# Artificial intelligence in ESG investing: a scoring model for accuracy and accountability

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**Abstract.** This article meticulously examines the utilization of big data and artificial intelligence (AI) to tackle the significant challenges encountered in ESG (Environmental, Social, and Governance) investments. These challenges primarily include the inconsistent ESG ratings across different rating agencies and the lack of transparency in AI models, which can hinder informed decision-making. The study meticulously constructs an AI-based ESG scoring model by integrating advanced techniques such as natural language processing (NLP), topic modeling, and machine learning. It also proposes a comprehensive explainable AI framework to enhance investment confidence and provide clear insights into the decision-making process. According to the research reports, these techniques significantly boost the effectiveness and granularity of ESG analysis, allowing for more precise and reliable assessments. However, the study acknowledges persistent challenges such as algorithmic bias, data heterogeneity, style issues, and conceptual problems that need to be addressed. It provides some thoughtful recommendations for future research to tackle these issues effectively. This review aims to bolster investor and business confidence and improve the overall performance of ESG investing by promoting more transparent and consistent practices.

## 1 Introduction

ESG stands for Environmental, Social, and Governance. These are three places that help determine how a corporation behaves beyond money. These elements are used by ESG investing to help consumers in finding reliable companies. Today, some business owners are concerned with more than just their income. They want to see companies that support the rule of law, community, and standard of living [1]. Nevertheless, this growth in ESG value is hindered by large problems, especially the dilemma in ESG scores and the lack of efficiency in AI models.

ESG data is frequently contradictory because different position agencies have different standards, which results in various firm scores [2]. Consumers may become perplexed by this

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dilemma, which could affect their ability to believe the rankings. To improve the effectiveness and uniformity of ESG investing, this study examines the differences between ESG scores and the lack of accountability in AI forms.

This problem may be solved by big data and AI. Large amounts of data may be processed by AI. It can be found in publications, reports, and cultural advertising. AI can learn more from big data. These tools may enable ESG investing in a faster and better approach [3]. This assessment examines how AI and big data is securely increase ESG investing in order to address these issues.

NLP can read thousands of articles in seconds. Machine learning can predict outcomes from past behavior. These tools are already used in many fields. Now they are entering ESG analysis too [4, 5].

However, some investors still do not trust AI. They worry that models are biased or hard to understand. If AI makes a decision, people want to know why. Explainable AI can help with this. It can show the steps the model took [6].

The specific objectives of this study are to develop an AI and big data-based ESG scoring model to enhance score consistency and accuracy and to design an explainable AI framework to increase investor trust in AI models. This study contributes to the existing literature by filling the gap in research on the application of AI in ESG investing, providing new theoretical and empirical support for the field. By providing new insights into the application of AI in ESG investing, this study aims to contribute to the growing body of literature and offer practical guidance for investors and firms.

## 2 Literature review

### 2.1 Problems with ESG scores

Score companies often assign companies ESG scores, but their analysis methods usually result in various business positions. This difference stems from unique information resources, analysis conditions, and specific meanings [2]. For example, some ESG editions heavily rely on self-declared information, while others incorporate third-party analysis of social media or online sentiment [7]. The analysis of ESG scores is impacted by this technological shift, which raises concerns about fairness and responsibilities.

Users who want accurate and trustworthy costs are perplexed by this lack of consistency. Some achievement methods have been criticized as a "black box", where the reasoning behind the results is difficult to comprehend [6]. Because there are not any foreign ESG monitoring requirements, assessments perhaps use more popular performance indicators to show their operational priorities [7].

To mitigate these issues, researchers have proposed cross-referencing multiple ESG sources and leveraging AI-based tools like NLP to enrich data input and reduce bias [4, 5]. Others advocate for standardizing ESG disclosure frameworks to improve transparency and score comparability across rating agencies [2]. The title is set in bold 16-point Arial, justified. The first letter of the title should be capitalised with the rest in lower case. You should leave 22 mm of space above the title and 6 mm after the title.

### 2.2 Problems with ESG scores

News and social media can give early signs of ESG problems. They show what people think about a company. Bapat et al. used tweets to study ESG [5]. They used FinBERT to read the tweets. Many had negative tones.

Zeidan et al. studied news stories [1]. They read 13,000 articles. They found that bad news often matched poor stock results. Still, many investors did not use this data.

So, useful data exists. But it is not always used. AI can help by turning that data into simple signals [4]. In particular, real-time analysis of media can provide daily ESG risk assessments. These dynamic scores can be more responsive than annual ESG reports.

### 2.3 ESG Topics

Topic modeling helps find trends in ESG texts. One method is LDA. It groups articles by subject. Khoruzhy et al. used it to study ESG topics [3]. They found key issues like pollution and worker safety.

Zhang et al. also used this method [4]. They tracked which ESG issues appeared most over time. This helps show what matters to the public.

Investors can use this to find risks early. If more articles mention emissions, that may show trouble ahead. Automated topic clustering can also support regulatory bodies in identifying high-risk industries or regions before formal violations occur.

### 2.4 Predicting ESG with AI

Some studies use AI to guess ESG scores. This can help when ratings are missing or unclear. D'Amato, D'Ecclesia, & Levantesi used Random Forest models [8]. He found that profits, debt, and other numbers could help predict ESG scores.

Zhang used a mix of NLP and XGBoost [4]. She studied how ESG reports link stock risk. She found that a company's own words said a lot about its future risk.

These studies show AI can support ESG analysis. AI can give extra help or even replace older tools [9]. Some researchers also test ensemble models that combine multiple AI techniques. This approach can reduce overfitting and improve prediction reliability.

### 2.5 Ethics and Trust

Many scholars emphasize that AI models used in ESG must be transparent and accountable. Minkkinen, Niukkanen, and Mäntymäki argue that explainability is key to building trust [6]. Building on this idea, this study aims to integrate explainable AI into ESG analysis tools by demonstrating how transparency mechanisms—such as SHAP values and interpretable models—can be applied in practice to increase stakeholder trust.

This matters in ESG. If a model says a company is bad, investors need to know why. That is why XAI is important. As De Almeida et al. emphasize, fairness and clarity must be embedded in ESG tools to ensure ethical compliance [8]. Trust is also linked to repeatability. If a model produces stable results under different conditions, users gain confidence. ESG models should be auditable and include feedback loops. This literature review highlights the significant contributions of previous studies in the field of ESG investing. However, it also reveals some gaps and limitations, such as the lack of standardized ESG scoring methods, underutilization of social media and news data, and the need for more robust and explainable AI models. This study aims to fill these gaps by developing a comprehensive AI and big data-based ESG scoring model and an explainable AI framework to enhance the transparency and credibility of ESG investing.

## 3 Methodology

This research uses AI methods, like natural language processing ( NLP), topic modeling, and machine learning, to target two important issues in ESG study: conflicting information and a lack of design value. These methods are chosen because they have proven successful in earlier studies. And their suitability for handling the complexities of ESG data. Specifically:

Textual data from various sources, like company data and media accounts, is processed and analyzed by NLP. This exposes hidden ESG problems as well as providing important insight from disorganized information. Because it can effectively represent ESG risks in intellectual data, as Zhang demonstrated, NLP is a potent instrument for raising the quality of ESG analysis. [4].

Topic modeling may help identify and categorize important ESG problems in word papers. For studying large expression levels and defining new problems and patterns, this approach provides a planned framework. et as., Khoruzhy et cetera. used topic modeling to monitor ESG issues over time to better understand how changing ESG threats are [3].

ESG scores are based on financial and academic data in response to machine learning ideas like Random Forest and XGBoost. These concepts allow for precise forecasts and handle complex relationships between variables. D'Amato properly explored the monetary factors that influence ESG scores by using Random Forest, demonstrating the potential for machine learning to improve the precision of ESG analysis [9].

Utilizing a Feinberg sentiment analysis, the view to ESG-related video material is likewise examined. This process helps know public perception and attitude toward businesses, which is essential for a complete ESG investigation. when, Bapat et cetera., etc. provided valuable insight for ESG position models and demonstrated FinBERT's ability to effectively evaluate financial and ESG-related word sentiment [5].

### 3.1 Data

The ESG text data is collected from multiple sources, including from company sustainability reports, news aggregators like Reuters and Bloomberg, and social media APIs (mainly Twitter). The raw text undergoes a multi-step cleaning process: punctuation is removed, text is converted to lowercase, stop words are eliminated, and lemmatization is applied to unify word forms. For news articles, only headlines and lead paragraphs are extracted to maintain consistency in input data.

ESG ratings are sourced from both MSCI and Refinitiv databases. These ratings are standardized to a common scale for comparison. Financial indicators are obtained from Compu stat and Bloomberg Terminal, with variables selected based on their relevance in past ESG prediction models [9]. These indicators are normalized using z-scores to reduce scaling effects, and outliers beyond three standard deviations are minimized.

ESG assessments are conducted using MSCI and Refinitiv data. These scores are based on a standard range of standards. The company's methodology's variation, which may result in standing bias, is a known requirement. [2].

But, there is a known limitations to the variability in the business methodology, which may lead to standing bias. Different ESG position companies may possess bias because of their unique methodologies [2]. In order to tackle this, assessments are standardized to a standard size and are used in music versions to lessen the impact of specific prejudices. Problems are even raised by data quality. Data quality: Organization reports does miss adverse events, while social media data may have good or equipment. Unique information resources are combined to address these issues, and powerful algorithms are used to lower errors. Typical information evaluations and anomaly recognition techniques are also suggested in order to maintain information integrity.

### 3.2 Sentiment analysis

The text data undergoes a multi-step cleaning process. This includes lowercasing, removal of punctuation, numbers, and stop words. Then the text is tokenized into individual words. Lemmatization is also applied to standardize word forms. Next, the Term Frequency–Inverse Document Frequency (TF-IDF) method is applied to convert the cleaned text into numerical vectors. This step allows the model to evaluate word importance across documents.

Sentiment analysis is conducted using FinBERT, a language model pre-trained specifically for financial and ESG-related language. Each sentence is classified as positive, negative, or neutral [1, 5]. The sentiment scores are normalized and added as numeric predictors into the machine learning modelSudden shifts in sentiment across time or topics are also tracked. Sentences that show unusually strong polarity are flagged as anomalies to increase the model's robustness.

To mitigate the known limitations of sentiment analysis models such as FinBERT, several strategies are proposed. For contextual understanding, it is recommended to incorporate additional context-aware models, such as BERT variants fine-tuned on ESG-specific corpora. For multilingual support, if the dataset includes non-English text, FinBERT's performance may degrade. In such cases, multilingual models like mBERT or XLM-R are suggested to handle diverse languages.

### 3.3 Topics

LDA helps find topics in texts. Some topics may focus on labor practices, while others may focus on climate change. Each text is assigned to a topic label. Khoruzhy et al. used this to find ESG trends, and Zhang tracked topic changes over time, helping investors see what ESG issues are growing [3, 4]. Topics are manually validated to reduce false positives, and term frequency heatmaps are also generated to track issue trends across sectors.

While LDA provides basic topic identification, it may face limitations in interpretability and temporal dynamics. To enhance interpretability, it is recommended to use more advanced topic modeling techniques, such as Non-Negative Matrix Factorization (NMF) or supervised topic models. In addition, as ESG topics may evolve over time, incorporating dynamic topic modeling approaches is suggested to capture temporal changes in topic prevalence.

### 3.4 Machine learning

Machine learning models, including Random Forest, XGBoost, and Logistic Regression, are trained to predict ESG scores. Inputs include financial indicators, text sentiment, and topic weights. Results are tested using training and test sets [4, 9]. Models are tuned with grid search, and stratified sampling ensures balanced training data. Model drift is monitored with periodic retraining.

Despite their predictive power, machine learning models can face issues such as overfitting and complexity. To mitigate overfitting, techniques such as cross-validation, regularization, and early stopping are recommended. While XGBoost and Random Forest offer high performance, their computational demands can be intensive. Exploring simpler models like Logistic Regression as baselines and applying model ensembling is suggested to balance performance and complexity.

### 3.5 Model checking

Model performance is evaluated using both regression and classification metrics. For numerical predictions such as ESG scores, Mean Absolute Error (MAE) and Root Mean

Squared Error (RMSE) are calculated. These metrics measure how close the predicted scores are to the actual values, with lower values indicating better accuracy.

For categorical predictions like ESG risk categories (high, medium, low), Accuracy, F1-score, and AUC-ROC are employed. Accuracy shows how many predictions are correct. F1 balances precision and recall, which is important when class imbalance exists. AUC-ROC is used to evaluate the model's ability to distinguish between classes.

To interpret model outputs, SHAP (SHapley Additive Explanations) values are applied [6]. SHAP assigns an important value to each input feature, based on game theory, helping to explain how much each variable contributed to a specific prediction. For example, if a high debt ratio consistently lowers ESG scores, SHAP will capture that effect. These tools ensure the model is not a black box. Users can understand and trust how decisions are made.

While SHAP values provide insights into feature importance, they may not fully explain complex interactions within models like XGBoost. The use of additional interpretability tools, such as LIME (Local Interpretable Model-agnostic Explanations), is recommended to generate more granular explanations. Despite SHAP's contributions, the overall transparency of the model may remain limited. Incorporating model-agnostic interpretability frameworks is suggested to enhance transparency and user trust.

### 3.6 Ethics

This study adheres to strict ethical guidelines. Only publicly available data are used to ensure privacy and compliance with regulations. Models are rigorously checked for bias to ensure fairness and transparency. The design philosophy emphasizes open and interpretable models, allowing stakeholders to understand and trust the results [6, 8]. Stakeholder feedback is actively sought to refine future versions of the models, ensuring they meet the needs of diverse users.The research follows data privacy norms. Model explainability is included in reports. Stakeholder feedback is collected to refine future versions.

Even with rigorous checks, subtle biases may still exist. The implementation of fairness metrics and bias mitigation techniques—such as re-weighting data or applying fairness-aware algorithms—is recommended.

As regulations evolve, continuous monitoring and adaptation are necessary. Establishing a regulatory compliance framework is suggested to ensure ongoing adherence to data privacy and ethical standards.

## 4 Case study: Ant Group's intelligent risk control system

Ant Group, one of China's largest fintech platforms, has revolutionized personal credit assessment through its Sesame Credit system. Sesame Credit, a division of Ant Financial Services, incorporates customer behavior, usage patterns, and factual data to create dynamic, AI-driven credit scores. It is usually used as a technique for online credit report in developing nations and serves hundreds of millions of people in China. [10].

### 4.1 Overview of Sesame Credit

Sesame Credit was established in 2015 to help those who have little or no connection to their credit record. Based on five elements, including payment history, intellectual pursuits, character consistency, business success, and cultural associations, it earns a credit rating of 350 to 950. Using various information options, such as mobile apply, Alipay exchange details, and e-commerce behavior, is Sesame Credit's power [10].

The method expands its scope beyond financing options to incorporate visa programs, mortgage discounts, and historical value systems as a result of partnerships with retailers, national authorities, and financial institutions. This ecosystemic contact reflects the child's significant role in China's online purchase system [11].

### 4.2 Data ecosystem and feature engineering

Sesame Credit obtains its information from Ant Group's extensive digital footprint, which includes economic deals, talk logs, and online methods files. To make real-time client information, the software particles both structured and unstructured data. Feature engineering techniques include using course patterns, organic personal sequences, and emotional consistency indexes [10].

To evaluate the validity of social network, the device even incorporates graph-based pictures and natural language processing. For example, having reliable, high-scoring peers can positively impact a person's report. The consumer- information' granularity and social precision are enhanced by this broad have space [11].

### 4.3 AI Architecture and real-time risk control

The method of Sesame Credit is built on a mega- layered AI software. It includes managed training tips like gradient boosting and tremendous learning materials for reputations in the temporal and social styles. To help successful range updating and real-time information inhalation, these forms are deployed in a cloud-based environment. [10].

Its flexible network architecture, which allows plug-and-play type parts based on use-case differences like option chance or fraud detection, is a distinct feature. Relative-time-tracking dashboards create compliance thresholds, enable slide recognition, and maintain continuous confirmation based on user feedback or make changes. [11].

### 4.4 Application scenarios

In practical terms, Sesame Credit is used in the following areas:

Loan approval: Partnered micro-lending platforms use the score as a creditworthiness benchmark.

Dynamic credit limits: The platform adjusts borrowing thresholds in response to behavioral signals like repayment frequency and spending volatility.

Fraud prevention: AI monitors anomalous activity such as geographic inconsistencies or sudden transaction spikes, flagging high-risk behaviors [10].

The combination of machine learning and human-in-the-loop supervision ensures rapid yet explainable decisions. Furthermore, the integration of credit scoring into lifestyle services makes credit status an active part of daily digital life.

### 4.5 Analysis of impact, strengths, and weaknesses

Financial assistance has been greatly impacted by the Sesame Credit approach. It gives people who were formerly underrepresented in regular payment systems subjection to microloans, maintenance, and other financial assets. Its strengths are behavioral-based prediction, detailed info integration, and real-time analysis [10].

Despite this, there are still flaws. The system is criticized for its accountability, making it difficult for consumers to understand how results are determined. This lack of transparency raises ethical concerns and challenges linear AI's knowledge. Customers outside of this life

may also be severely punished or excluded because the data primarily comes from Alibaba's habitat [10, 11].

In terms of requirements, the program is "grey area". Despite having an unusual financial strategy, it raises concerns about customer approval, algorithmic bias, and data protection. In computing decision-making, more scrutiny is necessary, particularly to maintain justice, accountability, and transparency [11].

The advantages and drawbacks of an AI-driven credit rating system are illustrated by Ant Group's Sesame Credit method, in conclusion. It is a major event in the discussion about various growth, scientific leadership, and virtual funding.

## 5 Challenges, limitations and recommendations

The addition of AI into ESG funds rating systems has led to an extraordinary level of efficiency and length. But, it also brings substantial limitations that must be addressed to keep justice, duties, and safety. This area uses four main categories of problems: algorithmic bias, reliability, data secret, and sensible risks, using ebooks and real-world examples of Ant Group's Sesame Credit.

### 5.1 Algorithmic bias and fairness

In the area of algorithmic bias, AI-based record rating is still a hot topic. Traditional data, which may have cultural and functional preconceptions, are often used as the foundation for these types. If payment default charges have historically been higher in underbanked places as a result of structural inequalities, the site might learn to manage people there seriously [12].

In the case of Ant Group's Sesame Credit, biases may develop if the item inflates people's behavior in Alibaba's animals, such as sports use or buying speed, while underestimating inside fiscal responsibility. Despite robust economic methods around the world, this may cause harm to users who are less integrated into Alibaba's sites..

Diverse lowering approaches are suggested to address these problems. Justice enhancements have been clearly demonstrated after applying justice metrics and mitigation tactics like re-weighting kind data, changing training objectives, and adjusting outputs to improve analytical equality [12]. Typical reviews can also be used to identify and correct flaws in the design, keeping it smooth and transparent [13].

### 5.2 Explainability and transparency

Despite their efficacy, deep learning techniques are usually unambiguous. This is a vital part of ESG strategies when close people, soldiers, and fans require price. Some ranking systems use "black-box" technologies, which undermines confidence and raises cultural issues when giving credit, insurance, or employment [14].

Ant Group has adopted some explainable AI techniques, such as SHAP values, in places like techniques diagnosis and effective record control organizing. However, these programs are typically inside and not accessible to customers. Lachuer and Ben Jabeur believe that starting thoughts should increase transparency and foster management. [14].

To boost the victim's dependability and usefulness, two management techniques are suggested. Next, explainable AI tools like SHAP values and LIME can be used to describe style choices clearly. In addition to improving trust and accountability, these resources can assist consumers and regulators in understanding the decision-making approach [13]. Secondly, user-friendly software can be created to allow users to interact with the item and

demonstrate its principles. This can help customers better understand the factors that influence their payment scores and make judgments about what to do [6].

### 5.3 Data privacy and regulatory constraints

AI models used by Ant Group and similar platforms rely heavily on behavioral data, including mobile activity, spending history, and even location data. While this helps create more holistic user profiles, it also raises critical concerns about privacy and data ethics [10].

Without enough controls, ESG programs may provide sensitive information. In response to rules like the Personal Information Protection Law, Ant Group was forced to change its practices in China due to the rapid shift in the regulations governing certain information [10].

To address personal issues and ensure compliance with regulations, two critical approaches are suggested. Next, privacy-preserving methods like differential privacy and federated learning can be used to safeguard customer information while letting the model to learn from a variety of data sources [15]. Next, a governmental compliance framework may be developed to ensure continued adherence with social standards and data protection. One of those points is compliance with laws like China's Personal Information Protection Law and GDPR [10].

### 5.4 Operational risks and model drift

Lastly, ESG ranking methods are impacted by operational issues like form fall and unhappy manipulation. When kind data transmission changes, such as during the COVID- 19 crises, where spending habits greatly shift, AI types become damaged over time.

To minimize drop, Ant Group uses numerous treatment sessions and real-time monitoring screens. However, these activities require robust surveillance systems and significant tools. Additionally, the stability of the state may be impacted by angry problems like those that cause credit scores to rise.

Mitigation Strategies:

Use real-time surveillance dashboards and regular rehabilitation cycles to identify and correct system drift. This can aid in maintaining the model's uniformity and continuity [12].

Develop counterproductive defense strategies to spot and halt hostile attacks. This might include challenging training techniques and anomaly detection [15].

## 6 Recommendations and future directions

In brightness of the problems and limitations listed below, the following suggestions are made to improve the design and control of AI- driven ESG money methods:

Integrate explainable AI tools like SHAP and LIME to clearly explain design decisions, creating trust and accountability, and promote clear AI for value.

Use federated learning and differential privacy to encrypt customer information while allowing the design to choose from a variety of options.

Create healthy data-sharing protocols to enhance education datasets and enhance design statement and justice.

Growing Regulatory Oversight and Auditing: Do thorough, independent reviews to find out whether someone is discriminated against, how different types of people are, and whether or not they are in compliance with data protection laws..

Advanced analysis of domain- conscious AI and understanding graphs: Develop economic knowledge graphs to create machine learning more organic and policy-independent..

In order to enhance the use of AI in ESG funds ratings, the analysis really concentrate on a number of crucial places. Next, greater fairness and discrimination drop is essential. Making use of cutting-edge tools to identify and correct bias in AI modifications to address the persistent issue of algorithmic bias may guarantee justice for all consumer groups. Next, it is necessary to investigate both active and passive day products. These techniques may be able to immediately respond to customer behavior and data distribution as a result of more suitable and versatile ESG investigations. Through international cooperation, third-party needs and best practices might been developed. Uniform systems may be employed to maintain continuity and stability in native and industry-specific AI-driven ESG money rankings. Another idea is to use a user-centric construction method. Making sure AI systems are available, good, and good to stop users will improve customer trust and acceptance. Lastly, it is crucial to assess the validity of cutting-edge techniques like cryptography and classic. These advancements may lead to new developments in the field, improving the safety, performance, and transparency of ESG funds score methods. Coming analysis is considerably improve the development of stronger, fair, and apparent AI- driven ESG funds rating systems by focusing on these areas.

## 7 Conclusion

To create an AI- and big-data-driven ESG scoring model, this analysis incorporates topic modeling, natural language processing (NLP), and machine learning methods. It even recommends an explainable AI program to increase investor confidence in the child's results. These techniques significantly improve the clarity and precision of ESG analysis, according to the results: topic modeling identifies important ESG designs, NLP exposes hidden ESG challenges in academic information, and machine-learning models accurately predict ESG scores based on combined intellectual and financial inputs. Nevertheless, the findings also indicate that model explainability and data privacy remain pivotal challenges to achieving fairness and transparency in ESG credit-scoring systems.

Although the study makes progress in reducing ESG-rating inconsistency and AI model opacity, several limitations persist. First, the varied provenance and uneven quality of data can undermine both accuracy and generalizability. Second, despite multiple safeguards against overfitting, the performance of complex machine-learning models on new data still requires further validation. Third, even with explainable-AI tools, overall transparency and user comprehension could be improved. Finally, algorithmic bias and a rapidly evolving regulatory landscape continue to threaten fairness and compliance.

Future work should explore how cross-institutional collaboration, international standard setting, and emerging technologies can bolster the fairness, transparency, and data-protection capabilities of ESG credit-scoring systems. Priority areas include: developing more advanced bias-detection and mitigation methods; creating real-time, adaptive AI systems that can respond to dynamic data; establishing global ESG scoring standards to promote consistency across regions and industries; employing user-centric design to raise transparency and acceptance; and investigating the potential of blockchain, quantum computing, and other emerging technologies for secure and efficient ESG scoring. Collectively, these efforts can offer new theoretical and practical foundations for building more reliable, equitable, and transparent ESG credit-scoring systems.

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