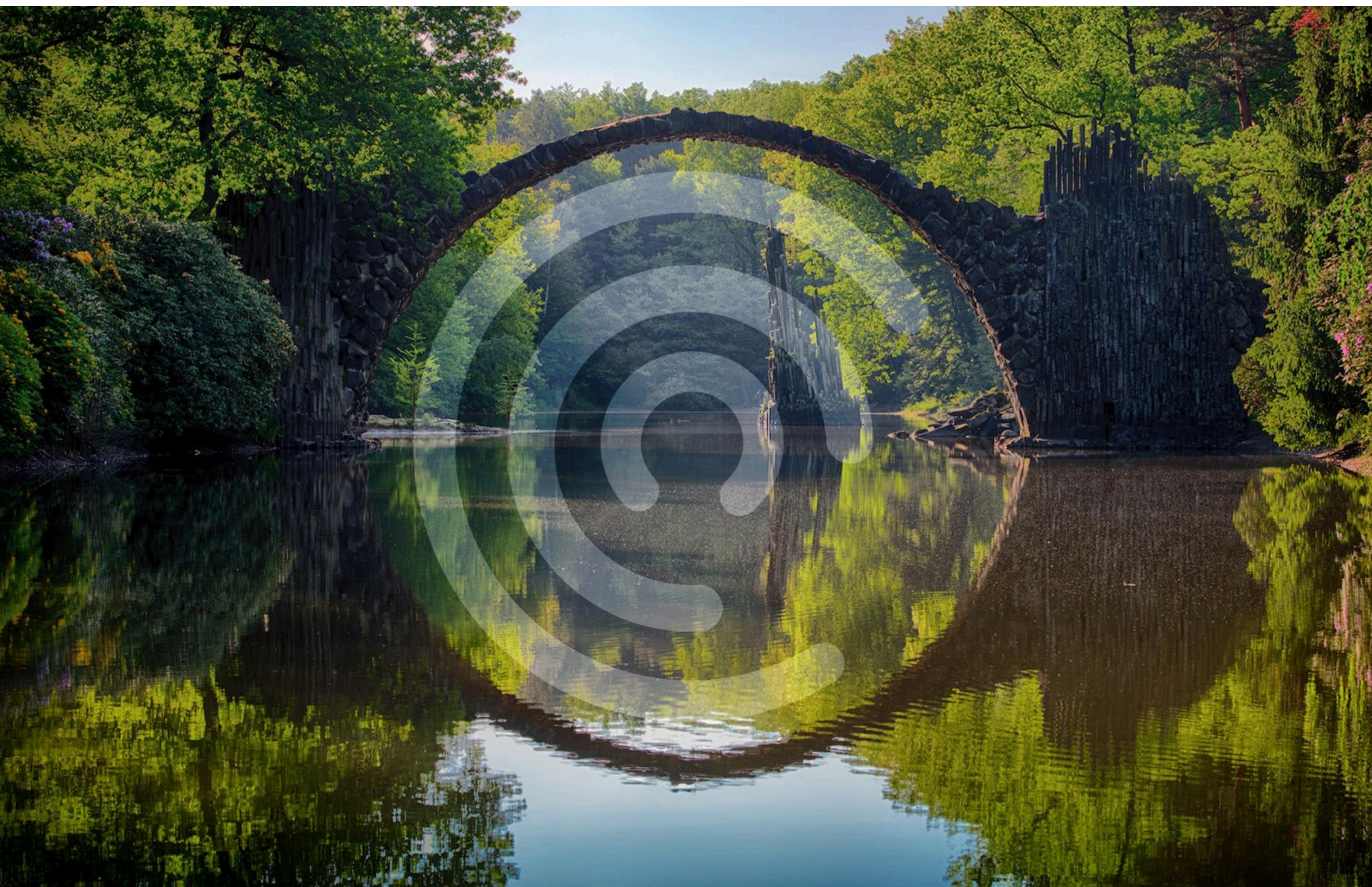




Clarity AI ESG Ratings

Methodology Document

Version 1.1, October 2026

Version History

Document Title	ESG Ratings Methodology
Version	1.1
Version Date	October 2026
Description of key changes from the previous version	Revision of the Methodology Governance section

Executive Summary

The Clarity AI ESG Rating measures financially material environmental, social, and governance (ESG) risks and opportunities compared to their peers within the same industry classification. The assessment provides a standardized numerical rating from 1 to 100, where 100 represents the highest performance level (i.e., lowest risk level).

The scoring process utilizes a multi-layered hierarchy that aggregates individual KPIs into subcategories, categories, and the three fundamental pillars: Environmental, Social, and Governance. The final output integrates three distinct types of indicators: quantitative metrics reflecting current performance, policy (or qualitative) metrics assessing the existence of risk management frameworks, and controversy metrics capturing news events and serving as real-world validation. Controversies penalize a company's rating based on the severity of those events or incidents.

To ensure global scale and reliability, the methodology leverages advanced Artificial Intelligence, including Machine Learning models to estimate missing data points using as inputs more than 300 company features. In addition, Natural Language Processing (NLP) and Large Language Models (LLMs) are used to monitor controversies from a wide range of news sources. This allows Clarity AI to increase coverage of ESG Ratings to over 37,000 entities. In addition, coverage is extended to approximately 86,000 companies through inheritance, leveraging company parent-subsidiary relationships.

The framework is rule-based and transparent, ensuring that every rating is auditable, independent and of high-quality. The methodology is reviewed by a dedicated Methodology Committee at least annually, taking into account evolving regulatory standards such as CSRD. This ensures that investors receive systematic, objective, and up-to-date insights to integrate sustainability risks into their long-term financial decision-making.

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1. Methodology Scope

1.1. Definition and Scope

The Clarity AI ESG Rating quantifies an organization's exposure to, and management of, financially material sustainability risks. The methodology assesses the potential impact of these risks on long-term financial performance by evaluating the intersection of quantitative performance data, qualitative policy indicators, and unstructured controversy data. Grounded in the principle of financial materiality, the assessment focuses exclusively on "outside-in" risks that affect a company's financial condition or business model.

1.2. Objective and Rating Interpretation

The ESG Rating aims to provide a standardized and comparable assessment of how effectively an entity manages financially material sustainability risks. It evaluates the extent to which an organization identifies and mitigates ESG factors that could impact its long-term financial stability.

The ESG Rating is measured on a numerical scale from **1 to 100**, interpreted as follows:

- **Rating of 1 (lowest performance):** Indicates severe exposure to material ESG risks coupled with a lack of adequate management frameworks or evidence of effective mitigation in relation to its peers.
- **Rating of 100 (highest performance):** Signifies robust sustainability governance, advanced risk management frameworks, and minimal unmanaged ESG risk exposure in relation to its peers.

ESG Ratings are based on a methodology that focuses on financial risk exposure and are not intended to serve as a broad measure of an entity's overall environmental or social impact.

ESG Ratings are monitored on an ongoing basis and updated as new information becomes available, including company disclosures, model updates, and identified controversies. Client communication on rating and data updates depends on the type of change. For continuous updates, our standard process is to send clients information on what is being updated and why (e.g., new reported data that is collected, new controversies have been detected) as well as a statistical analysis of overall ratings' changes, 1 week in advance. For methodological updates (e.g., our annual methodology update based on market developments), the standard process is to send clients information on how the methodology will be updated and why as well as a statistical analysis of overall ratings' changes.

changes, at least 60 days in advance. At a minimum, all ratings are subject to a formal review at least annually.

The valid time horizon of the rating is defined as the time between data releases (typically two weeks for strictly rules-based ratings). Our ratings are updated and made available to users at regular intervals through our platform or other delivery channels. A change in an entity's rating occurs if new information becomes available, if an identified data error is remedied, or if there is a material change to the methodology.

1.3. Key Features

The ESG Rating is derived from the aggregation of multiple data layers designed to capture distinct dimensions of sustainability risk: **quantitative performance** (e.g., carbon emissions), **qualitative management** (e.g., corporate policies), and **dynamic risk events** (unstructured controversy data).

The methodology is characterized by the following core features:

- **Dual-Layer Scoring Logic:** The framework integrates two distinct evaluative approaches:
 - **Relative Metrics:** Most quantitative indicators are benchmarked against industry peers to assess competitive performance within a specific industry context.
 - **Absolute Metrics:** Policies, controversies, and a selected set of quantitative indicators are assessed on their own merits, reflecting the structural integrity of risk management frameworks and real-world behavioral signals, independent of peer comparisons.
- **Traceability and Auditability:** The framework ensures total transparency, allowing stakeholders to trace the scoring logic from individual KPI metrics through category and pillar levels to the final ESG Rating.
- **Data Freshness and Relevance:** ESG Ratings are monitored and updated on an ongoing basis as new information becomes available, including company disclosures, model updates, and identified controversies. To maintain an up-to-date risk profile, the assessment excludes data older than four years. Given the pace at which companies evolve through changes in strategy, operations, management, and the regulatory environment, data beyond this threshold is no longer considered representative of a company's current ESG performance and risk profile. As such,

any data points exceeding this limit are treated as missing until more recent information becomes available.

Our ratings are a combination of rules-based and analyst-driven assessments. When human analysts are involved, structured scoring guides that codify what to look at, what evidence counts, and how to translate that evidence into a rating, are used to ensure assessment consistency. Our ratings are updated and made available to users at regular intervals through our platform or other delivery mechanisms. A change in an entity's rating occurs if new information becomes available or if there is a material change to the methodology.

1.4. Rated Items

The ESG Ratings methodology is designed specifically for **corporate entities**, though it may also be applied to agencies and supranational institutions whose activities are comparable in nature to those of rated corporate entities (e.g., the International Finance Corp). The scope of this methodology is limited to entity-level assessments; it does not independently rate or assign distinct ESG ratings to individual financial instruments, debt instruments, or financial products issued by these entities. Wherever a rating is shown at the level of financial instruments, it reflects the underlying issuer-level rating.

As a matter of standard practice, the methodology is applied to the assessed universe on an unsolicited basis, relying exclusively on publicly available information.

Clarity AI provides ESG Ratings across two distinct universes:

- **High Relevance Universe:** This universe corresponds to Clarity AI's internally defined Collection Universe, which comprises approximately **16,000 companies** drawn from major global equity indices. Companies in this universe are primarily rated using reported data.
- **All Companies Universe:** This universe expands coverage beyond the High Relevance Universe from 16,000 to approximately **37,000 companies** through the use of estimated data, enabling companies to receive an ESG Rating based solely on estimated data and controversies.

In both universes, for an entity to receive a final ESG Rating, it must meet the **Minimum Scoring Requirements**, which ensure that sufficient underlying data is available to produce a statistically meaningful and reliable assessment.

Coverage is further expanded through the application of parent-subsidary inheritance logic, whereby a subsidiary may inherit its parent company's ESG Rating if it does not meet the **Minimum Scoring Requirements** to receive an ESG Rating of its own.

- The High Relevance Universe is expanded from 16,000 to **60,000 companies**
- The All Companies Universe is expanded from 37,000 to **86,000 companies**

The methodology may also apply on a solicited basis, to specific rated items. Dedicated controls are in place to ensure the consistent application of the methodology to both unsolicited and solicited ratings, ensuring their comparability.

2. Risk Factors Assessment Framework

2.1. High-Level Overview

Clarity AI's ESG Ratings framework is structured as a multi-layered hierarchy designed to provide granular insights while maintaining overall comparability across the investment universe.

The **Total ESG Rating** for each entity is derived from the aggregation of three core **Pillars (Environmental, Social, and Governance)**. Each Pillar is further decomposed into specific **Categories (Risk Factors)**, which represent the fundamental areas of sustainability risk. These Categories are subdivided into **Subcategories (Issues)** that address specific ESG issues, which are ultimately informed by a comprehensive set of **Metrics (Indicators)**.

As illustrated in Figure 1, this bottom-up aggregation logic ensures total transparency, allowing users to trace the impact of a single raw data point from the metric level through the intermediate themes and categories up to the final entity-level rating.

Figure 1. Structure of rating levels



2.2. Categories and Subcategories

The methodology for evaluating entities is structured around 12 ESG categories encompassing 22 ESG subcategories. Each category represents a broad area of environmental, social, or governance performance, while its subcategories capture the specific issues assessed within it.

The category and subcategory taxonomy structure is grounded in the European Sustainability Reporting Standards (ESRS), which provide a comprehensive, science-based framework of relevant sustainability topics¹. The ESRS topical standards represent a rigorous and widely recognized codification of ESG issues in the regulatory landscape, making them a natural foundation for an ESG rating methodology that aims to reflect market expectations on relevant sustainability matters.

There is a near-complete correspondence between the ESRS topical standards and the categories used in this methodology². The five environmental categories E1 through E5 map directly to ESRS E1 (Climate Change), ESRS E2 (Pollution), ESRS E3 (Water and Marine Resources), ESRS E4 (Biodiversity and Ecosystems), and ESRS E5 (Resource Use and Circular Economy). The four social categories S1 through S4 map directly to ESRS S1 (Own Workforce), ESRS S2 (Workers in the Value Chain), ESRS S3 (Affected Communities), and

¹ Although the ESRS are structured around the principle of double materiality, the topics are an equally relevant foundation for the financial material lens that Clarity AI's ESG Rating uses.

² N.B. As of April 2026 the ESRS are under review by the European Commission and the topics and subtopics are subject to change.

ESRS S4 (Consumers and End-Users). The Corporate Ethics and Behavior category (G2) corresponds to ESRS G1 (Business Conduct).

Two categories extend beyond the ESRS topical standards to ensure complete coverage of relevant ESG issues:

- **G1: Corporate Governance.** The ESRS framework addresses governance primarily through cross-cutting disclosure requirements (ESRS 2) rather than a dedicated topical standard. Because corporate governance — including board composition, executive compensation, audit practices, and governance mechanisms — is a fundamental pillar of ESG assessment, this category consolidates governance-related metrics that are otherwise distributed across multiple ESRS standards into a single, dedicated category. This ensures that governance quality is assessed with the same depth and specificity as environmental and social topics.
- **E6: Environmental Management.** This category captures cross-cutting environmental management practices — such as environmental certifications, management systems, and supply chain environmental criteria — that support and underpin performance across all environmental topics but do not fall within the scope of any single ESRS environmental standard. Including it as a standalone category ensures that the assessment reflects a company's overarching environmental governance and operational controls, which are material indicators of its capacity to manage environmental financial risk.

Environmental Categories

- **Category E1: Climate Change**

The Climate Change category assesses the financial risks arising from a company's contribution to and response to climate change. It covers issues such as carbon emissions, energy consumption, and the transition to sustainable energy sources, evaluating the company's strategies, policies, and practices to manage climate-related financial risk.

- **Subcategory E1.1: Mitigation and Adaptation.** Evaluates a company's strategies, policies, and practices to address climate change through emission reductions, clean energy development, and climate resilience. It captures the financial risks associated with insufficient climate action.
- **Subcategory E1.2: Energy.** Evaluates a company's strategies, policies, and practices related to energy efficiency, renewable energy adoption, and sustainable product development. It captures the financial risks associated

with dependence on non-renewable energy and failure to adopt sustainable energy practices.

- **Category E2: Pollution**

The Pollution category assesses the financial risks arising from a company's contribution to pollution. It covers issues such as toxic emissions, air and water pollution, and the costs associated with pollutant emissions, evaluating the company's strategies and policies to manage pollution-related financial risk.

- **Subcategory E2.1: Pollution.** Evaluates a company's strategies, policies, and practices to manage and reduce harmful emissions and pollutants. It captures the financial risks associated with air and water pollution and non-compliance with environmental standards.

- **Category E3: Water**

The Water category assesses the financial risks arising from a company's water usage and its impact on water resources. It covers issues such as water scarcity, inefficient use, and water stress in supply chains, evaluating the company's strategies, policies, and practices to manage water-related financial risk.

- **Subcategory E3.1: Water.** Evaluates a company's strategies, policies, and practices to manage water usage, efficiency, and sustainability. It captures the financial risks associated with water scarcity, inefficient water management, and excessive water consumption or pollution.

- **Category E4: Biodiversity and Ecosystems**

The Biodiversity and Ecosystems category assesses the financial risks arising from a company's reliance on and management of natural habitats and biodiversity. It covers issues such as habitat destruction, land degradation, and the disruption of ecosystems caused by business operations, evaluating the company's strategies, policies, and practices to manage biodiversity-related financial risk.

- **Subcategory E4.1: Biodiversity and Ecosystems.** Evaluates a company's strategies, policies, and practices with regards to activities relying on or related to natural habitats and biodiversity. It captures the financial risks associated with damaging sensitive areas and unsustainable practices affecting ecosystems.

- **Category E5: Circular Economy**

The Circular Economy category assesses the financial risks arising from resource inefficiency, waste generation, and unsustainable material use throughout a company's operations. It covers issues such as excessive waste, inefficient resource management, and inadequate recycling practices, evaluating the company's strategies, policies, and practices to manage resource- and waste-related financial risk.

- **Subcategory E5.1: Resource Inflows and Outflows.** Evaluates a company's management of natural resource use and packaging. It captures the financial risks associated with unsustainable resource consumption, non-compliance with sustainable sourcing requirements, and inadequate packaging practices.
- **Subcategory E5.2: Waste.** Evaluates a company's strategies, policies, and practices related to waste management and reduction. It captures the financial risks associated with improper waste disposal, inefficient waste handling, and environmental pollution caused by hazardous or unrecycled waste.

- **Category E6: Environmental Management**

The Environmental Management category assesses the financial risks arising from a company's environmental practices and the sustainability of its operations. It covers issues such as failure to meet environmental standards, lack of certification, and poor supply chain environmental criteria, evaluating the company's strategies, policies, and practices to manage environmental management-related financial risk.

- **Subcategory E6.1: Environmental Management.** Evaluates a company's strategies, certifications, and policies to ensure sustainable operations and supply chain practices. It captures the financial risks associated with non-compliance with environmental standards and the lack of recognized certifications such as ISO 14000 or real estate sustainability credentials.

Social Categories

- **Category S1: Own Workforce**

The Own Workforce category assesses the financial risks arising from a company's management of employee welfare, rights, and working conditions. It covers issues such as labor rights violations, health and safety concerns, inadequate remuneration, and lack of diversity and equal opportunity, evaluating the company's strategies, policies, and practices to manage workforce-related financial risk.

- **Subcategory S1.1: Labor Rights.** Evaluates a company's policies and practices to protect the rights of its own workforce and ensure fair labor conditions. It captures the financial risks associated with violations related to child labor, forced labor, and restrictions on freedom of association.
- **Subcategory S1.2: Health and Safety for Employees.** Evaluates a company's ability to protect its workforce from accidents, injuries, and fatalities. It captures the financial risks associated with poor safety standards and high incident rates.
- **Subcategory S1.3: Equal Treatment and Opportunities.** Evaluates a company's efforts to ensure fair compensation, career development, and equal opportunities for all employees. It captures the financial risks associated with inadequate diversity and equality practices.

- **Category S2: Workers in the Value Chain**

The Workers in the Value Chain category assesses the financial risks arising from the treatment of workers within a company's supply chain. It covers issues such as labor rights violations, health and safety concerns, human rights abuses, and unethical practices by suppliers, evaluating the company's strategies, policies, and practices to manage supply chain labor-related financial risk.

- **Subcategory S2.1: Health and Safety for Suppliers.** Evaluates a company's efforts to ensure the health and safety of workers in its supply chain. It captures the financial risks associated with unsafe working conditions or accidents within supplier operations.
- **Subcategory S2.2: Suppliers' Human Rights and Ethics.** Evaluates a company's ability to manage risks related to labor rights, human rights violations, and ethical practices within its supply chain. It captures the financial risks associated with unethical practices or violations at the supplier level.

- **Category S3: Affected Communities**

The Affected Communities category assesses the financial risks arising from a company's impact on local communities and human rights. It covers issues such as negative effects on local populations, human rights violations, and inadequate community engagement practices, evaluating the company's strategies, policies, and practices to manage community-related financial risk.

- **Subcategory S3.1: Affected Communities.** Evaluates a company's impact on local communities, focusing on human rights and social well-being. It captures the financial risks associated with negative local impacts and the failure to implement effective policies.

- **Category S4: Consumers and End-Users**

The Consumers and End-Users category assesses the financial risks arising from a company's responsibility to protect consumer rights and uphold product integrity. It covers issues such as data privacy violations, misleading advertising, and the safety and social responsibility of products, evaluating the company's strategies, policies, and practices to manage consumer-related financial risk.

- **Subcategory S4.1: Customer Experience.** Evaluates a company's ability to protect customer data and maintain ethical advertising and media practices. It captures the financial risks associated with data privacy breaches, misleading marketing, and media ethics violations.
- **Subcategory S4.2: Product Responsibility.** Evaluates a company's commitment to ensuring product quality, safety, and social responsibility. It captures the financial risks associated with unsafe products, lack of transparency, or failure to meet social and environmental expectations.

Governance Categories

- **Category G1: Corporate Governance**

The Corporate Governance category assesses the financial risks arising from the structure, transparency, and accountability of a company's leadership. It covers issues such as conflicts of interest, poor board diversity, inadequate auditing practices, and executive compensation misalignment, evaluating the company's strategies, policies, and practices to manage governance-related financial risk.

- **Subcategory G1.1: Board Composition.** Evaluates a company's strategies, policies, and practices related to the structure and diversity of its board. It captures the financial risks associated with insufficient gender diversity, lack of independent board members, or inadequate non-executive representation.
- **Subcategory G1.2: Compensation.** Evaluates a company's strategies, policies, and practices related to executive compensation and its alignment with sustainability, health and safety, and social responsibility goals. It

captures the financial risks associated with excessive CEO pay, lack of compensation committee independence, or misaligned incentives.

- **Subcategory G1.3: Accounting and Audit.** Evaluates a company's strategies, policies, and practices related to transparent financial reporting and audit processes. It captures the financial risks associated with inaccurate accounting, lack of audit committee expertise, or insufficient independence.
- **Subcategory G1.4: Corporate Governance Mechanisms.** Evaluates a company's strategies, policies, and practices related to maintaining strong governance structures and fair decision-making processes. It captures the financial risks associated with unequal voting rights, lack of independence in the nomination committee, and weak governance mechanisms.

- **Category G2: Corporate Ethics and Behavior**

The Corporate Ethics and Behavior category assesses the financial risks arising from unethical business practices, corruption, and violations of laws and regulations. It covers issues such as bribery, conflicts of interest, intellectual property theft, and non-compliance with international standards like the UN Global Compact and OECD Guidelines, evaluating the company's strategies, policies, and practices to manage ethics-related financial risk.

- **Subcategory G2.1: Business Ethics.** Evaluates a company's adherence to ethical practices, including integrity, anti-corruption measures, and respect for animal rights. It captures the financial risks associated with corruption, unethical sourcing, and violations of intellectual property.
- **Subcategory G2.2: ESG Compliance and Responsibility.** Evaluates a company's adherence to global standards such as the Ten Principles of the [UN Global Compact](#) and [OECD Guidelines for Multinational Enterprises on Responsible Business Conduct](#). It captures the financial risks associated with non-compliance or lack of integration of ESG factors.

2.3. Metrics and Indicators

To calculate ESG Ratings for companies, Clarity AI employs a comprehensive catalog of 124 KPIs, which are referred to as **metrics** throughout this document, in line with Clarity AI's terminology. Some of these metrics are universally relevant across all industries, while others are specifically tailored to address the unique challenges and characteristics of particular industries.

Metrics are classified into **three types** depending on the nature of the underlying raw data and the sources from which they are derived:

- Quantitative metric type: **Structured numerical information** that is measurable and comparable, either reported directly by companies or estimated through Clarity AI's proprietary machine learning models. This data reflects **current performance** and is useful for identifying **trends over time**.
- Policy metric type: **Structured qualitative information** that encompasses policies, processes, and targets. It provides insights into the measures companies implement to manage sustainability-related risks. These forward-looking metrics offer an indication of a company's potential **future performance** based on its **risk management strategies**.
- Controversy metric type: **Unstructured information** derived from open-text news and reports, which are used to assess **incidents of controversial behavior** and evaluate exposure to reputational risks. These metrics provide insights into how effectively companies are **managing current ESG risks**.

Metric selection is driven by two criteria: alignment with internationally recognised sustainability disclosure regulation and standards, and data coverage.

The first and primary criterion is alignment with established regulations, international agreements, and recognized sustainability reporting standards. The methodology therefore uses core metrics common to well established standards such as the European Sustainability Reporting Standards (ESRS), the Sustainable Finance Disclosure Regulation (SFDR), the Sustainability Accounting Standards Board (SASB) Standards and the Global Reporting Initiative (GRI). The methodology also draws on international commitments such as the Paris Agreement – to ensure that climate-related financial risk is assessed in line with globally agreed decarbonization pathways.

The second criterion is data coverage, defined as the availability of sufficient, reliable data to enable meaningful and comparable assessments across a broad universe of companies. A metric may be conceptually relevant but practically unusable if reported by too few companies to support robust cross-sectional analysis. Metrics with limited data coverage were therefore deprioritized or excluded from the framework.

Together, these two criteria ensure that the metric framework is both normatively grounded and empirically robust, capturing the sustainability issues that matter most to financial risk assessment while maintaining the comparability and reliability required of an ESG rating methodology.

The ESG Rating does not explicitly assess an entity's overall commitment or alignment with international environmental or climate agreements as a standalone dimension. While

certain policy metrics capture elements related to such commitments (e.g., emission reduction targets or Net Zero commitments), these are incorporated as individual indicators within the broader metric framework. Their influence is limited to their respective weights and does not constitute a separate assessment of alignment with international agreements. These indicators are treated as proxies of risk management practices, in line with the methodology's focus on financial materiality.

For social and governance factors, international agreements and standards are reflected only through individual metrics, in particular subcategory G2.2 (ESG Compliance and Responsibility), which evaluates adherence to the Ten Principles of the UN Global Compact and the OECD Guidelines for Multinational Enterprises.

While the EU Taxonomy framework is a valuable tool within the European regulatory context, it is not explicitly incorporated due to its limited applicability across the global coverage universe. As the ESG Rating assesses companies worldwide, many of which are not subject to EU Taxonomy requirements, its inclusion could reduce comparability and introduce regional bias. Instead, the framework relies on indicators with a minimum level of global coverage to ensure consistency and scalability.

3. ESG Ratings Calculation Process

3.1. Individual Metric Rating Calculation

The first step in the scoring process is the evaluation of individual indicators. Clarity AI categorizes metrics into three distinct types: **Quantitative, Policy, and Controversy** (detailed definitions are provided in [Section 2.3](#)).

Regardless of the metric type, the output of the calculation is always standardized to a numerical scale between **1 and 100**, where 100 represents the best possible performance and 1 represents the poorest. The scoring logic for each type is defined as follows:

3.1.1. Quantitative Metrics rating calculation

Quantitative indicators are rated using one of two distinct approaches:

3.1.1.1. Peer-based metric scoring

This type of rating only applies to quantitative metrics and it is based on a relative peer comparison (best-in-class) approach. This calculation has three stages, namely:

Step 1 - Conversion of raw data to comparable metrics

The sourced raw data (e.g., tons of CO₂) is **normalized** using a sizing metric to derive an **intensity metric** (e.g., tons of CO₂ per million USD). This normalization allows us to compare organizations of different sizes.

The sizing metrics used for normalization can be:

- Sector-agnostic: Revenues / Headcount
- Industry-specific, production based metrics: RPK for airlines / GWh for electric utilities

Step 2 - Outlier treatment

The next step is to identify and treat extreme values from the intensity metrics distributions (i.e., limit outliers in the statistical data) to prevent skewing the results.

- **Outlier treatment:** statistical methods are applied to minimize noise in the value distributions used for comparing performance and calculating final ratings. Clarity AI deals with outliers as follows:
 - **Outlier detection:** an intensity data point is deemed an outlier if it deviates significantly (its value is below the $Q1-(3*IQR)$ or above $Q3+(3*IQR^3)$) from the intensities of the rest of the industry peers for that metric.
 - **Range adjustment:** outliers are excluded from the intensity metrics distributions and are rated separately. This means that the range of intensity metrics used for peer comparison provides a more accurate and representative view of peer performance, avoiding distortions that extreme values can cause.

Step 3 - Rating calculation

Quantitative metric ratings following a peer comparison approach are then calculated by comparing a company's performance on a given ESG issue with that of other rated companies in the same industry (please see [Section 3.3](#) for a detailed description of industry classification). A quantitative metric's rating equals 1 if an organization is the worst performer among industry peers (e.g., highest tons of CO₂/million USD), and 100 if it is the best performer (e.g., lowest tons of CO₂/million USD). Therefore, quantitative metric ratings will always be distributed between 1 (worst performer) and 100 (best performer) for a given industry.

3 1Q: First Quartile; 3Q: Third Quartile; IQR: Difference between the first and the third quartiles

3.1.1.2. Absolute metric scoring

This approach sets uniform expectations for each individual metric, applicable across all industries. An organization's performance is evaluated using a predefined rating framework, which defines different levels of performance based on recommendations from existing international guidelines or regulatory mandates. This method ensures consistency and alignment of the rating with global standards. Below, you'll find details on the metrics that employ absolute scoring and the frameworks defined for each.

Metric	Recommendation / Mandate	Buckets
Audit Committee Independence	OECD : 100%	1 (Insufficient): [0%,50%)
Audit Committee Non-Executive Members	International Finance Corp (IFC) : 100%	30 (Weak): [50%,70%) 70 (Adequate): [70%,100%) 100 (Strong): 100%
Nomination Committee Independence	IFC : Majority (>50%)	1 (Insufficient): [0%,25%)
Compensation Committee Independence	OECD on some jurisdictions : >50%	30 (Weak): [25%,50%)
Compensation Committee Non-Executive Members	OECD on some other jurisdictions : 100%	70 (Adequate): [50%,100%) 100 (Strong): 100%
Independent Board Members	IFC : >= 50%	1 (Insufficient): [0%,20%)
Non-Executive Board Members	OECD on some jurisdictions : >=50%	30 (Weak): [20%,33%) 70 (Adequate): [33%, 50%) 100 (Strong): [50%, 100%]
Women on Board	EU Directive : >= 33% by 2026 for large listed companies 30% Club : >= 30%	1 (Insufficient): [0%,15%) ∪ (85%, 100%] 30 (Weak): [15%,30%) ∪ (70%, 85%] 70 (Adequate): [30%, 40%) ∪ (60%,70%] 100 (Strong): [40%, 60%]
Employee Fatalities	Aim for 0 fatalities	1 (Severe): average of over 2 fatalities/year 30 (Moderate): average of 1-2 fatalities/year 70 (Minor): average of under 1 fatality/year 100 (None): average of 0 fatalities/year
Women Employees	Aim for parity (≈ 50%)	1 (Insufficient): [0%,15%) ∪ (85%, 100%]
Women Managers		30 (Weak): [15%,30%) ∪ (70%, 85%] 70 (Adequate): [30%, 40%) ∪ (60%,70%] 100 (Strong): [40%, 60%]
Gender Pay Gap	Aim for equality (≈ 100%)	1 (Insufficient): [0%,70%) ∪ (130%, +inf] 30 (Weak): [70%,80%) ∪ (120%, 130%] 70 (Adequate): [80%, 90%) ∪ (110%,120%] 100 (Strong): [90%, 110%]

3.1.1.3. Treatment of missing data

When raw data for a quantitative metric is unavailable, a rating is assigned based on rules specific to the selected universe:

- For the **High Relevance Universe**, a **low rating is assigned**, corresponding to the 1st percentile of the distribution for the relevant industry. This assignment implies a potential penalty for non-disclosure if the company's actual performance is better than that of the lowest-performing peers (sometimes referred to as the precautionary principle).
- For the **All Companies Universe**, a **mid rating is assigned**, corresponding to the median (50th percentile) of the distribution for the relevant industry. This assignment implies a potential penalty for non-disclosure if the metric is actually better than the median performers.

3.1.2. Policy Metrics rating calculation

Policy ratings equal 1 when the company hasn't established a given policy or target and 100 if it has. The calculation of policy ratings does not depend on the peer group of reference described for quantitative metrics.

3.1.3. Controversy Metric rating calculation

Controversy metrics are assigned ratings of **1, 20, 40, 60, 80, or 100**, ranging from the most severe controversies (1) to no controversy exposure (100).

These ratings are determined using advanced Natural Language Processing (NLP) and Machine Learning (ML) models, which detect incidents, classify them into relevant categories, and calculate the corresponding metric ratings. The most severe controversies are additionally reviewed by subject-matter experts, introducing a human-in-the-loop layer that complements the automated pipeline and helps ensure that high-impact cases receive the extra layer of validation they require.

3.2. Company-Level Rating Aggregation

Individual metric ratings are aggregated into subcategories, categories, and pillars using a rule-based methodology. This framework ensures objectivity, transparency, and replicability by eliminating ad-hoc adjustments and relying exclusively on predefined aggregation logic.

Subcategory, category, and pillar ratings are calculated as a **factor-weighted average** of their underlying quantitative and policy metrics. A controversy-based deduction is then

applied to this average, incorporating the real-world impact of operational failures (see Figure 2 and the [Materiality Section](#)).

The **controversy penalty** is proportional to an incident's severity and materiality. The materiality matrix defines the maximum possible deduction for a specific topic, while the controversy rating determines the actual penalty applied. Consequently, "Very Severe" incidents trigger the maximum deduction, whereas "Minor" cases or the absence of controversies result in minimal to zero impact.

Figure 2 -Simplified illustration of subcategory rating calculation



The aggregated rating is derived through the sequential application of the formulas below, which can be applied at any level of the hierarchy — subcategory, category, pillar, or total — where:

- Weighted average rating = the materiality-weighted average of metric ratings at the relevant aggregation level, calculated separately for each metric type (i.e., quantitative, policies, controversies), including only the metrics belonging to that type. For instance, the Quantitative weighted average rating exclusively incorporates quantitative metrics, and similarly for each other type.
- Metric rating = the rating of each individual metric underlying the relevant aggregation level (subcategory, category, pillar, or total)
- Metric materiality = the materiality of each individual metric underlying the relevant aggregation level (subcategory, category, pillar, or total)
- Maximum controversies deduction = the highest possible deduction applicable at any aggregation level (subcategory, category, pillar, or total). It represents the ceiling of the controversy's impact on the aggregated rating at that level.
- Controversies penalty = the actual deduction applied to the aggregated rating at the relevant aggregation level (subcategory, category, pillar, or total)

- Aggregated rating = the final rating at any aggregation level (subcategory, category, pillar, or total)

$$\text{Weighted average rating} = \frac{\sum(\text{metric rating} \times \text{metric materiality})}{\sum \text{metric materiality}}$$

$$\text{Maximum controversies deduction} = 100 \times \frac{\sum \text{metric materiality}_{\text{controversies}}}{\sum \text{metric materiality}_{\text{quantitative \& policies \& controversies}}}$$

$$\text{Controversies penalty} = (100 - \text{Weighted average rating}_{\text{controversies}}) \times \frac{\text{Maximum controversies deduction}}{99}$$

$$\text{Aggregated rating} = 1 + (\text{Weighted average rating}_{\text{quantitative \& policies}} - 1) * (1 - \frac{\text{Controversies penalty}}{99})$$

Figure 3 - Example of metric rating aggregation at the subcategory level

Metric	Materiality weight	Rating
Water Recycled Ratio	3.3%	75
Water Withdrawal Total	1.7%	80
Quantitative weighted average	5.0%	77
Water Efficiency Policy	1.4%	100
Water Efficiency Targets	1.4%	1
Policies weighted average	2.8%	51
Water Usage Incidents	1.7%	60
Supplier Water Usage Incidents	2.5%	80
Controversies weighted average	4.2%	72
Quantitative + Policies weighted average	7.8%	68
Maximum controversies deduction		35
Controversies penalty		10
E3.1 - Water	12.0%	58

Please note that the distribution of ratings at these aggregated levels for a given peer universe is unlikely to span the full 1 to 100 range. Such a distribution would imply the existence of one company that ranks as the *worst performer in every ESG issue* and another that ranks as the *best in every ESG topic*. Instead, ratings will typically fall within a narrower range (e.g., between 20 and 90).

3.3. Industry Classification

Quantitative peer-based ratings are relative to 169 sub-industries based on the GICS-4 classification⁴. This framework groups entities with similar operational risk profiles and business models to ensure performance benchmarks are representative of their specific economic activities.

While the Global Industry Classification Standard (GICS) level 4 serves as the structural foundation, it was not originally designed to group companies based on sustainability-related factors. To address this limitation, this methodology applies targeted refinements to high-impact sectors — such as energy and utilities — to better reflect their distinct transition risks and regulatory environments. These adjustments ensure that peer comparisons remain meaningful and that ratings accurately reflect the structural characteristics of each sub-industry.

For example, GICS' Construction Materials sub-industry has been split into Construction Materials and Cement, given that cement production is one of the most carbon-intensive industrial processes and presents a distinctly different sustainability risk profile from other construction materials manufacturers.

3.4. Materiality

Clarity AI proposes an ESG materiality matrix aligned with widely recognised industry standards. In order to define the specific weights for each metric within the Clarity framework, we consider multiple inputs:

- Regulatory requirements: Metrics are mapped to applicable regulatory standards, including the Principal Adverse Indicators defined under the SFDR regulation and other relevant disclosure requirements.
- SASB⁵ Materiality Map: SASB's industry-specific disclosure topics and their associated accounting metrics were systematically interpreted and mapped to Clarity AI's metrics across all 169 sub-industries. Beyond the direct metric mapping, additional information on SASB's disclosures — including the ranking given to each topic, wording, emphasis, and repetition of topics — was analysed to derive the relative importance of each metric within a given sub-industry, informing the specific weight assigned to each metric in the materiality matrix.

⁴ The [Global Industry Classification Standard](#) (GICS) is an industry taxonomy developed by MSCI and Standard & Poor's (S&P).

⁵ The [Sustainability Accounting Standards Board \(SASB\)](#) is an organization that provides industry-specific standards to guide companies in disclosing financially material, decision-useful environmental, social, and governance (ESG) information to investors.

- Academic and industry literature: Additional inputs include peer-reviewed research, investment bank reports, and sector-specific frameworks such as GRESB⁶ for real estate companies.

Materiality weights are specific to each metric and sub-industry, resulting in 169 distinct materiality matrices — one per sub-industry. The chart below illustrates the distribution of materiality weights across industries for each of the three pillars:

Figure 4 - Distribution of pillar materiality weights across sub-industries



3.5. Parent-Subsidiary Relationships

If an ESG rating can't be calculated for a company due to limited disclosure or insufficient available data, it is assigned the ratings of its parent organization. The subsidiary inherits all ratings (total, category, subcategory and metric ratings), even if it is in a different sub-industry from the parent. Inheritance occurs after scoring, so metric ratings from peers are not impacted by inheritance, but a portfolio's coverage and rating are.

A company can only have one parent, but its parent may have a parent. Clarity AI assigns the company the rating of the first parent with an available rating. For example, for Company A > Company B > Company C: if Company B has data, Company C would inherit from Company B, meaning Company B and Company C would have identical data, distinct from Company A. However, if Company B doesn't have data, both Company B and Company C would inherit from Company A.

⁶ [GRESB \(Global Real Estate Sustainability Benchmark\)](#) is a global ESG benchmarking framework for real estate and infrastructure investments.

3.6. Fund / Portfolio Aggregation

Portfolio ratings can be derived and aggregated at any level — from individual metrics up through subcategories, categories, pillars, and the total. At each level, the rating is calculated as the weighted average of all covered holdings — such as corporations, governments, or funds — weighted by both each holding's allocation percentage within the portfolio and the materiality of the relevant issue for the corresponding entity.

In Table 1, an example of the Environmental (E) pillar rating calculation at portfolio level is detailed, where:

- Allocation weight = the percentage of the total portfolio value invested in a given holding, reflecting its relative size within the portfolio.
- E Rating = the Environmental pillar rating of a given holding
- E materiality weight = the materiality weight assigned to the Environmental pillar for a given holding, reflecting the relative importance of environmental risks for that specific entity.
- Normalized weight = the allocation weight of a holding rescaled so that the weights of all holdings sum to 100%, ensuring a consistent and comparable basis for the weighted average calculation.

Table 1 - Illustrative example of portfolio-level Environmental (E) pillar rating calculation

Portfolio component	Allocation weight	E Rating	E materiality weight	Allocation weight * E weight	Normalized weight	Normalized weight * E Rating
Company A	20.0%	45	35.0%	7.0%	31.9%	14.4
Company B	25.0%	72	20.0%	5.0%	22.8%	16.4
Company C	15.0%	90	28.0%	4.2%	19.1%	17.2
Government A	25.0%	10	5.0%	1.3%	5.7%	0.6
Government B	15.0%	53	30.0%	4.4%	20.5%	10.9
Total	100%			22%	100%	59

4. Data Review and Quality Assurance

4.1. Data Collection and Sources

For our ESG rating activities, the primary source for ESG data on companies are publicly available data from company reports or public websites. We also use third-party data and generate in-house data estimates.

This methodology relies exclusively on publicly available information; non-public data is not incorporated.

Therefore, data used in order to build ESG Ratings comes from four key sources:

4.1.1. Data Collection from Corporate Disclosures

In line with our data quality standards, we source company data directly from a variety of corporate disclosures, including but not limited to sustainability and integrated reports. This includes, where applicable, regulatory disclosures prepared under frameworks such as the Corporate Sustainability Reporting Directive (CSRD), as well as other reporting standards. These reports may or may not have been subject to an external assurance assessment.

For primary data collection, we use a proprietary platform that allows combining human collectors and automatic collection. Human collectors are typically a mix of external resources (outsourced service) and internal resources that are in charge of quality controls and collection of more complex data. The platform has embedded quality controls and a menu of different human-in-the-loop workflows to ensure only high-quality data inputs are processed further.

4.1.2. Controversies Data

To identify corporate controversies, Clarity AI uses in-house Natural Language Processing (NLP) and Large Language Models (LLMs) that monitor a wide range of sources, including a global news monitoring service providing access to media publishers from across 200 countries, with over 250,000 news articles added per day. These models detect and classify controversy signals across ESG categories, supporting continuous and scalable monitoring of corporate conduct to ensure assessments remain current and comprehensive.

4.1.3. Third-party Data Providers

We also use third-party data (i.e., information collected by others and licensed as a data package to us) for certain metrics, primarily company reference data (e.g., industry code)

and fundamental data (e.g., revenues, headcount). The selection of third-party data follows our outsourcing procedure.

4.1.4. Data Estimation

In case of certain ESG metrics where reported data is not available, data estimation models are created as a cross-functional effort. The process relies on a clear separation of duties between those who define what needs to be estimated and the underlying quality requirements, those who determine how to estimate it, and those who decide when to release it.

Once the models are built and the estimates are generated—provided they have met the pre-defined quality criteria—a Full Impact Review is conducted. This review assesses additional dimensions, such as shifts in data coverage and data stability over time, to ensure the final output is reliable for market release. The validation framework at Clarity AI ensures that machine learning estimates meet rigorous quality standards before client delivery.

4.2. Data Validation and Quality Controls

We operate a structured data quality control framework applied at each stage of the data ingestion, processing, and release process. The framework covers pre-release validation of raw data, validation of ratings, a defined remediation process, and a policy for the revision of historical data.

For rule-based ratings, prior to each data release, we perform a validation of the candidate raw data dataset proposed for release. The validation covers all metrics in scope for the release. Illustrative examples of the checks applied include:

Coverage checks: unexpected losses in metric, provider, or entity coverage relative to the prior release are investigated. Losses affecting priority metrics are treated as release blockers;

Value range checks: data points are verified against pre-defined acceptable ranges for each metric. Points outside those ranges are flagged for review;

Absolute value change checks: individual data point values are compared between the candidate release and the version in production. Unexpected deviations are flagged for review;

Historical series consistency: Z-scores are calculated per metric for each entity across all available years. Year-on-year changes are also monitored, with large deviations between consecutive years triggering a flag on both affected data points;

Related metrics consistency: internal consistency across logically related metrics is verified, for example, by checking that the sum of component values does not exceed the corresponding total;

Policy metric checks: transitions in policy values are monitored, with particular attention to losses of previously reported policies. Data points inconsistent with the prevailing industry profile are subject to sample-based review.

All blocked data points are documented and tracked in dedicated tickets. Issues that cannot be resolved within the validation window are discussed on a case-by-case basis. Following raw data validation, relevant experts perform additional product-level checks on ratings, and approve the ratings.

For human analyst based ratings we track human input and require additional approvals for high stake calls.

The Regulated Entity maintains a policy for the revision of historical data, reflecting the fact that companies regularly restate previously reported figures. Restatements are classified by reason — corrections, methodology updates, boundary updates, fiscal year adjustments, or unspecified — and are identified systematically during the collection process. All restatements are documented and traceable.

Historical data updates can also be triggered by data incidents. The Regulated Entity has established a structured and transparent process for reporting, categorizing, and resolving incidents related to its data, in order to uphold data integrity, accuracy, and reliability as defined in the Regulated Entity's quality framework.

4.3. Missing Data and Estimations

Missing data and estimations are covered in three sections: the rating treatment of missing quantitative metric data is set out in Section 3.1.1.3 (Treatment of missing data), the estimation process in Section 4.1.4 (Data Estimation), and the estimation models in Section 5.1.1 (Estimated data).

5. Use of Models, AI, Assumptions and Limitations

5.1. Use of Quantitative Models and AI

Data Collection: The Regulated Entity uses AI, specifically Large Language Models (LLMs), to support the extraction of ESG data points from unstructured corporate disclosures (e.g., annual and sustainability reports). This extraction process is always grounded in the underlying source document.

The use of AI in this context involves inherent limitations and risks. These include the risk of "hallucination" (producing a plausible but unsupported value), "misinterpretation" (confusing units or materially different figures), and performance degradation over time ("drift") as reporting formats or the underlying LLMs evolve. Additionally, accuracy may be uneven across different sectors, languages, or company sizes (disparate performance). Extractors are also limited by the quality and content of the source documents provided.

These risks are systematically mitigated by designing our internal data extraction platform around the principle that AI outputs must be measured, reviewed, traceable, and reversible.

Quality and Consistency: Every new extractor version is rigorously tested against human-verified "ground-truth" annotations before deployment. All extractors running in production are under ongoing human monitoring, with review intensity adapted based on the extractor's historical performance. This continuous monitoring helps us catch drift and disparate performance proactively.

Transparency and Governance: Every value is transparently linked back to its source; most values are returned with the supporting quote and page location, ensuring full traceability. Strict human oversight on the extractor version is enforced through a two-stage workflow where only designated experts can approve and deploy an extractor version. This creates an auditable record of which AI configuration produced any given data point at any time, and allows for the quick disabling or downgrading of an extractor if input distributions change.

Methodology Implementation: The Regulated Entity integrates AI-assisted software development tools to facilitate the translation of approved ESG rating methodologies into production-ready code. In this capacity, AI functions as an engineering support tool to optimize efficiency and code quality by assisting with logic drafting, unit test generation, refactoring, and the systematic identification of potential edge cases or implementation defects.

AI is not deployed as an autonomous decision-maker; it does not independently define or modify rating methodologies. All methodology design, regulatory interpretation, and final deployment decisions remain the sole responsibility of our engineers and methodology owners, governed by established review protocols.

The integration of AI into methodology implementation introduces specific risks, including potential misinterpretation of requirements, subtle calculation errors, or the creation of technical debt through unmaintainable logic. Furthermore, there is a risk of over-reliance leading to insufficient independent validation or reduced traceability if implementation decisions are not rigorously documented and peer-reviewed.

These implementation risks are systematically mitigated through our standard software development lifecycle (SDLC) and rigorous engineering controls.

Human Accountability and Review: All AI-assisted implementations are fully owned and validated by Clarity AI engineers. AI tools are prohibited from approving code or deploying changes. Every methodology-related code change undergoes mandatory peer review to ensure correctness against approved requirements, architectural consistency, and data integrity.

Testing and Validation: AI-assisted code must adhere to a comprehensive testing pyramid, including unit tests for specific calculations, integration tests for data pipelines, and regression tests to ensure historical stability. Deterministic logic is validated against predefined test cases and controlled datasets to confirm the implementation aligns with the intended methodology behavior.

Good Engineering Practices: We apply standardized MLOps and engineering safeguards, such as version control, continuous integration, and static analysis. By enforcing small, reviewable pull requests and clear ownership of code changes, we maintain high standards of transparency and allow for the rapid rollback of production changes if anomalies are detected.

Traceability and Governance: Every technical implementation is transparently linked back to its underlying methodology documentation and acceptance criteria. AI-generated suggestions are only promoted if they are traceable to approved inputs, ensuring that AI remains a constrained tool within our broader methodology governance framework.

5.1.1. Estimated data

The deployment of advanced Machine Learning (ML) models is necessary to close data gaps.

Advanced ML models, while accurate to capture complex relationships, can sometimes obscure the reasoning behind an output (the "black box" problem). To ensure auditability and trust, we enforce strict documentation protocols and invest in explainability tools.

Furthermore, we rely on standardized operational and Data Governance frameworks designed to systematically validate model outputs. Every automated validation check is mapped back to real-world domain knowledge, ensuring the rejection or flagging of any estimate can be diagnosed.

We actively prevent the generation of unreliable data for industries with low public disclosure by enforcing strict minimum reporting thresholds. If an industry falls below the required data volume, the ML estimate is automatically suppressed to prevent unwarranted statistical extrapolation.

To prevent algorithms from predicting impossible scenarios, we integrate "Essential" validation checks that enforce physical constraints, automatically blocking outputs that violate physical realities, such as estimations of negative waste generation.

To ensure stable historical trends for financial applications, we apply temporal validations that detect and cap extreme year-on-year variations against expected industry distributions. This prevents artificial volatility and enforces trend consistency.

Finally, to actively mitigate the risk of algorithmic bias that could inadvertently facilitate greenwashing, our models are not solely optimized for prediction error minimization. Instead, we prioritize the accurate differentiation between industry leaders and laggards (relative rank preservation). We only deploy a complex ML model if it achieves a substantial performance gain (defaulting to a >20% improvement) over simpler, existing methods, ensuring the investment in complexity is justified.

5.1.2. News screening

Our ESG rating methodology integrates a specialized AI/ML pipeline to monitor global news and convert unstructured text into structured sustainability signals. The system processes high volumes of news through distinct models that handle entity extraction, company attribution, controversy detection, category mapping, severity scoring, and episode clustering to prevent double-counting. Additionally, large language models (LLMs) filter borderline content, summarize events, and evaluate data quality.

While highly efficient, using AI for news tracking involves inherent limitations. These include potential false positives or negatives, ambiguity in mapping multi-company news, classification or clustering errors, source coverage gaps, and LLM-specific risks like hallucination. If unmitigated, these limitations could present operational risks, such as score volatility, bias against highly covered organizations, and reputational or investment decision errors due to misattribution or missed information.

To safeguard data integrity, we combine technical and human-in-the-loop validation. Structurally, all AI models are benchmarked against human-labeled datasets, alternative approaches are systematically logged, and company names are masked during training to eliminate brand bias. Performance is continuously tracked using automated quality dashboards.

In addition, a dedicated team of subject-matter experts performs reviews of incidents using documented methodologies to monitor the quality of the models. For ratings that combine rule-based scoring and human analyst assessment, we enforce a multi tier review process to ensure quality. Human experts can override model outputs, correcting data points and ratings while simultaneously retraining and refining future AI model iterations.

5.2. Methodological Assumptions

The ESG Ratings methodology is predicated on the following core assumptions:

5.2.1. Conceptual Assumptions

- **Financial Materiality focus:** ESG factors are assumed to represent latent financial risks. Sustainability performance serves as a proxy for management quality and long-term operational resilience, specifically focusing on "outside-in" risks that impact financial value.
- **Industry Relevance:** Companies are assessed based on their GICS-4 sub-industry classification, which may provide a limited view of economic activities for diversified companies. As a result, the financial materiality framework applied at the company level may not fully account for company-specific factors — such as unique business models, or revenue mix — that could meaningfully influence the materiality assessment.
- **Peer Comparability:** Companies within the same GICS-4 sub-industry are assumed to face comparable systemic risks. The distribution of performance within these peer groups is considered a valid benchmark for identifying relative leadership or risk exposure.

- **Indicator Relevance:** The selected indicators and materiality structure may not fully capture all significant sustainability factors, and the relevance of specific metrics may evolve as regulatory standards, stakeholder expectations, and scientific understanding develop over time.
- **Policy and Controversy Framework:** Public disclosure of a formal policy is treated as a credible indicator of risk management commitment. Conversely, controversies are assumed to be "ex-post" evidence of risk management failures, serving as an objective measure of the gap between stated policies and actual operational performance.
- **Science-based approach:** The ESG Ratings methodology does not rely on climate scenario modelling or scientific pathways to derive ratings. Instead, it incorporates scientific evidence through the selection of metrics, which are informed by globally recognized regulatory standards & industry frameworks.

5.2.2. Data and Estimation Assumptions

- **Reliability of Disclosures:** Publicly disclosed information is assumed to provide a sufficiently reliable basis for assessing sustainability performance.
- **Proxy and Estimation Logic:** Where reported data is unavailable, the methodology assumes that estimations derived from AI models provide a sound representation of an entity's risk profile.
- **Entity Hierarchy:** Subsidiary entities are assumed to be exposed to the same ESG risks as their parent organization, reflecting the principle that risks — whether reputational, regulatory, or operational — propagate across corporate group structures. Additionally, ESG policies and governance frameworks are typically established at the group level and applied across subsidiaries, making the parent's profile a reasonable proxy for group-wide risk exposure. Where standalone data is insufficient, subsidiaries therefore inherit the parent's rating, though this approach may not fully capture entity-specific risks or local operational differences.

5.2.3. Technical Scoring Assumptions

- **Quantitative Missing Data:** In the absence of disclosure for quantitative metrics, the model assumes a penalty-based approach ("Low Rating") or a neutral position ("Mid Rating/Median") based on rules specific to the selected universe.

5.3. Data and Model Limitations

In addition, the ESG Ratings methodology is subject to the following inherent limitations:

- **Reliance on Public Disclosures:** The accuracy of the assessment is largely dependent on the quality, timeliness, and completeness of information disclosed by the entities. Inconsistent reporting standards across jurisdictions may affect the comparability of raw data.
- **Estimation Uncertainty:** While Machine Learning and proxy models are used to bridge data gaps, estimated values are statistical approximations and may not capture specific entity-level idiosyncratic factors that have not been publicly disclosed.
- **Time Lag in Data:** Sustainability reports and regulatory filings are typically published annually. Consequently, there may be a time lag between a change in an entity's ESG performance and its reflection in the ESG Rating, notwithstanding the mitigating impact of real-time controversy monitoring.
- **Backward-Looking Bias:** Many quantitative metrics (e.g., historical emissions or past fatalities) are backward-looking by nature. Policy indicators provide a forward-looking signal of intent to mitigate this bias.
- **Industry Classification Constraints:** Although GICS-4 provides a granular framework, diversified conglomerates or companies operating in niche emerging sectors may not perfectly align with a single sub-industry benchmark.
- **Subjectivity in Severity Assessment:** Controversy severity classification involves qualitative analysis of legal, financial, and reputational impacts. To minimize the inherent biases and uncertainty associated with such assessments, the process leverages Natural Language Processing (NLP) technology combined with a structured rubric and is further validated through consistent and rigorous expert review. Nonetheless, a residual degree of expert judgment remains intrinsic to any qualitative evaluation.
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6. Governance and Oversight

6.1. Governance of the Methodology Review and Update Process

The Regulated Entity maintains a robust methodology governance framework designed to ensure that all rating methodologies remain independent, rigorous, systematic, and impartial. To uphold these core principles, the Regulated Entity subjects its methodologies to a structured development, review, and approval process overseen by dedicated internal governance bodies, in line with our ESG Ratings Governance Policy.

Methodologies are reviewed on a regular basis and at least annually to verify that they remain fit for purpose. Emerging regulatory requirements, and market trends are

considered in those reviews. Reviewed methodologies are subject to a peer review and mandatory final approval by the Methodology Committee before any update can be deployed.

Changes to existing methodologies are applied across the entire rated universe, including corporate, financial instruments, or sovereign scores, where applicable. When a methodology modification is deemed material, an impact assessment is conducted prior to the scheduled release.

The Regulated Entity is committed to transparent communication to users and rated entities, and makes information about its methodologies publicly available.

Users, rated entities and other stakeholders may submit their feedback in respect of published methodologies via the existing communication channels.

6.2. Disclosure to Rated Items and Engagement Process

The methodology is applied to the assessed universe on an unsolicited basis, relying exclusively on publicly available information. Rated items do not participate in the assessment process.

Once the rating is issued, rated entities can access Clarity AI's platform for free to review it, including the underlying data used to calculate the rating, and to submit complaints in case there are any errors.

6.3. Solicited Ratings

Similar governance standards apply to solicited ratings. Aside from the data collection process, everything else follows the same process for rating determination, including that only publicly available information is to be accepted. In addition, disclosure is provided in case a rating is solicited.

7. Annexes

7.1. Annex 1 - Glossary and definitions

- **ESG Rating:** a score, an opinion or a combination of both regarding a rated item's profile or characteristics with regard to environmental, social, and human rights, or governance factors, or regarding a rated item's exposure to risks or impact on environmental, social, and human rights, or governance factors, that is based on both an established methodology and a defined ranking system of rating categories.
- **Financial Materiality:** Issues reasonably likely to have a significant impact on financial condition or operating performance.
- **Data Relevance:** A measure of available metric data weighted by the importance (materiality) of those metrics for a given company.
- **Inheritance:** Assigning a subsidiary the ratings of its parent organization when its own data is insufficient.
- **Rated Item:** a legal person, a financial instrument, a financial product, a public authority, or a body governed by public law which is explicitly or implicitly rated in the ESG rating.

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