmental impact assessment and ecological theory in sustainable textile development.

Author Contributions

Conceptualization – Yumei Huang; methodology – Yumei Huang and Xiaoying Xue; investigation – Xiaoying Xue; writing-original draft preparation – Yumei Huang and Xiaoying Xue. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

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