



台南應用科技大學  
TAINAN UNIVERSITY OF TECHNOLOGY

# 台南應用科技大學 永續發展暨大學社會責任(USR)系列講座



# 生成式AI與永續發展的應用

## Generative AI and Sustainable Development Applications

2024/06/26 (Wed) 10:30 - 12:00

L703, Tainan University of Technology (TUT), Tainan, Taiwan

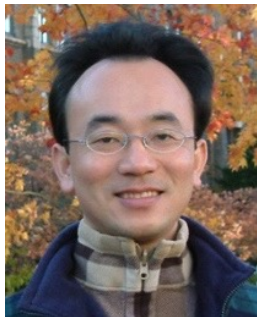
No.529, Zhongzheng Rd., Yongkang District, Tainan City 710302, Taiwan (R.O.C.)

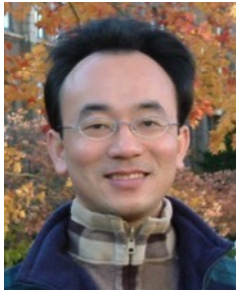
### 戴敏育 教授 (Prof. Min-Yuh Day)

國立臺北大學 資訊管理研究所 教授  
金融科技暨綠色金融研究中心 副主任  
永續辦公室 永續發展組 組長

<https://web.ntpu.edu.tw/~myday>

2024-06-26





# 戴敏育 教授

## Professor Min-Yuh Day

aws educate | Cloud Ambassador

2020 Cohort

**Professor, Information Management, NTPU**

**Visiting Scholar, IIS, Academia Sinica**

**Ph.D., Information Management, NTU**

**Director, Intelligent Financial Innovation Technology, IFIT Lab, IM, NTPU**

**Associate Director, Fintech and Green Finance Center, NTPU**

**Publications Co-Chairs, IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM 2013- )**

**Program Co-Chair, IEEE International Workshop on Empirical Methods for Recognizing Inference in Text (IEEE EM-RITE 2012- )**

**Publications Chair, The IEEE International Conference on Information Reuse and Integration for Data Science (IEEE IRI 2007- )**



# Outline

- 1. Generative AI:  
Powering Digital Sustainability Transformation**
- 2. Generative AI and Large Language Models (LLMs):  
Popular Generative AI Applications**
- 3. Generative AI for Sustainable Development  
Innovative Applications**

# 衡量企業永續關鍵指標

## 臺北大學獨創ESG永續評鑑系統

社會(S)	經濟(E)	環境(E)	揭露(D)
<ul style="list-style-type: none"> <li>1.人權</li> <li>2.員工溝通與福利</li> <li>3.人力資本發展</li> <li>4.多元組成與包容性</li> <li>5.供應鏈社會面向控管</li> <li>6.客戶關係管理</li> <li>7.產品安全</li> <li>8.企業公民與慈善</li> </ul>	<ul style="list-style-type: none"> <li>1.股東權益</li> <li>2.董事會結構與運作</li> <li>3.行為準則與內控</li> <li>4.風險及危機管理</li> <li>5.永續金融</li> <li>6.ESG創新</li> </ul>	<ul style="list-style-type: none"> <li>1.環境系統與治理</li> <li>2.空氣管理</li> <li>3.能源與氣候變遷</li> <li>4.水管理</li> <li>5.原物料與廢棄物管理/ 資源與廢棄物管理</li> <li>6.生物多樣性</li> <li>7.供應商及產品生命週期管理/ 供應鏈環境面向管理</li> </ul>	<ul style="list-style-type: none"> <li>1.ESG 揭露</li> </ul>



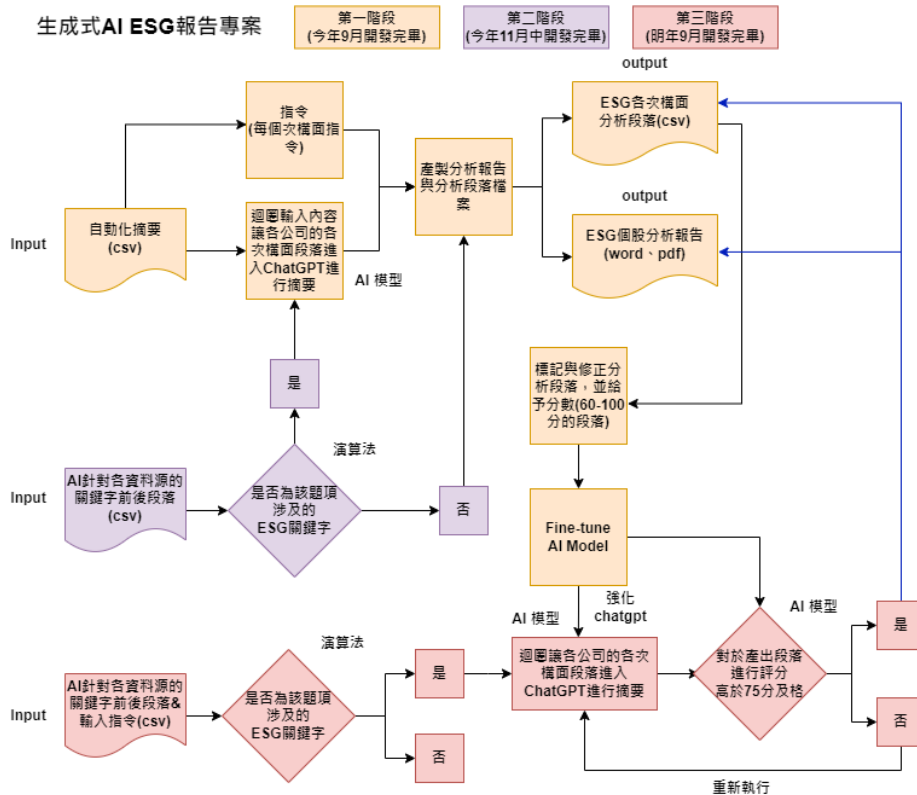
# 台灣永續評鑑

國立臺北大學商學院企業永續發展研究團隊

# 透過 AI SEED 提升評鑑效率



為使評鑑效率提升，與國立臺北大學資管所及資工所合作，開發相關程式，已有25%題項自動或半自動化，大幅提升評鑑效率，並持續開發機械學習，持續透過AI 輔助評鑑進行。另也透過AI SEED團隊持續將部分流程自動化，提升評鑑正確性，減少人力出錯可能。



題號	題目關鍵字	完成度
2-1-15	僅分派董監酬勞未分派股利	100%
2-2-3	獨董達董事席次1/2以上	100%
2-2-4	至少兩名獨董任期不超過9年	100%
2-2-14	設提名委員會且半數以上為獨董	100%
2-2-30	董事長兼任總經理	100%
2-2-31	1/3以上董事任期超過15年	100%
2-3-8	破產 / 面臨下市	100%
2-3-15	資安長或資訊安全委員會	100%
2-4-7	無保留意見	100%

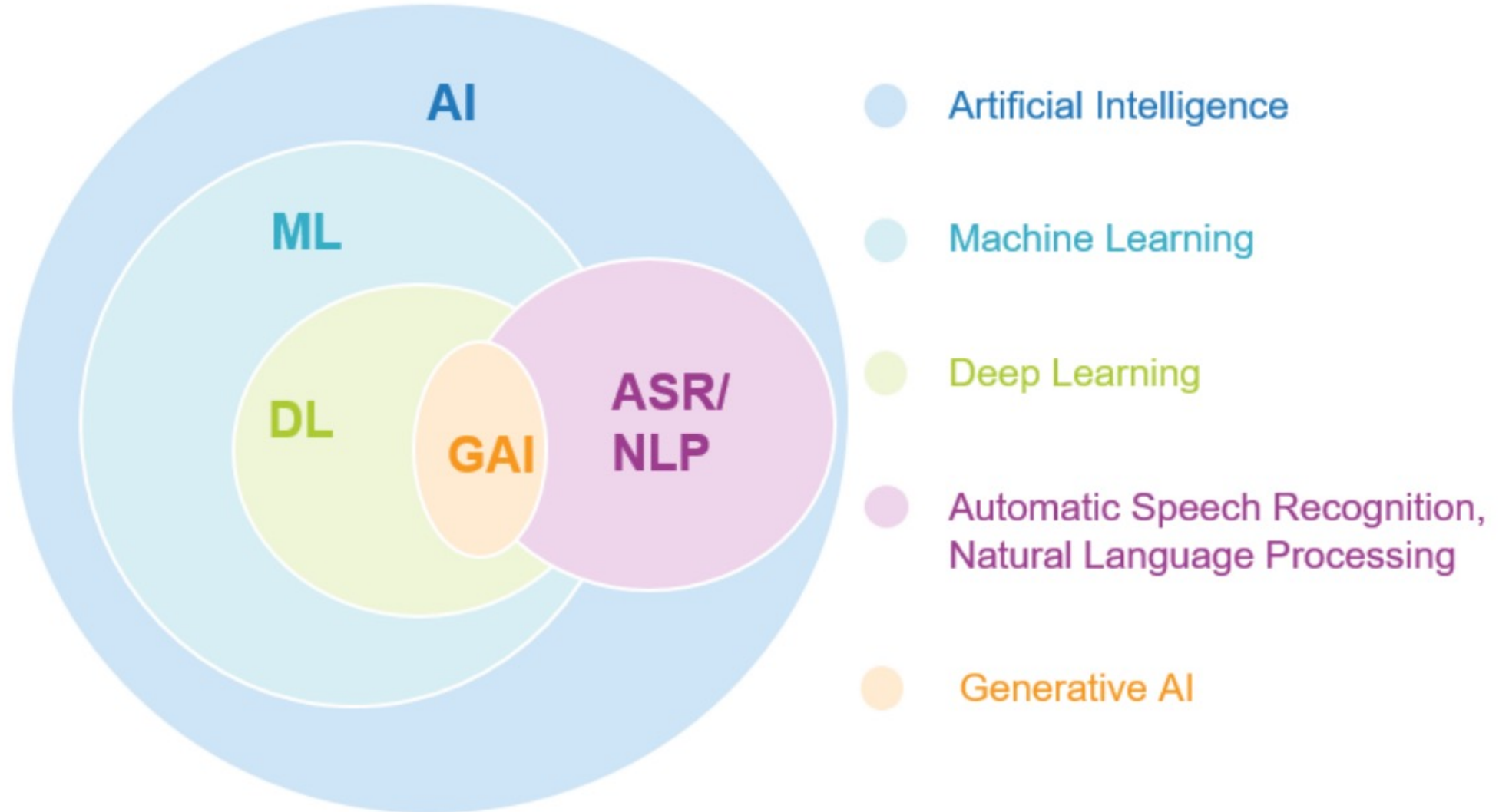
# Generative AI

## Powering

### Digital Sustainability

#### Transformation

# Generative AI



# Generative AI-Driven ESG Report Generation Technology

Industrial Technology Research Institute (ITRI),  
Fintech and Green Finance Center (FGFC, NTPU),  
NTPU-113A513E01, 2024/03/01~2024/12/31

# Sustainability and ESG Data Analytics



# Generative AI and LLMs for Sustainability and ESG Data Analytics





# Net-Zero Transformation

- **Ambition**

- Aligned to achieving global net zero by no later than 2050 & to limit warming to 1.5° C

- **Governance**

- Accountability driven from the top

- **Strategy**

- Embedded and aligned net zero into company strategy

- **Enterprise**

- Key operating model changes in support of transformation

- **Supply chains**

- Transformed net zero supply chains

- **Innovation**

- Developed innovation and technologies to deliver net zero

- **Finance**

- Financing the net zero transformation

- **Transparency**

- Communicating action

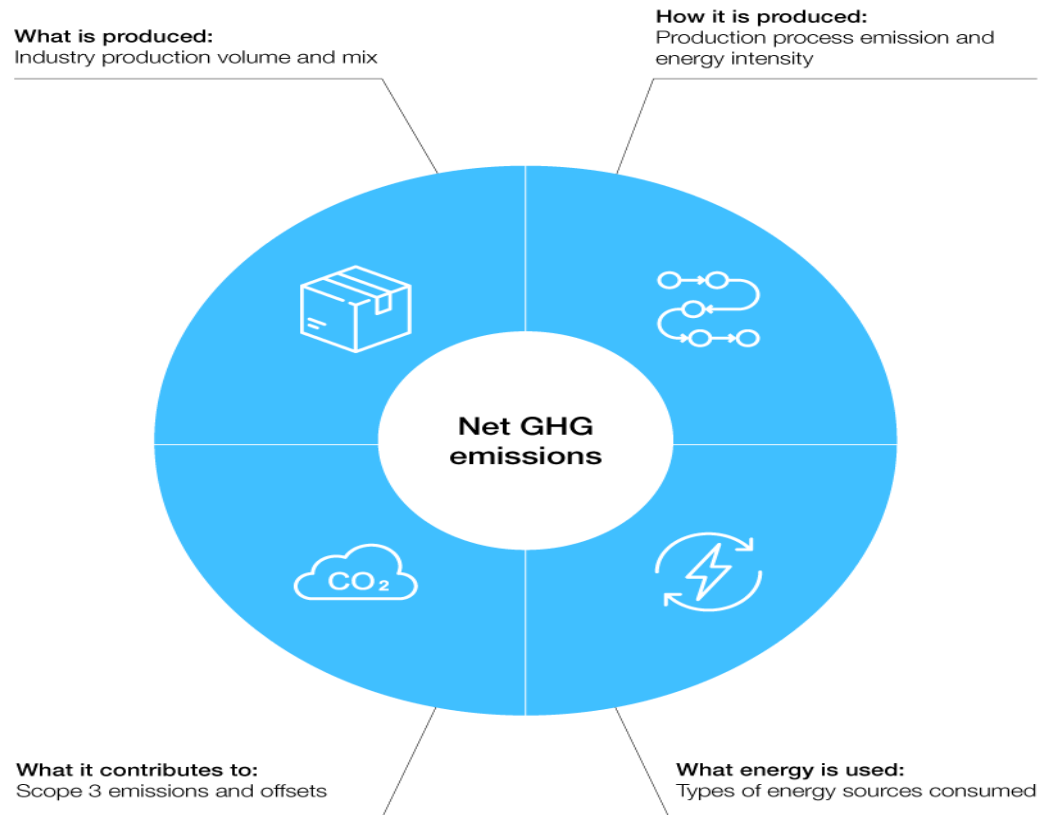
- **Engagement**

- Enhancing the pace and scale of net zero action

# Net-Zero Transformation Enablers

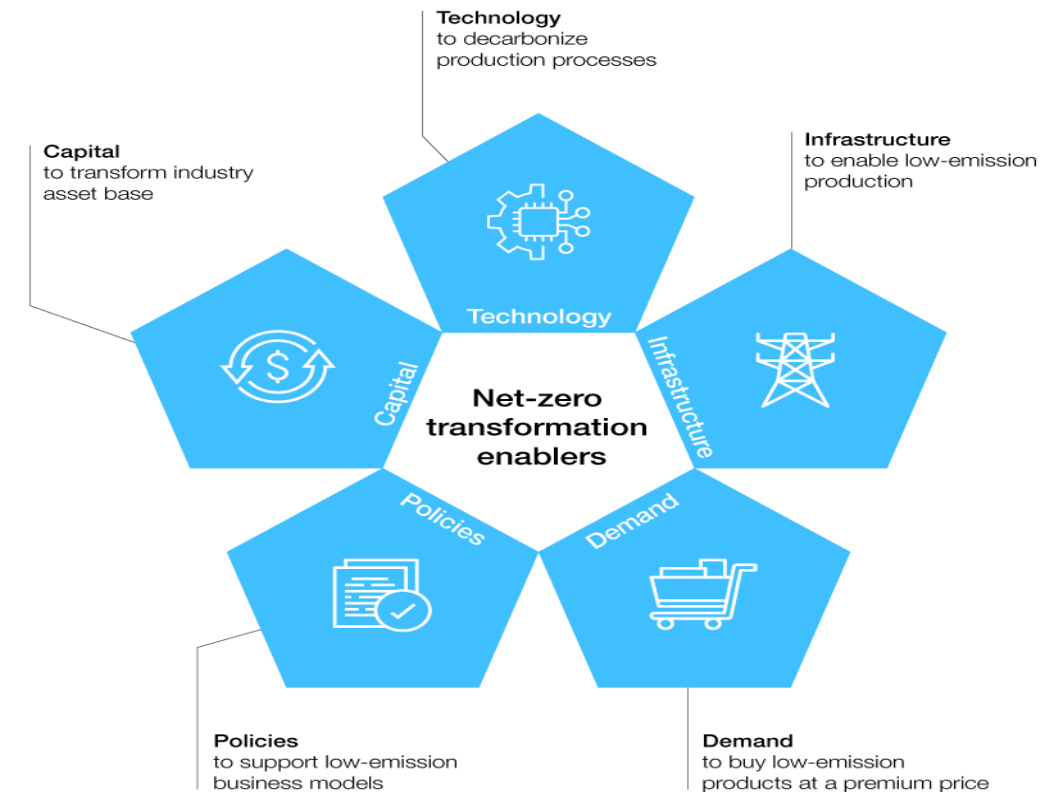
## Net-zero industry performance

The four drivers of industry net greenhouse gas (GHG) emissions:

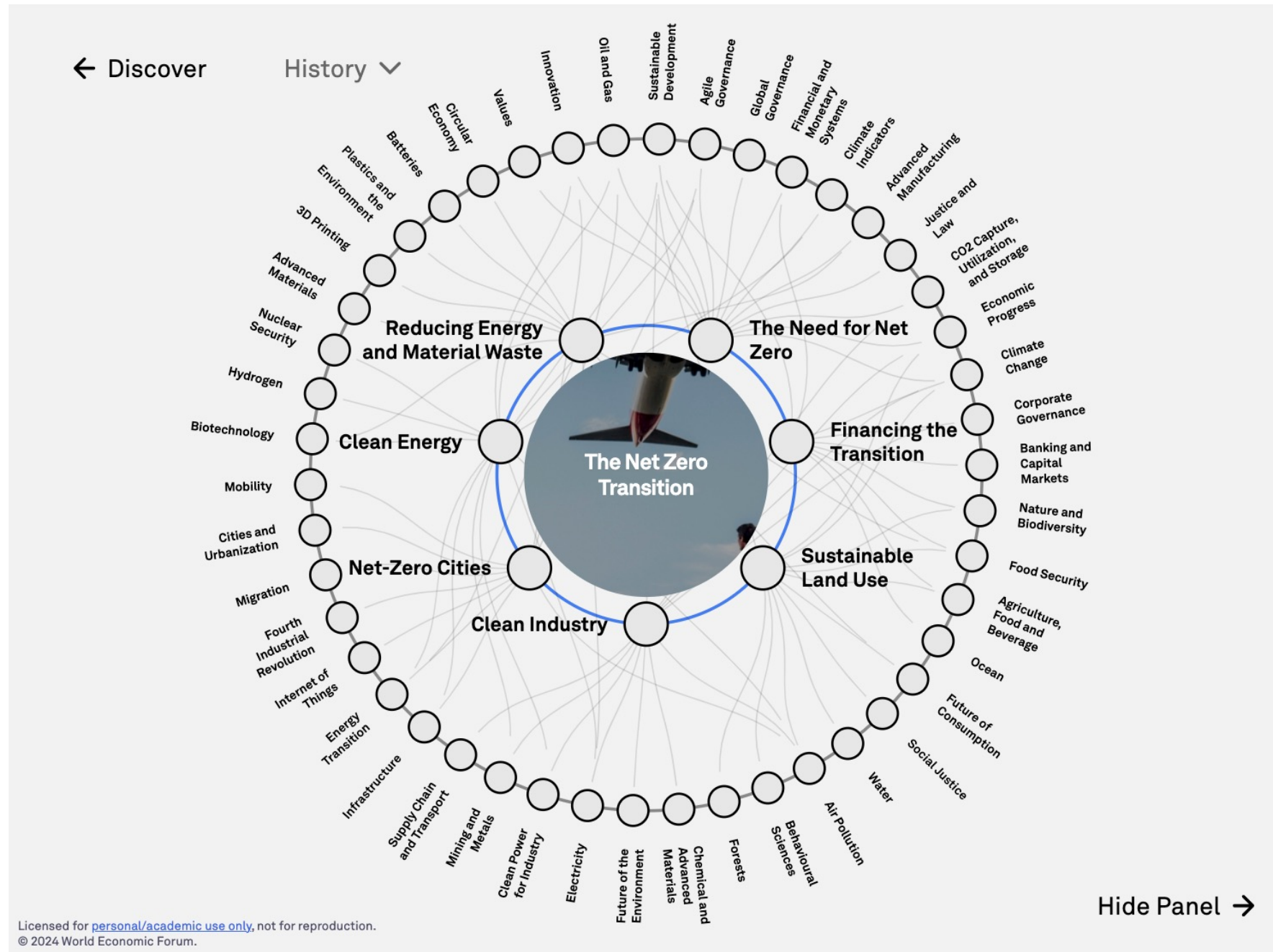


## Net-zero industry readiness

The five enabling dimensions of industry net-zero transformation:

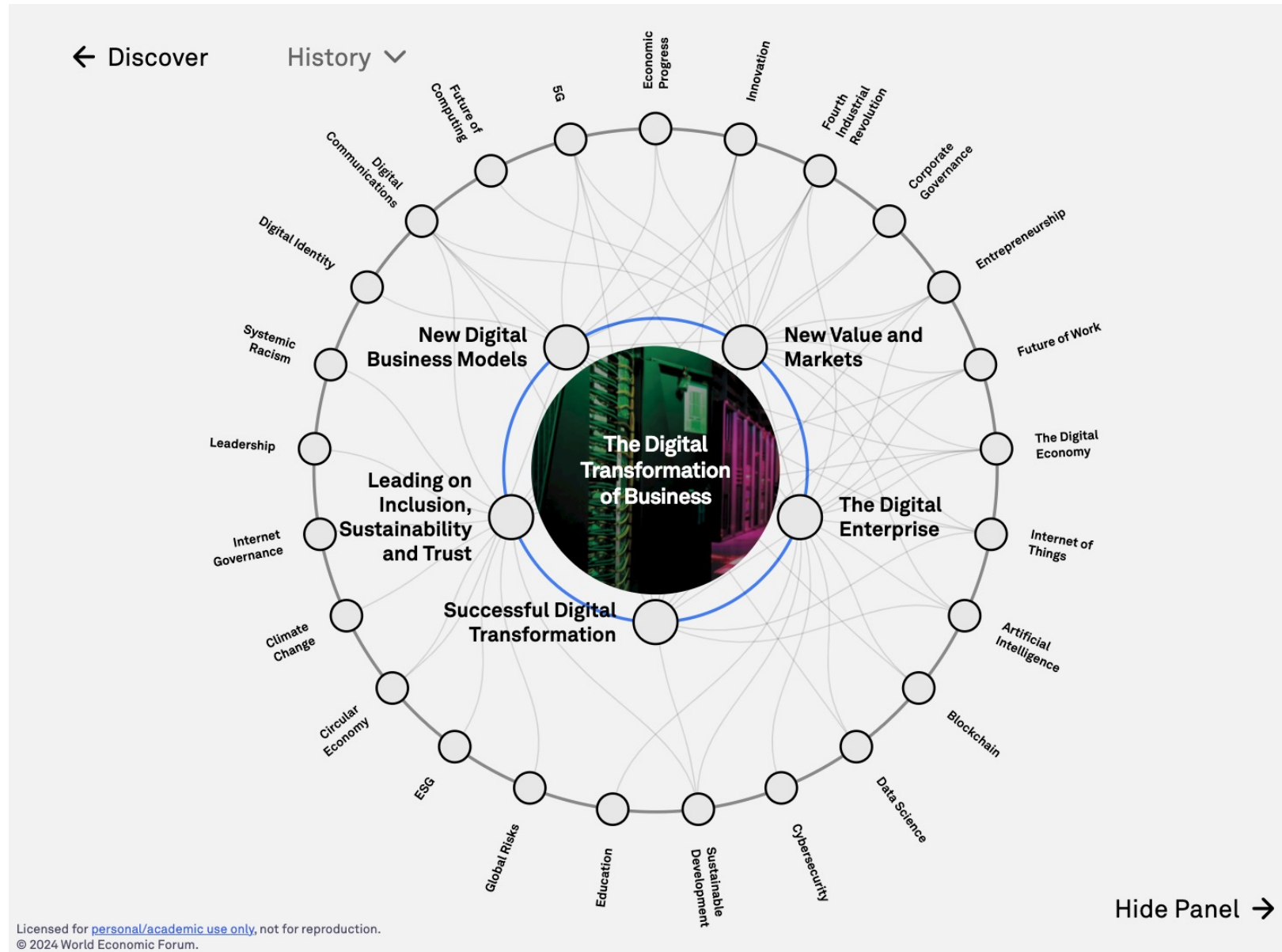


# The Net Zero Transition



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# The Digital Transformation of Business



# Digital Transformation

Dimensions	Categories
A. BUSINESS MODELS	Business Process Innovation Business Strategy
B. DIGITAL BUSINESS	Digital Culture, Literacy and Skills Digital Economy Innovation and Socio-technical Shared Values
C. TECHNOLOGIES	Technology and Innovation Management Artificial Intelligence Big Data Internet of Things Industry 4.0
D. SUSTAINABILITY	Sustainable Business Sustainable Competitive Advantage Sustainable Development Sustainable Innovation
E. HUMAN RESOURCES	Employee Experience Career Dynamics
F. SMART CITIES	Sustainable Smart Manufacturing Digital Manufacturing

**Generative AI and  
Large Language Models  
(LLMs):  
Popular Generative AI  
Applications**

# Generative AI

**Text, Image, Video, Audio  
Applications**

# Popular Generative AI

- **OpenAI ChatGPT (GPT-4o, GPT-4)**
- **Claude.ai (Claude 3.5)**
- **Google Gemini**
- **Chat.LMSys.org**
- **Perplexity.ai**
- **ChatPDF**
- **Stable Diffusion**
- **Video: D-ID, Synthesia**
- **Audio: Speechify**

# OpenAI ChatGPT (GPT-4o, GPT-4)

📄 ✎ ChatGPT 4o ▾

Model ⓘ

- ✦ GPT-4o  
Newest and most advanced model ✓
- ✦ GPT-4  
Advanced model for complex tasks
- ⚡ GPT-3.5  
Great for everyday tasks

---

🔄 Temporary chat



Morning routine  
for productivity

Study vocabulary

👉 Experience  
Seoul like a local

🦋 Superhero  
shark story

📎 Message ChatGPT

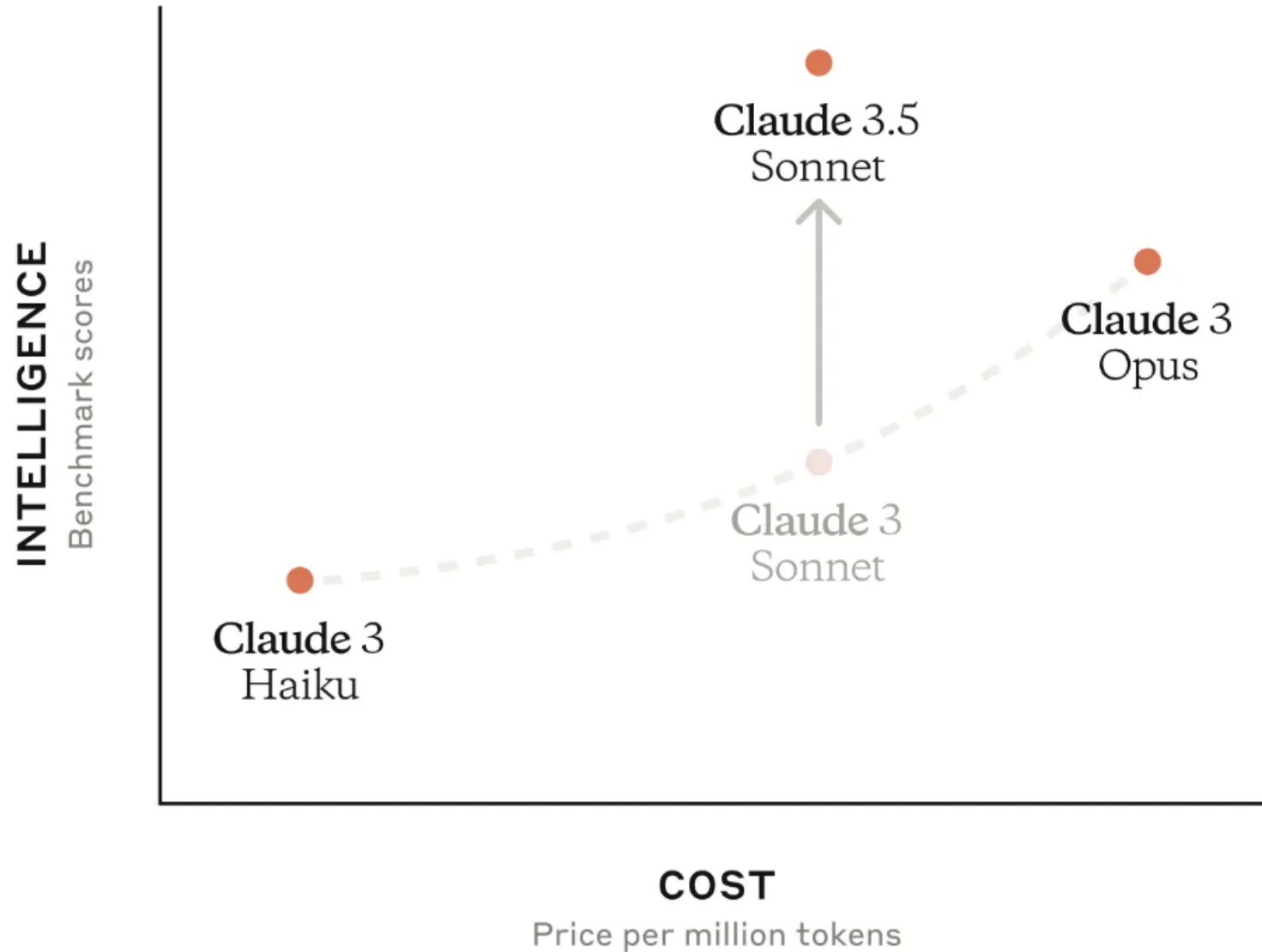


ChatGPT can make mistakes. Check important info.

<https://chat.openai.com/>



# Claude 3.5 Sonnet



# Claude 3.5, GPT-4o, Gemini 1.5 Pro

	Claude 3.5 Sonnet	Claude 3 Opus	GPT-4o	Gemini 1.5 Pro	Llama-400b (early snapshot)
Graduate level reasoning <i>GPQA, Diamond</i>	<b>59.4%*</b> 0-shot CoT	<b>50.4%</b> 0-shot CoT	<b>53.6%</b> 0-shot CoT	—	—
Undergraduate level knowledge <i>MMLU</i>	<b>88.7%**</b> 5-shot	<b>86.8%</b> 5-shot	—	<b>85.9%</b> 5-shot	<b>86.1%</b> 5-shot
	<b>88.3%</b> 0-shot CoT	<b>85.7%</b> 0-shot CoT	<b>88.7%</b> 0-shot CoT	—	—
Code <i>HumanEval</i>	<b>92.0%</b> 0-shot	<b>84.9%</b> 0-shot	<b>90.2%</b> 0-shot	<b>84.1%</b> 0-shot	<b>84.1%</b> 0-shot
Multilingual math <i>MGSM</i>	<b>91.6%</b> 0-shot CoT	<b>90.7%</b> 0-shot CoT	<b>90.5%</b> 0-shot CoT	<b>87.5%</b> 8-shot	—
Reasoning over text <i>DROP, F1 score</i>	<b>87.1</b> 3-shot	<b>83.1</b> 3-shot	<b>83.4</b> 3-shot	<b>74.9</b> Variable shots	<b>83.5</b> 3-shot Pre-trained model
Mixed evaluations <i>BIG-Bench-Hard</i>	<b>93.1%</b> 3-shot CoT	<b>86.8%</b> 3-shot CoT	—	<b>89.2%</b> 3-shot CoT	<b>85.3%</b> 3-shot CoT Pre-trained model
Math problem-solving <i>MATH</i>	<b>71.1%</b> 0-shot CoT	<b>60.1%</b> 0-shot CoT	<b>76.6%</b> 0-shot CoT	<b>67.7%</b> 4-shot	<b>57.8%</b> 4-shot CoT
Grade school math <i>GSM8K</i>	<b>96.4%</b> 0-shot CoT	<b>95.0%</b> 0-shot CoT	—	<b>90.8%</b> 11-shot	<b>94.1%</b> 8-shot CoT

\* Claude 3.5 Sonnet scores 67.2% on 5-shot CoT GPQA with maj@32

\*\* Claude 3.5 Sonnet scores 90.4% on MMLU with 5-shot CoT prompting

# Claude 3.5 Sonnet State-of-the-art vision

	Claude 3.5 Sonnet	Claude 3 Opus	GPT-4o	Gemini 1.5 Pro
Visual math reasoning <i>MathVista (testmini)</i>	<b>67.7%</b> 0-shot CoT	<b>50.5%</b> 0-shot CoT	<b>63.8%</b> 0-shot CoT	<b>63.9%</b> 0-shot CoT
Science diagrams <i>AI2D, test</i>	<b>94.7%</b> 0-shot	<b>88.1%</b> 0-shot	<b>94.2%</b> 0-shot	<b>94.4%</b> 0-shot
Visual question answering <i>MMMU (val)</i>	<b>68.3%</b> 0-shot CoT	<b>59.4%</b> 0-shot CoT	<b>69.1%</b> 0-shot CoT	<b>62.2%</b> 0-shot CoT
Chart Q&A <i>Relaxed accuracy (test)</i>	<b>90.8%</b> 0-shot CoT	<b>80.8%</b> 0-shot CoT	<b>85.7%</b> 0-shot CoT	<b>87.2%</b> 0-shot CoT
Document visual Q&A <i>ANLS score, test</i>	<b>95.2%</b> 0-shot	<b>89.3%</b> 0-shot	<b>92.8%</b> 0-shot	<b>93.1%</b> 0-shot

# Google Gemini

Largest and most capable AI model  
Making AI more helpful for everyone



# Chat with Open Large Language Models

[chat.lmsys.org](https://chat.lmsys.org)

## ✂ Chatbot Arena ✂ : Benchmarking LLMs in the Wild

[Mixtral of experts](#): A Mixture-of-Experts model by Mistral AI

[Gemini](#): Gemini by Google

[GPT-4-Turbo](#): GPT-4-Turbo by OpenAI

[Claude Instant](#): Claude Instant by Anthropic

[Llama2-70B-SteerLM-Chat](#): A Llama fine-tuned with SteerLM method by NVIDIA

[Starling-LM-7B-alpha](#): An open model trained using RLAI by Berkeley

[Llama 2](#): Open foundation and fine-tuned chat models by Meta

[Code Llama](#): Open foundation models for code by Meta

[Qwen 1.5](#): A large language model by Alibaba Cloud

[DeepSeek LLM](#): An advanced language model by DeepSeek

[GPT-3.5](#): GPT-3.5-Turbo by OpenAI

[Nous-Hermes-2-Mixtral-8x7B-DPO](#): Nous Hermes finetuned from Mixtral 8x7B

[pplx-online-llms](#): Online LLM API by Perplexity AI

[Tulu 2](#): An instruction and RLHF model by UW/AllenAI

[Vicuna](#): A chat assistant fine-tuned on user-shared conversations by LMSYS

[WizardLM](#): An instruction-following LLM using evol-instruct by Microsoft

[Bard](#): Bard by Google

[StripedHyena-Nous](#): A chat model developed by Together Research and Nous Research.

[Claude](#): Claude 2 by Anthropic

[OpenChat 3.5](#): An open model fine-tuned on Mistral-7B using C-RLFT

[OpenHermes-2.5-Mistral-7B](#): A mistral-based model fine-tuned on 1M GPT-4 outputs

[Yi-Chat](#): A large language model by 01 AI

[Zephyr](#): A chatbot fine-tuned from Mistral by Hugging Face

<https://chat.lmsys.org/>

# Large Language Models for Data Science

## Llama 2-70b-chat

llama-2-70b-chat

Model A

Large Language Models for Data Science

Large language models have gained significant attention in recent years for their ability to process and analyze natural language data. These models have been successfully applied in various fields such as natural language processing, text classification, sentiment analysis, and machine translation. In data science, large language models can be used for a variety of tasks, including data cleaning, data transformation, and data analysis.

In this article, we will explore the use of large language models for data science tasks and discuss their advantages and limitations. We will also provide examples of large language models that can be used for data science applications.

Advantages of Large Language Models for Data

## Mistral-7b-instruct

mistral-7b-instruct

Model B

Large Language Models for Data Science

Large Language Models (LLMs) are becoming increasingly important in data science due to their ability to understand and generate natural language text. Here are some of the key ways that LLMs can be used in data science:

1. Text classification: LLMs can be trained on large datasets of labeled text and then used to classify new text into different categories. This can be useful in a variety of applications, such as sentiment analysis, spam filtering, and topic classification.
2. Named entity recognition: LLMs can also be used to identify and extract specific pieces of information from text, such as names of people, organizations, and locations. This can be useful in applications such as information extraction

<https://chat.lmsys.org/>

# Chat with Open Large Language Models: Chatbot Arena

# Chatbot Arena Leaderboard

## LLM Leaderboard

Rank* (UB) ▲	Model ▲	Arena Elo ▲	95% CI ▲	Votes ▲	Organization ▲	License ▲	Knowledge Cutoff ▲
1	<a href="#">GPT-4o-2024-05-13</a>	1287	+3/-3	46179	OpenAI	Proprietary	2023/10
2	<a href="#">Claude 3.5 Sonnet</a>	1272	+6/-8	7278	Anthropic	Proprietary	2024/4
2	<a href="#">Gemini-Advanced-0514</a>	1267	+3/-4	36867	Google	Proprietary	Online
2	<a href="#">Gemini-1.5-Pro-API-0514</a>	1263	+4/-4	39321	Google	Proprietary	2023/11
4	<a href="#">Gemini-1.5-Pro-API-0409-Preview</a>	1257	+3/-3	55731	Google	Proprietary	2023/11
4	<a href="#">GPT-4-Turbo-2024-04-09</a>	1257	+3/-3	68075	OpenAI	Proprietary	2023/12
7	<a href="#">GPT-4-1106-preview</a>	1251	+2/-2	84482	OpenAI	Proprietary	2023/4
7	<a href="#">Claude 3 Opus</a>	1248	+2/-2	136753	Anthropic	Proprietary	2023/8
7	<a href="#">GPT-4-0125-preview</a>	1246	+3/-2	77746	OpenAI	Proprietary	2023/12
10	<a href="#">Yi-Large-preview</a>	1240	+3/-3	43372	01 AI	Proprietary	Unknown
11	<a href="#">Gemini-1.5-Flash-API-0514</a>	1229	+3/-4	36996	Google	Proprietary	2023/11
12	<a href="#">Yi-Large</a>	1215	+6/-6	7930	01 AI	Proprietary	Unknown
12	<a href="#">Bard (Gemini Pro)</a>	1208	+7/-5	11853	Google	Proprietary	Online
12	<a href="#">GLM-4-0520</a>	1208	+8/-7	6258	Zhipu AI	Proprietary	Unknown
12	<a href="#">Llama-3-70b-Instruct</a>	1207	+3/-2	139037	Meta	Llama 3 Community	2023/12
12	<a href="#">Nemotron-4-340B-Instruct</a>	1205	+5/-5	13461	Nvidia	NVIDIA Open Model	2023/6

# Perplexity.ai



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Try Pro  
Upgrade to Claude-2 or GPT-4, boost Copilot uses, and upload more files.  
Learn More

Download

## Large Language Models for Data Science

### Sources

- What Is a Large Language Model and What Can... snowflake · 1
- What are Large Language Models? | NVIDIA nvidia · 2
- Catch Up On Large Language Models | by... towardsdatascien... · 3
- View 3 more

### Answer

Large Language Models (LLMs) are advanced AI systems designed to understand human language intricacies and generate intelligent, creative responses to queries <sup>1</sup>. They are deep learning algorithms that can recognize, summarize, translate, predict, and generate content using very large datasets <sup>2</sup>. LLMs are trained on enormous data sets typically measured in petabytes, sourced from books, articles, websites, and other text-based sources <sup>1</sup>. They are dynamic tools that are continuously updated and refined as new data becomes available <sup>1</sup>.

In the field of data science, LLMs can potentially transform how teams source, manage, and analyze data <sup>1</sup>. They are used in numerous data science applications, and their ability to process and interpret vast amounts of text data has made them an indispensable part of m

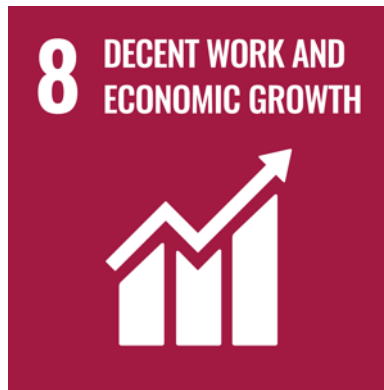
Ask follow-up... Copilot

social media posts or customer reviews, to determine whether the overall sentiment is

<https://www.perplexity.ai/>

**Generative AI for  
Sustainable  
Development  
Innovative Applications**

# Sustainable Development Goals (SDGs)



# Evolution of Sustainable Finance Research



Source: Kumar, S., Sharma, D., Rao, S., Lim, W. M., & Mangla, S. K. (2022). Past, present, and future of sustainable finance: Insights from big data analytics through machine learning of scholarly research. *Annals of Operations Research*, 1-44.

# Sustainable Development Goals (SDGs) and 5P

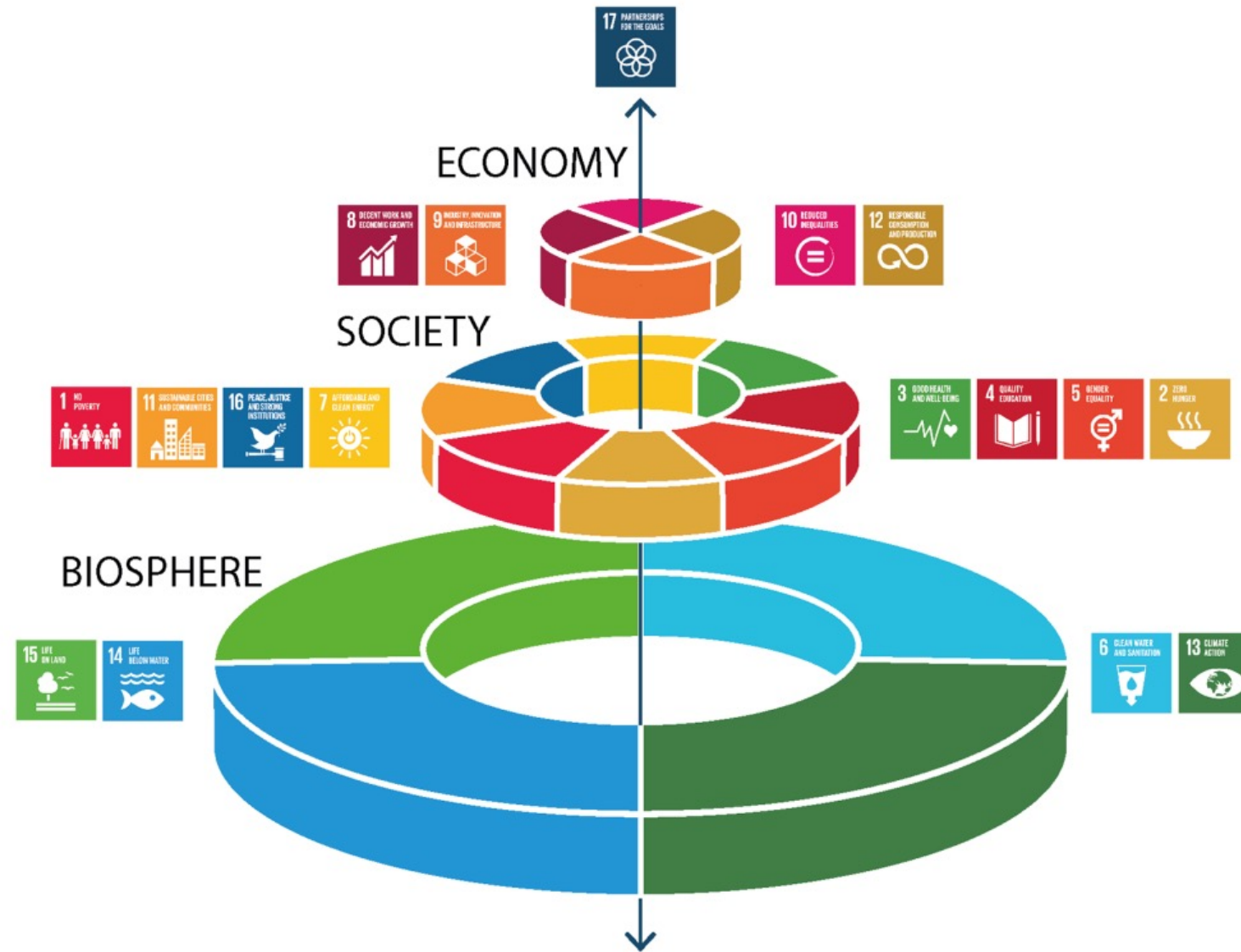
Partnership

Peace

Prosperity

People

Planet



# ESG to 17 SDGs

## ENVIRONMENT



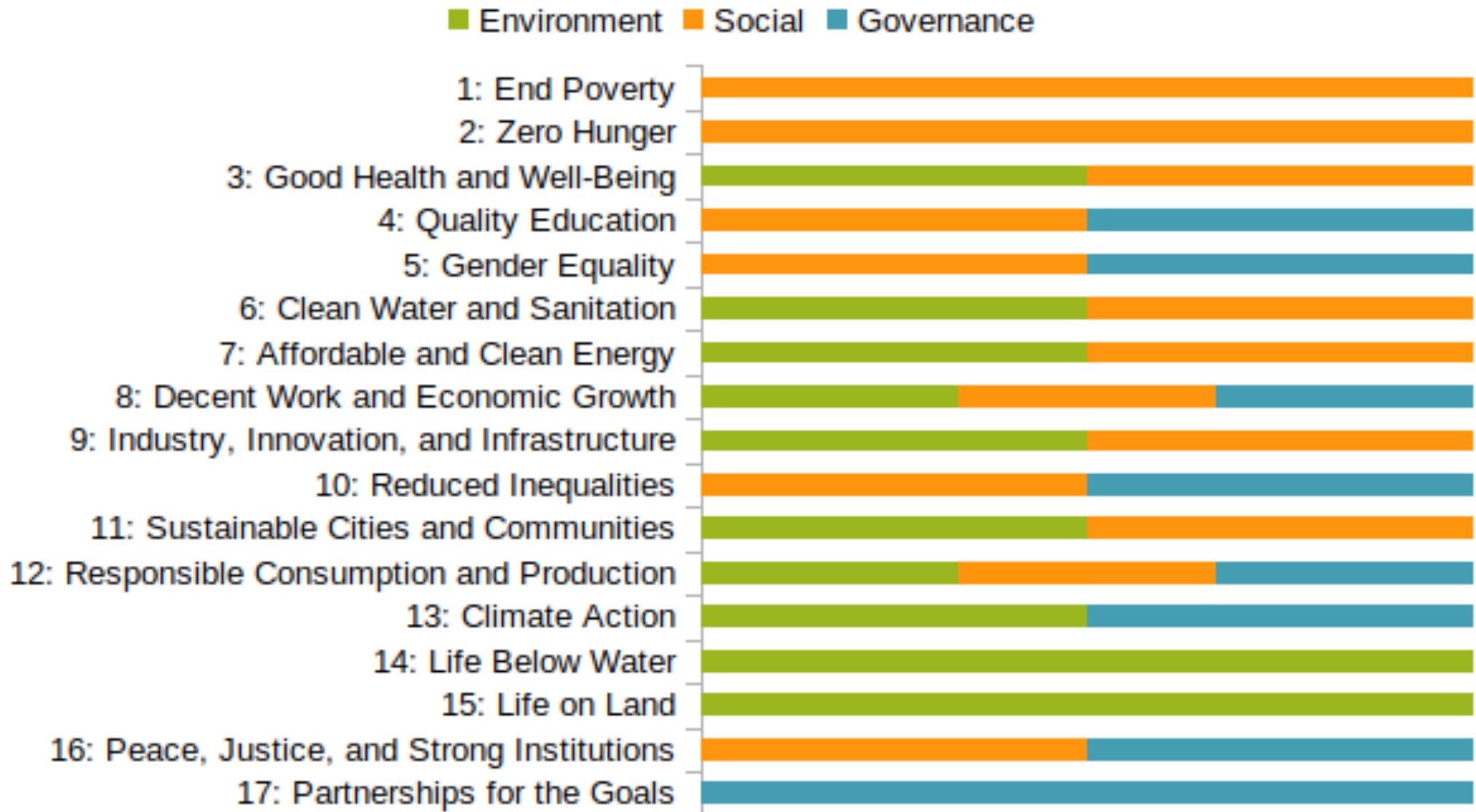
## SOCIAL



## GOVERNANCE



# ESG to 17 SDGs



# Digital Transformation: Enabler and Challenge

- **Enabler**

- **Data-driven decision-making, efficiency gains, new business models, collaboration**
- **AI optimizing renewable energy**

- **Challenge**

- **Energy consumption, e-waste, planned obsolescence, AI ethics**
- **AI servers representing increased energy use**

# Mapping the ESG Standards Landscape

- **The most prevalent ESG reporting frameworks**
  - **GRI (Global Report Initiative)**
  - **CDP (Carbon Disclosure Project)**
  - **SASB (Sustainability Accounting Standards Board)**
  - **ISSB (International Sustainability Standards Board)**
  - **TCFD (Task Force on Climate-related Financial Disclosures)**
- **How companies choose**
  - **Materiality, industry-specific standards, investor alignment**

# GRI (Global Report Initiative)



Standards ▾

How to use the GRI Standards ▾

Reporting support ▾

Public policy & partnerships ▾

About GRI ▾

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Goals and targets database

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## The global leader for impact reporting

Welcome to GRI. For over 25 years, we have developed and delivered the global best practice for how organizations communicate and demonstrate accountability for their impacts on the environment, economy and people.

We provide the world's most widely used sustainability reporting standards, which cover topics that range from biodiversity to tax, waste to emissions, diversity and equality to health and safety. As such, GRI reporting is the enabler for transparency and dialogue between companies and their stakeholders.

[Access the GRI Standards →](#)

Feedback

# CDP (Carbon Disclosure Project)



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CDP is a not-for-profit charity that runs the global disclosure system for [investors](#), [companies](#), [cities](#), [states and regions](#) to manage their environmental impacts. Over the past 20 years we have created a system that has resulted in unparalleled engagement on environmental issues worldwide. Find out more about [how we work](#).

<https://www.cdp.net/>

# SASB (Sustainability Accounting Standards Board)

IFRS Foundation

Other Resources: [The ISSB](#) [Integrated Reporting Framework](#)



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An aerial photograph of a landscape featuring a winding river through green fields and a dense forest of trees with some autumn-colored foliage.

**SASB Standards: Your pathway to ISSB**

[Learn more](#)

<https://sasb.org/>

# ISSB (International Sustainability Standards Board)



ABOUT US | IFRS ACCOUNTING | IFRS SUSTAINABILITY

Home > International Sustainability Standards Board

## International Sustainability Standards Board

ABOUT

MEMBERS

MEETINGS

RESOURCES

NEWS

### About the International Sustainability Standards Board

The Trustees of the IFRS Foundation announced the formation of the International Sustainability Standards Board (ISSB) on 3 November 2021 at COP26 in Glasgow, following strong market demand for its establishment. The ISSB is developing—in the public interest—standards that will result in a high-quality, comprehensive global baseline of sustainability disclosures focused on the needs of investors and the financial markets.

Sustainability factors are becoming a mainstream part of investment decision-making. There are increasing calls for companies to provide high-quality, globally comparable information on sustainability-related risks and opportunities, as indicated by feedback from many consultations with market

#### Related information

[Sustainability FAQs](#)

[General Sustainability-related Disclosures project](#)

[Climate-related Disclosures project](#)

[Consolidated organisations](#)

<https://www.ifrs.org/groups/international-sustainability-standards-board/>

# TCFD

## (Task Force on Climate-related Financial Disclosures)



<https://www.ifrs.org/sustainability/tcf/>



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Home > ISSB and TCFD

### ISSB and TCFD

The Financial Stability Board has announced that the work of the TCFD has been completed, with the ISSB's Standards marking the '**culmination of the work of the TCFD**'.

Companies applying IFRS S1 *General Requirements for Disclosure of Sustainability-related Financial Information* and IFRS S2 *Climate-related Disclosures* will meet the TCFD recommendations as the recommendations are fully incorporated into the ISSB's Standards.

Companies can continue to use the **TCFD recommendations** should they choose to do so, and some companies may still be required to use the TCFD recommendations. Using the recommendations is a good entry point for companies as they move to use the ISSB's Standards.

The IFRS Foundation has **published a comparison** of the requirements in IFRS S2 and the TCFD recommendations.

#### Related Information

[IFRS Foundation welcomes culmination of TCFD work and transfer of TCFD monitoring responsibilities to ISSB from 2024](#)

[Comparison: IFRS S2 Climate-related Disclosures with the TCFD Recommendations](#)

[Resource: Making the transition from TCFD to ISSB](#)

[IFRS Sustainability Standards Navigator](#)

<https://www.fsb-tcf.org/>

# The En-ROADS Climate Solutions Simulator



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## THE EN-ROADS CLIMATE SOLUTIONS SIMULATOR

En-ROADS is an online simulator that provides policymakers, educators, businesses, the media, and the public with the ability to test and explore cross-sector climate solutions.

[EXPLORE THE EN-ROADS SIMULATOR >](#)

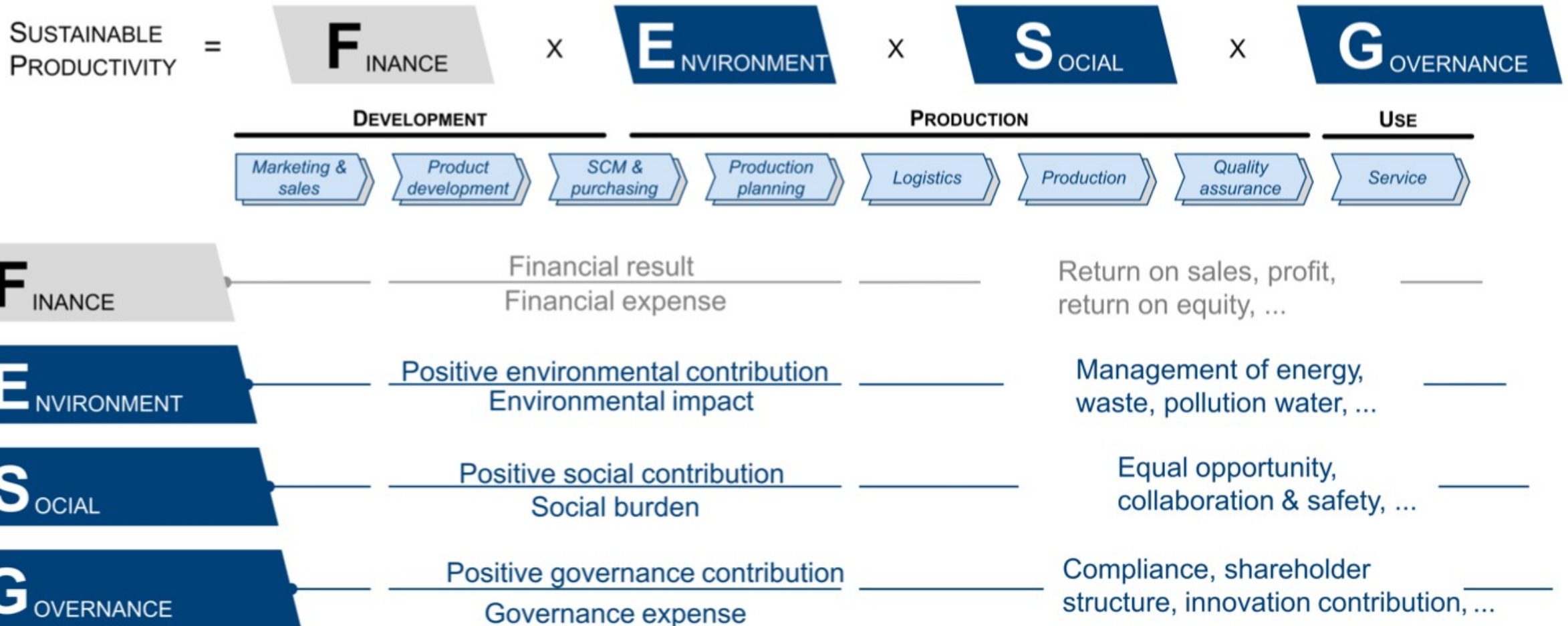
<https://www.climateinteractive.org/en-roads/>

# The Human Impact of ESG Choices

- **Digital Initiatives**
- **This isn't abstract, it's about improving lives**
- **Positive potential when ESG is prioritized**

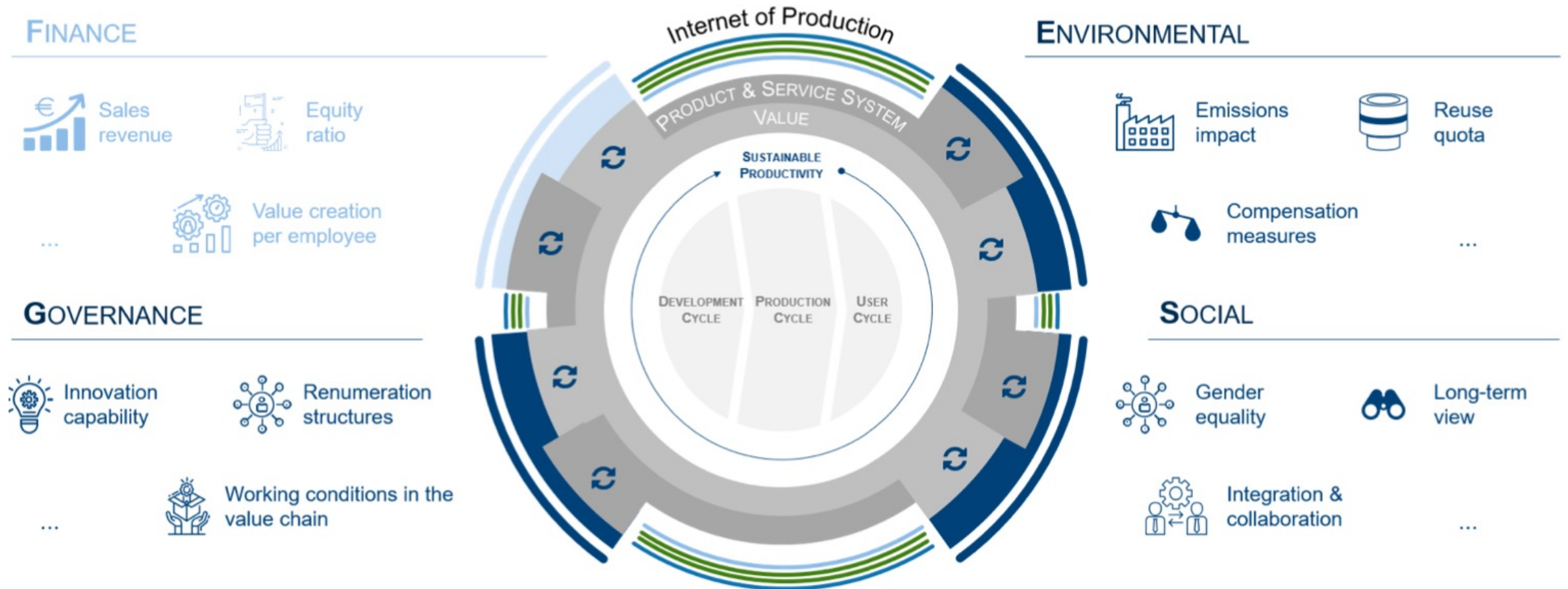


# Sustainable Productivity: Finance ESG



# Sustainable Resilient Manufacturing

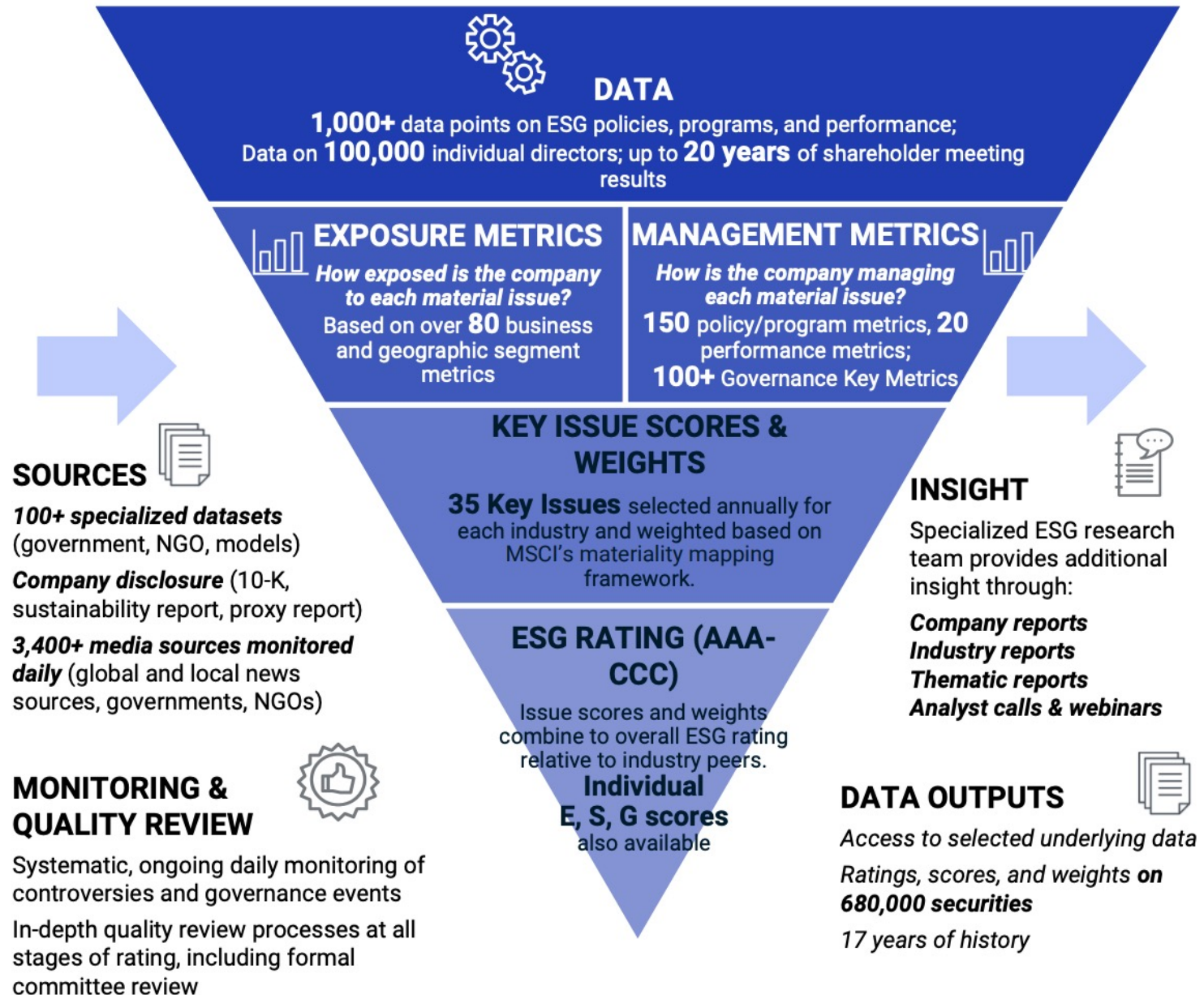
## ESG



# ESG Indexes

- **MSCI ESG Index**
- **Dow Jones Sustainability Indices (DJSI)**
- **FTSE ESG Index**

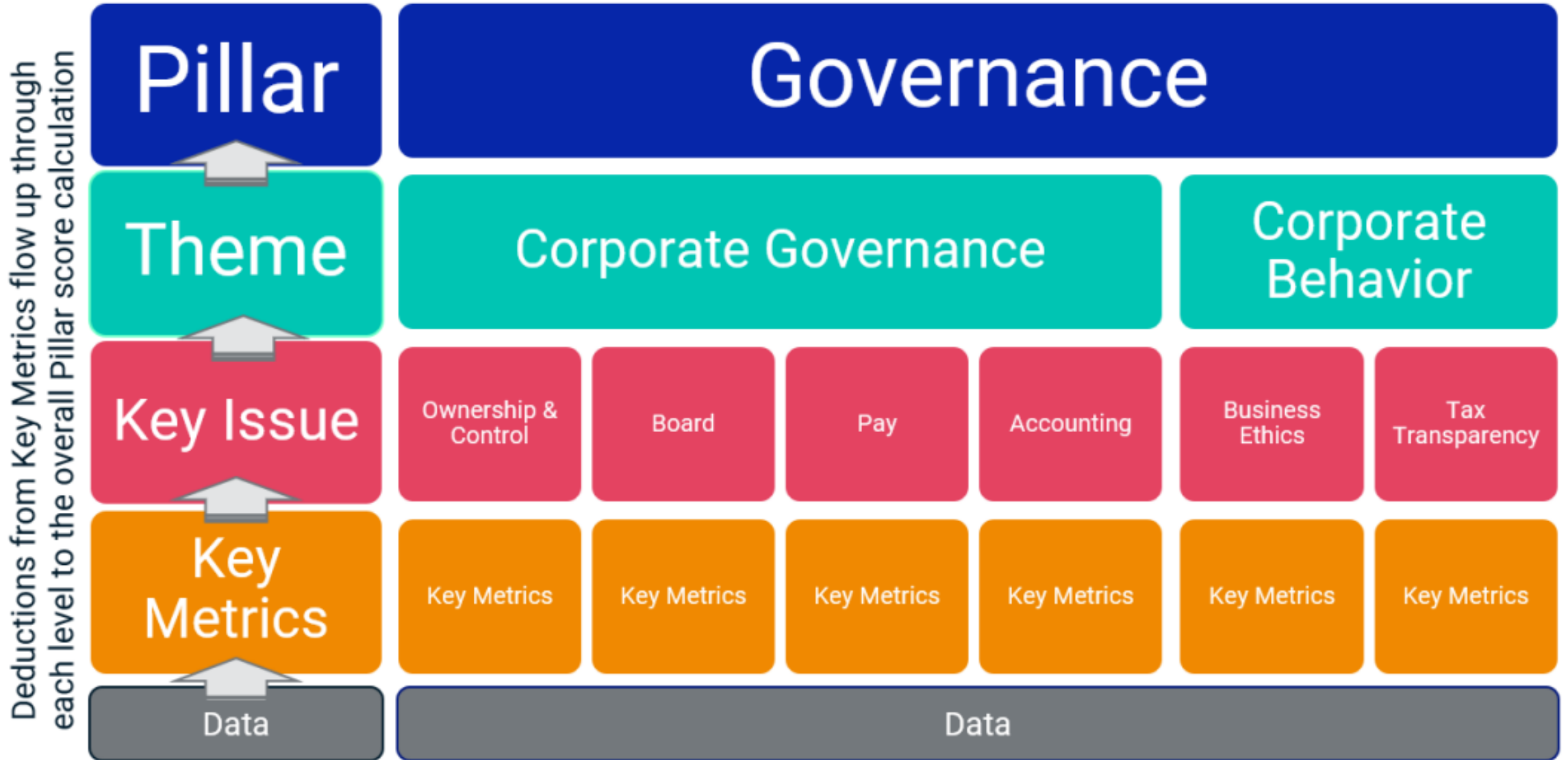
# MSCI ESG Rating Framework



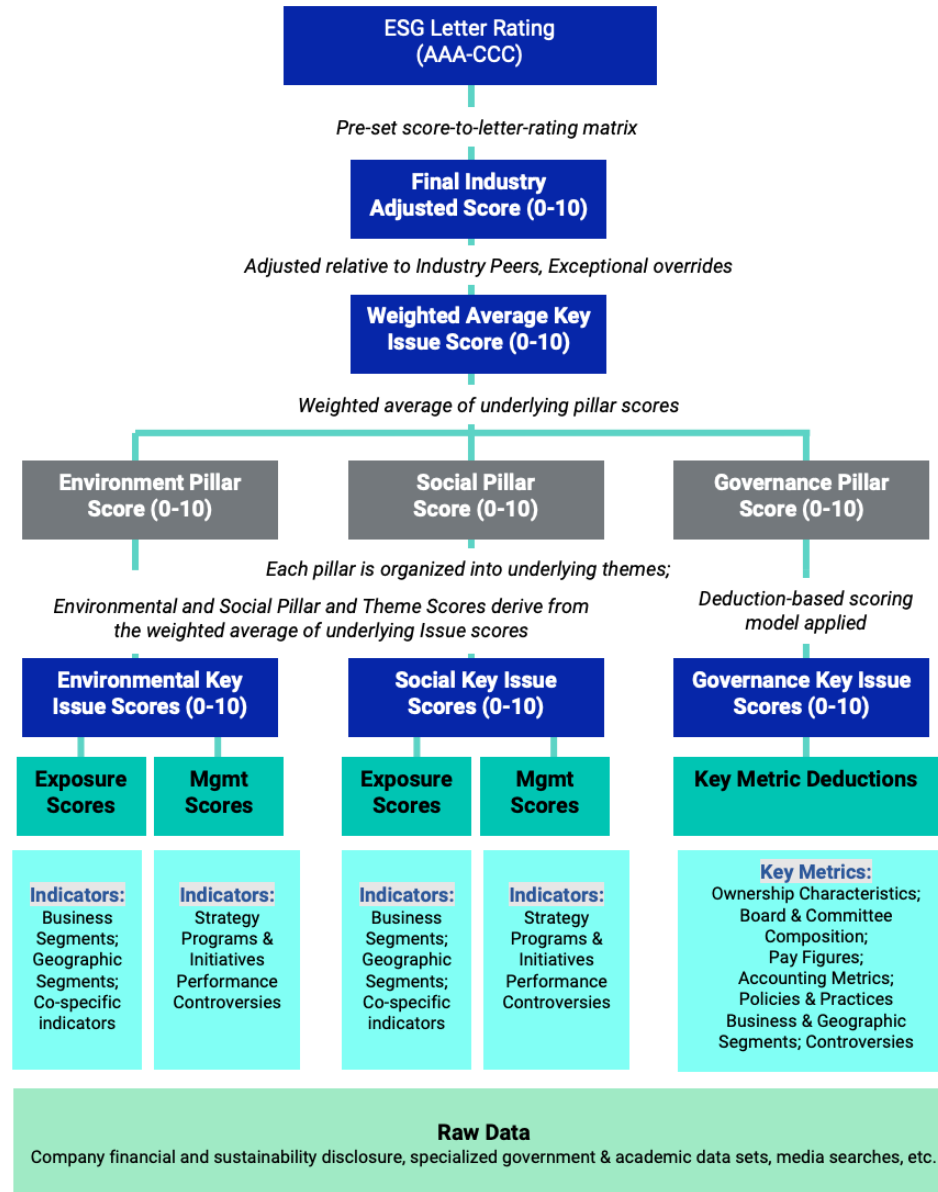
# MSCI ESG Key Issue Hierarchy

3 Pillars	10 Themes	35 ESG Key Issues	
<b>Environment</b>	<b>Climate Change</b>	Carbon Emissions Product Carbon Footprint	Financing Environmental Impact Climate Change Vulnerability
	<b>Natural Capital</b>	Water Stress Biodiversity & Land Use	Raw Material Sourcing
	<b>Pollution &amp; Waste</b>	Toxic Emissions & Waste Packaging Material & Waste	Electronic Waste
	<b>Environmental Opportunities</b>	Opportunities in Clean Tech Opportunities in Green Building	Opportunities in Renewable Energy
<b>Social</b>	<b>Human Capital</b>	Labor Management Health & Safety	Human Capital Development Supply Chain Labor Standards
	<b>Product Liability</b>	Product Safety & Quality Chemical Safety Consumer Financial Protection	Privacy & Data Security Responsible Investment Health & Demographic Risk
	<b>Stakeholder Opposition</b>	Controversial Sourcing Community Relations	
	<b>Social Opportunities</b>	Access to Communications Access to Finance	Access to Health Care Opportunities in Nutrition & Health
<b>Governance</b>	<b>Corporate Governance</b>	Ownership & Control Board	Pay Accounting
	<b>Corporate Behavior</b>	Business Ethics Tax Transparency	

# MSCI Governance Model Structure



# MSCI Hierarchy of ESG Scores

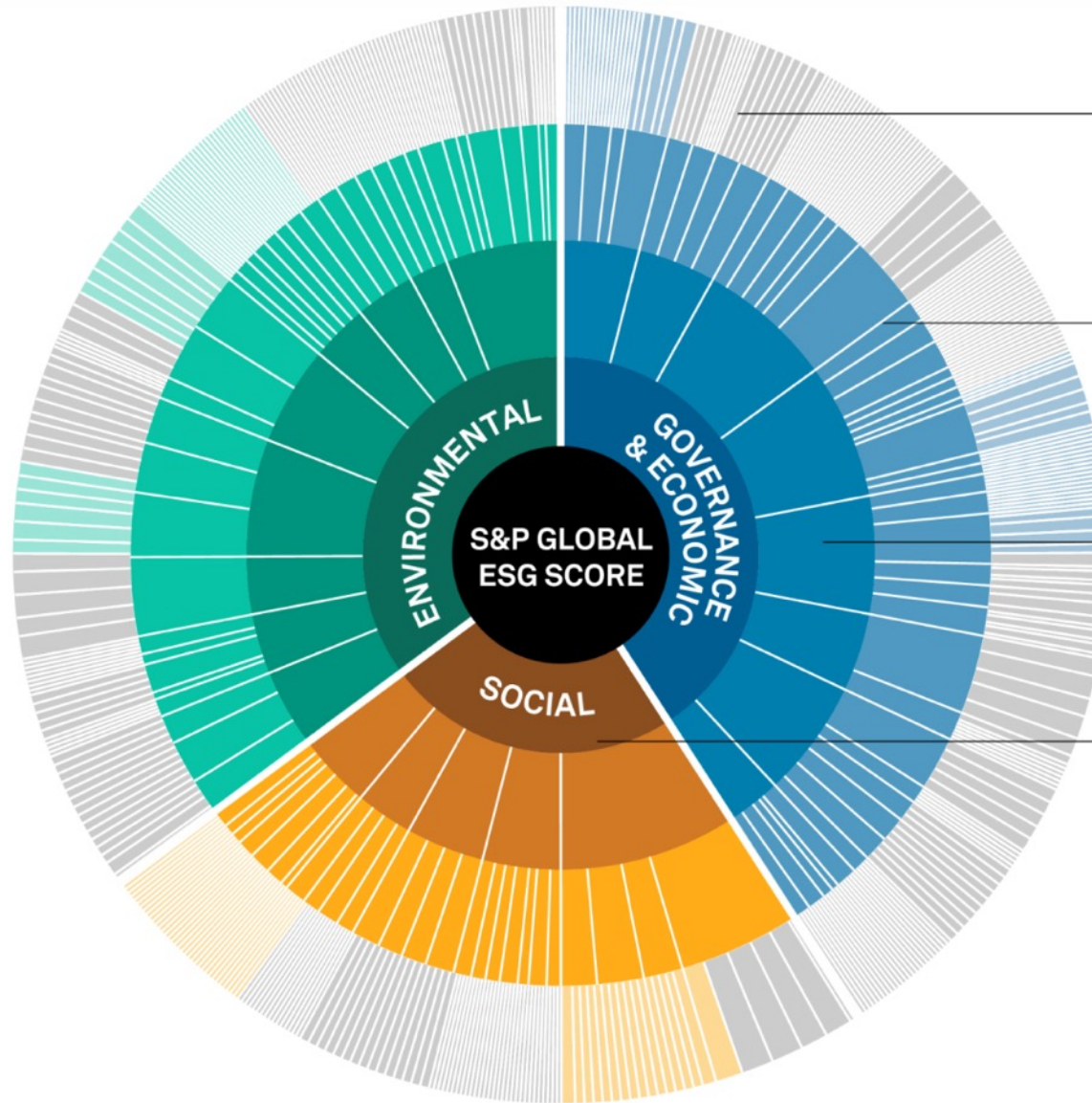


# DJSI S&P Global ESG Score

**8,000**  
Companies

**90%**  
Global market capitalization

**340,000+**  
Current Research Universe and Active Securities



Approx.  
**1,000**  
Datapoints

**Assessed values, text, checkboxes, documents**  
Sources: Web-based questionnaire and company documents

**130+**  
Questions

**Weighted data point scores**  
Up to 50% industry-specific

Ave.  
**30+**  
Criteria scores

**Weighted question scores**  
61 industry specific approaches, with tailored questions, criteria and related weightings

**3**  
Dimension scores

**Weighted criteria scores**  
Adjusted for corporate ESG controversies where applicable

**1**

**S&P Global ESG Score**

**Sum of weighted dimension scores**

# FTSE Russell ESG Ratings



# Sustainalytics

## ESG Risk Ratings

Analyst-based  
approach

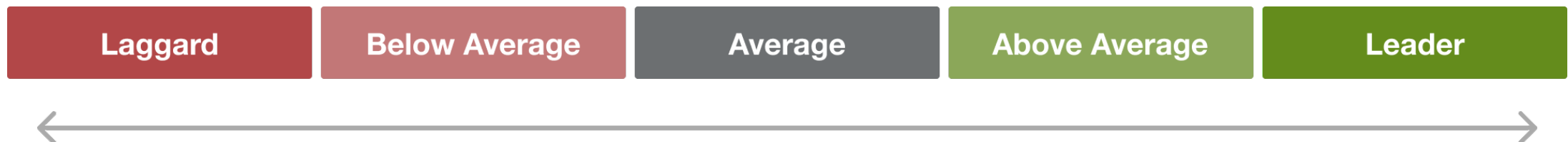
Sustainalytics' ESG Risk Ratings measure a company's exposure to industry-specific material ESG risks and how well a company is managing those risks.

Negligible	Low	Medium	High	Severe
0 - 10	10 - 20	20 - 30	30 - 40	40+

# Truvalue ESG Ranks

Machine-based  
approach

- **Truvalue Labs** applies **AI** to analyze over **100,000 sources** and uncover **ESG risks** and opportunities hidden in **unstructured text**.
- The ESG Ranks data service produces an overall company rank based on industry percentile leveraging the **26 ESG categories** defined by the **Sustainability Accounting Standards Board (SASB)**.
- The data feed covers **20,000+** companies with more than **13 years** of history.



# Analyst-driven vs. AI-driven ESG

## Analyst-driven ESG research

Derives ratings in a structured data model

## Sustainalytics



*Analyst role at the end of the process allows subjectivity to color results*

## AI-driven ESG research

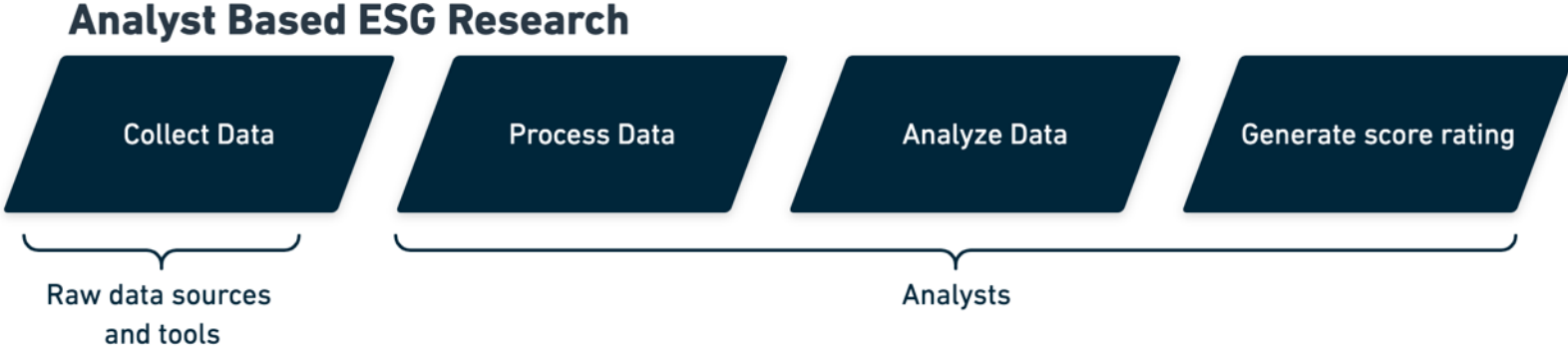
Derives signals from unstructured data

## Truvalue Labs

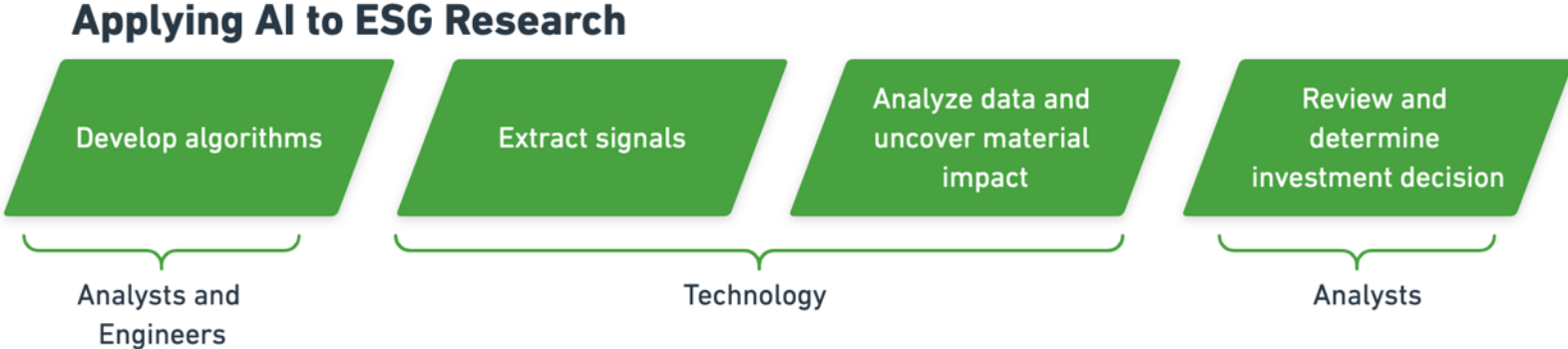


*Analyst expertise at the beginning of the process produces consistent results*

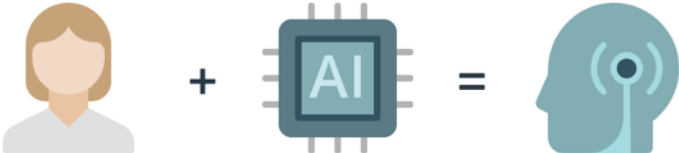
# Analyst based ESG Research



# AI based ESG Research

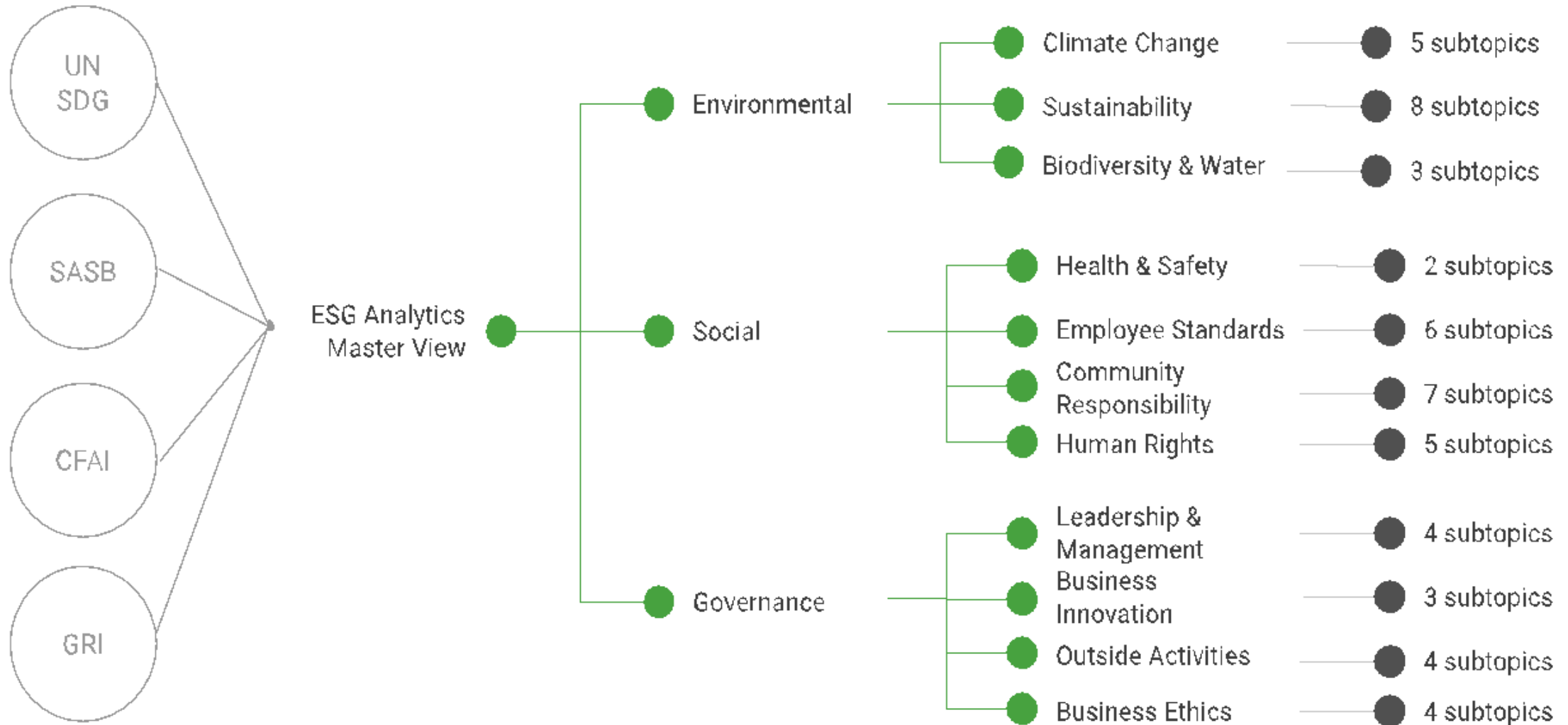


**It would take an analyst over 5 years to do what our AI can in 1 week**  
Combining analysts with AI creates gives you the full picture



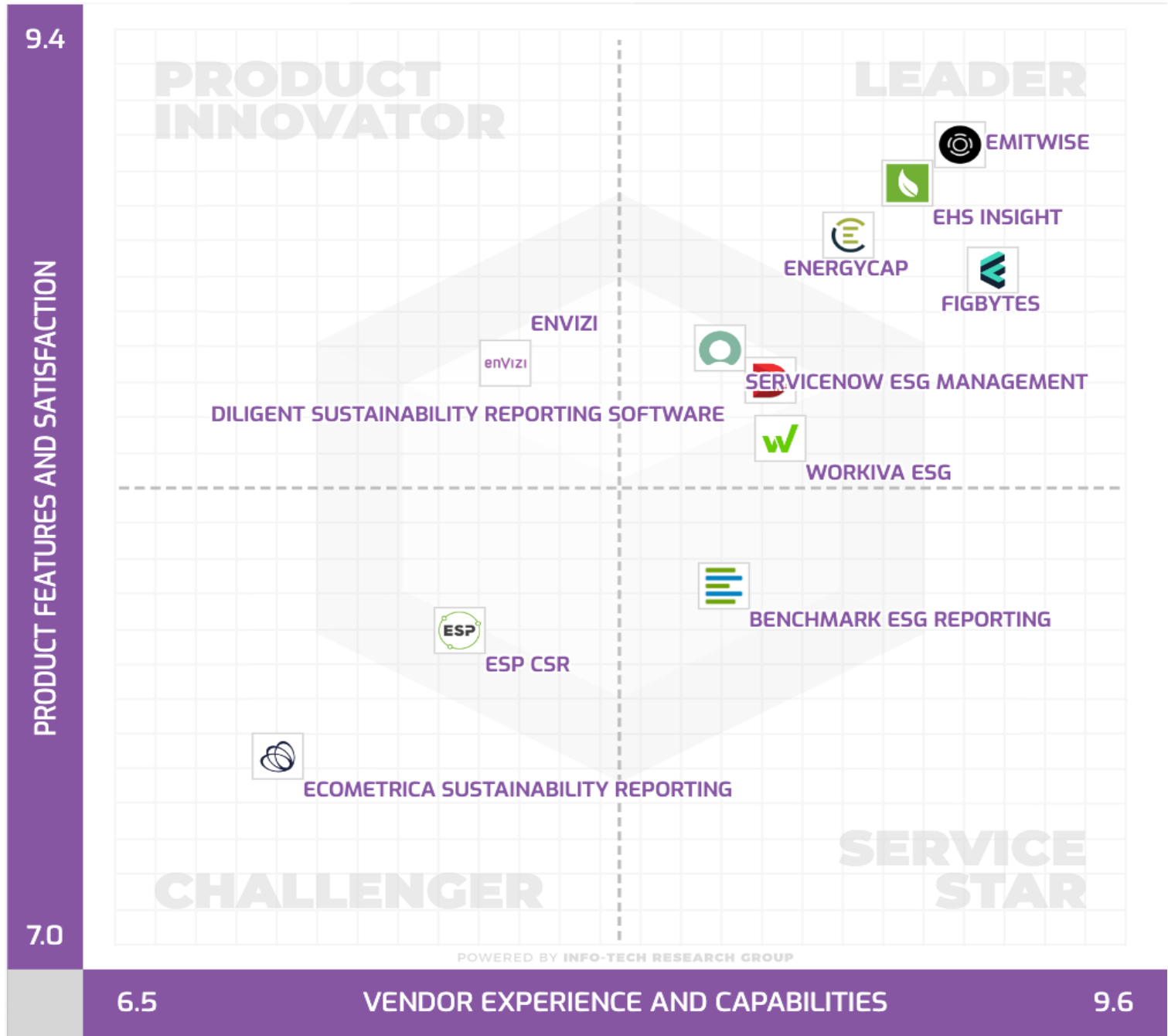
**ESG ANALYTICS**  
Invest where it matters.

# ESG Analytics: NLP Taxonomy

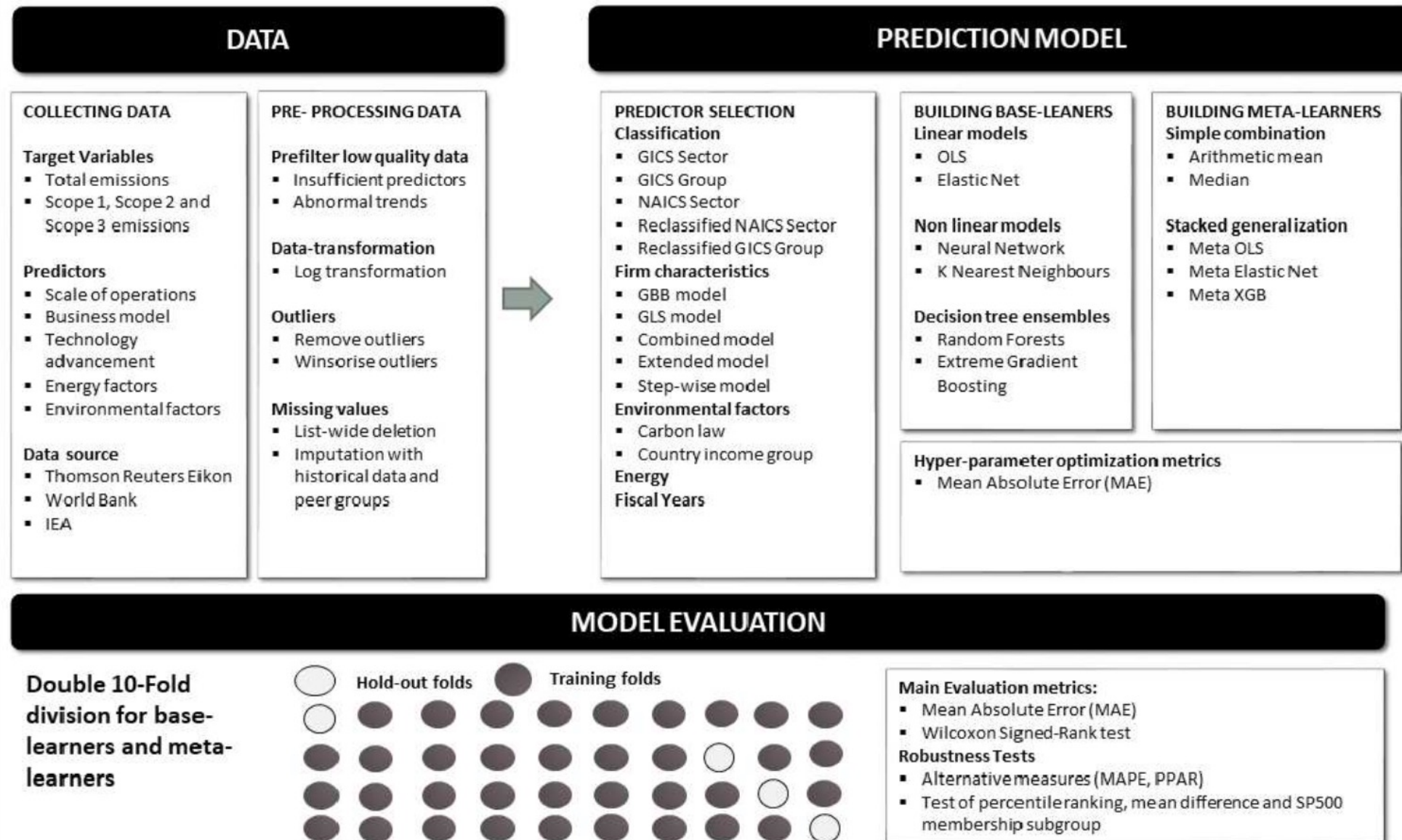


# Top ESG Reporting Software

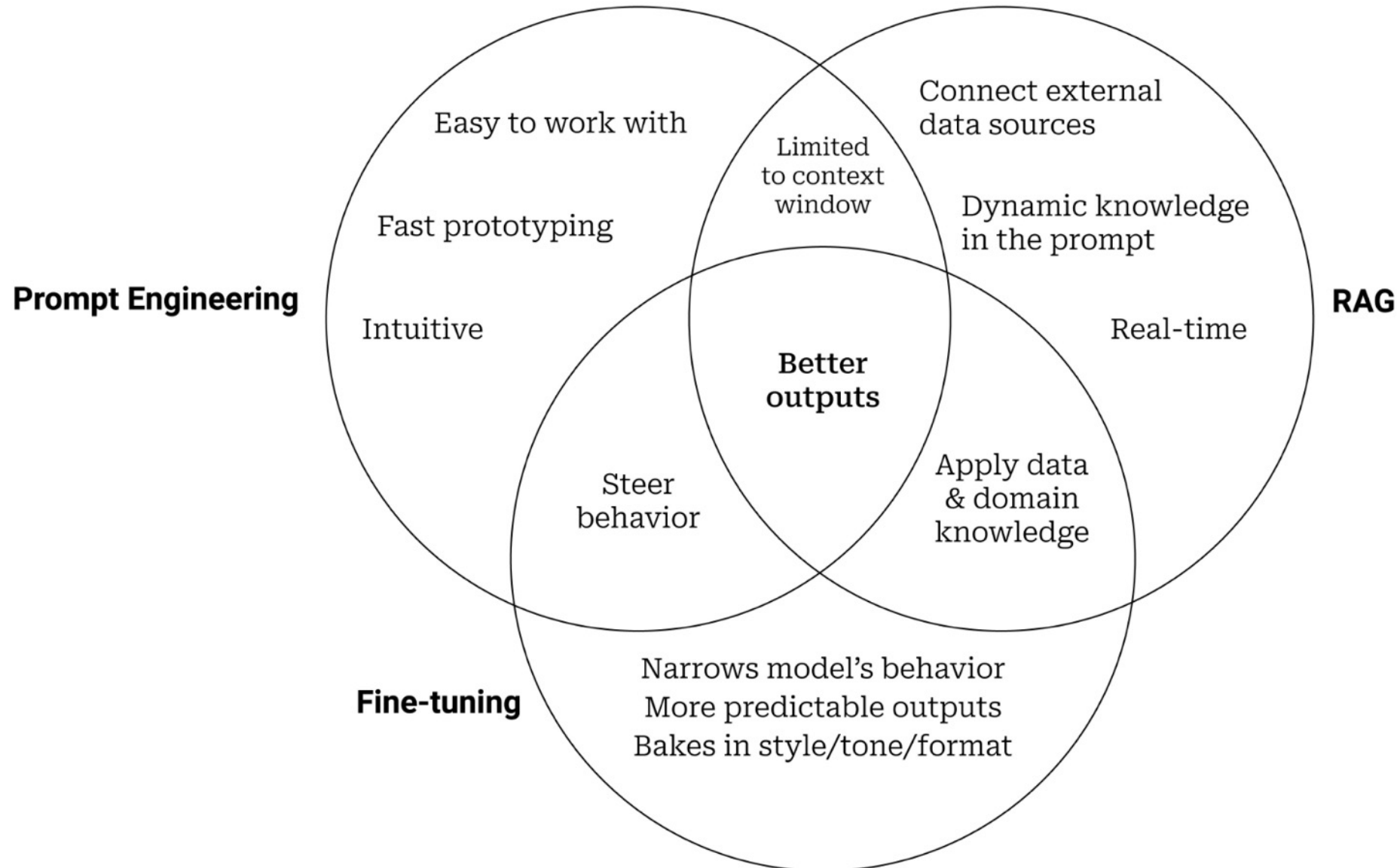
Environmental, Social and Governance (ESG) Reporting software or Sustainability software helps organizations manage their operational data, evaluate their impact on the environment and provide reporting to perform audits.



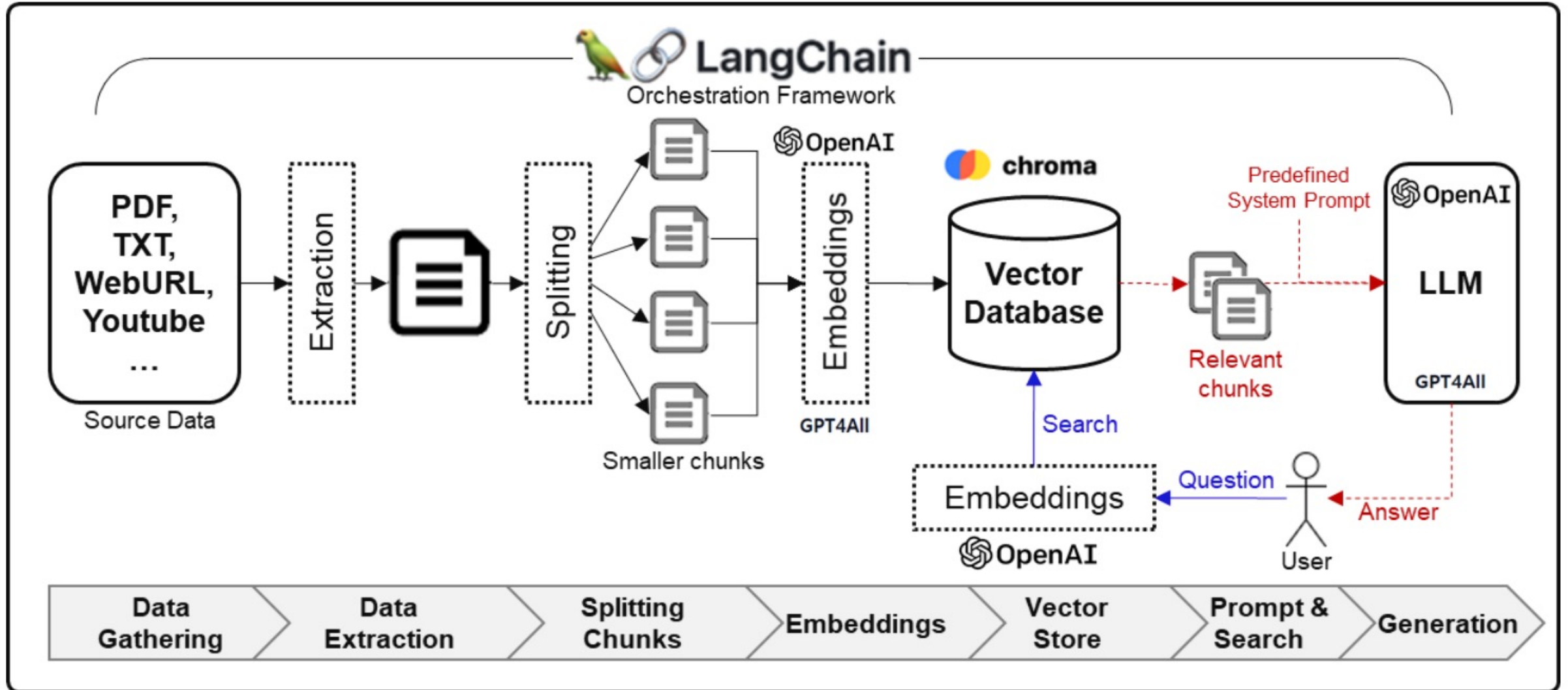
# Modelling Strategy to Forecast Carbon Emissions with AI



# Prompt Engineering, Fine-tuning, and RAG

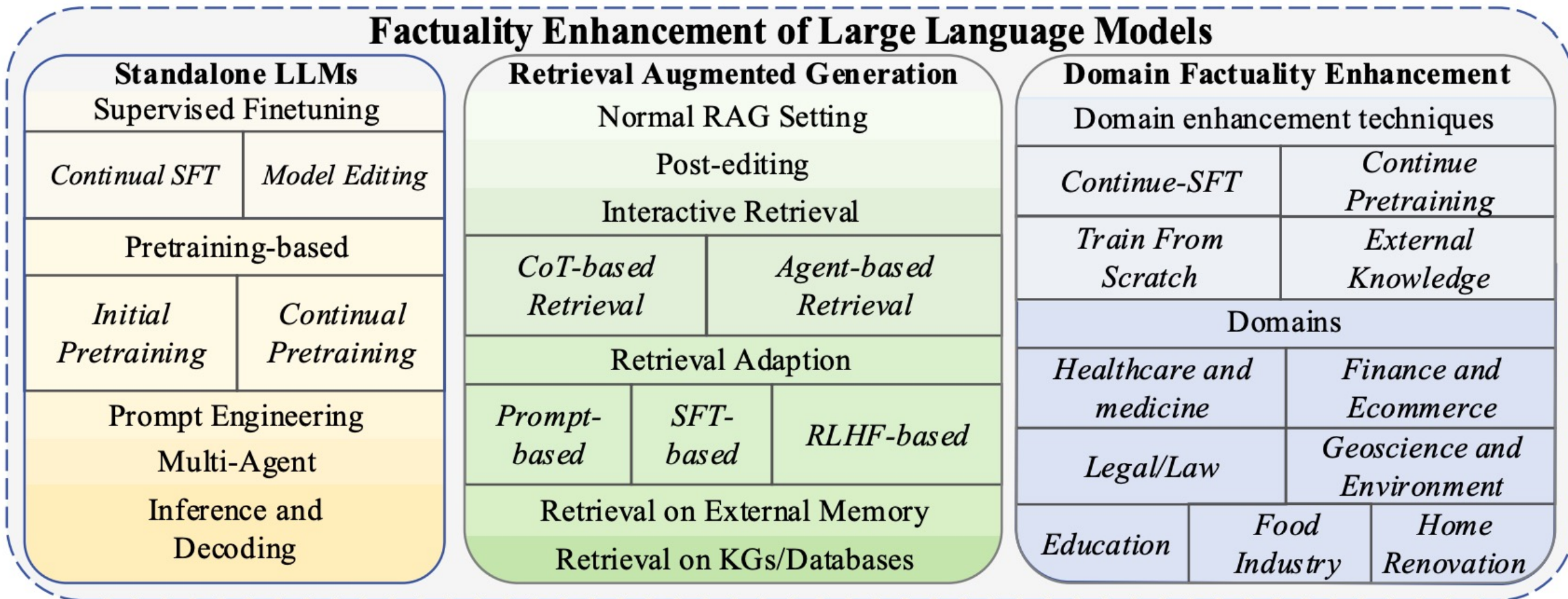


# Framework for Implementing Generative AI Services using RAG Model



# Factuality Enhancement of Large Language Models (LLMs)

## Factuality Enhancement of Large Language Models



# IMNTPU at the NTCIR-16 FinNum-3 Task: Data Augmentation for Financial Numclaim Classification

<sup>1</sup> Information Management, National Taipei University, New Taipei City, Taiwan

<sup>2</sup> Zeals Co., Ltd. Tokyo, Japan



Yung-Wei Teng<sup>1</sup>



Pei-Tz Chiu<sup>1</sup>



Ting-Yun Hsiao<sup>1</sup>



Mike Tian-Jian Jiang<sup>2</sup>



Min-Yuh Day<sup>1,\*</sup>

[myday@gm.ntpu.edu.tw](mailto:myday@gm.ntpu.edu.tw)

# IMNTPU Dialogue System Evaluation at the NTCIR-16 DialEval-2 Dialogue Quality and Nugget Detection

<sup>1</sup> Information Management, National Taipei University, New Taipei City, Taiwan  
<sup>2</sup> Zeals Co., Ltd. Tokyo, Japan



Ting-Yun Hsiao<sup>1</sup>



Yung-Wei Teng<sup>1</sup>



Pei-Tz Chiu<sup>1</sup>



Mike Tian-Jian Jiang<sup>2</sup>



Min-Yuh Day<sup>1,\*</sup>

[myday@gm.ntpu.edu.tw](mailto:myday@gm.ntpu.edu.tw)

# NTCIR 2022 NTCIR-16 Best Poster Presentation Award

## NTCIR-16 FinNum-3



Yung-Wei Teng<sup>1</sup>, Pei-Tz Chiu<sup>1</sup>, Ting-Yun Hsiao<sup>1</sup>, Mike Tian-Jian Jiang<sup>2</sup> and Min-Yuh Day<sup>1,\*</sup>

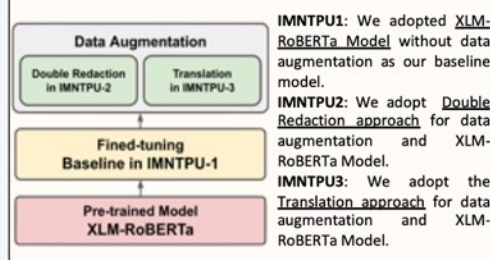
<sup>1</sup> Information Management, National Taipei University, New Taipei City, Taiwan

<sup>2</sup> Zeals Co., Ltd. Tokyo, Japan

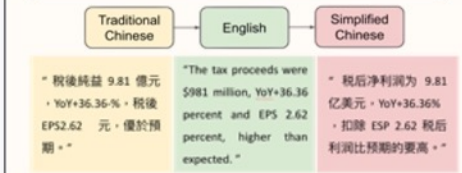
\* myday@gm.ntpu.edu.tw

This paper provides a detailed description of IMNTPU team at the NTCIR-16 FinNum-3 shared task in formal financial documents. We proposed the use of the XLM-RoBERTa-based model with two different approaches on data augmentation to perform the binary classification task in FinNum-3. The first run (i.e., IMNTPU-1) is our baseline through the fine-tuning of the XLM-RoBERTa without data augmentation. However, we assume that presenting different data augmentations may improve the task performance because of the imbalance in the dataset. Accordingly, we presented double redaction and translation method on data augmentation in the second (IMNTPU-2) and third (IMNTPU-3) runs, respectively. The best macro-F1 scores obtained by our team in the Chinese and English datasets are 93.18% and 89.86%, respectively. The major contribution in this study provide a new understanding toward data augmentation approach for the imbalanced dataset, which may help reduce the imbalanced situation in the Chinese and English datasets.

### Research Architecture and Proposed Method



### Translation Approach



### Tokenization Tricks

**Input:** Good day and welcome to the Apple Inc. Third Quarter Fiscal Year 2018 Earnings Conference Call. Today's call is being recorded.

**XLM-RoBERTa Tokenizer**

**Output:** <s> Good day and welcome to the Apple Inc. Third Quarter Fiscal Year xxnum 2018 Earnings Conference Call. Today's call is being recorded. </s>

**Double Redaction**

**Output:** <s> <mask> Good day and <mask> to the Apple <mask> Third Quarter Fiscal Year xxnum 2018 Earnings Conference Call. Today's call is <mask> recorded. </s>

### Algorithm of Double Redaction

1. Shuffle the tokens in sentence
2. Delete the duplicated tokens in sentence
3. Copy the remaining tokens as  $\beta$
4. SET the  $\delta$  and  $\gamma$
5. for specific token in  $\beta$  do
6.   if  $\gamma$  less than  $\delta$  then
7.     Replace original token with <mask> token
8.   else
9.     Cover original token as <mask> token
10.   end if
11. end for
12. while True do
13.   Model predict the original token of <mask> and <mask>
14. end while

### Performance

Run	Chinese Dataset		English Dataset	
	Dev Set F1-Score (%)	Test Set F1-Score (%)	Dev Set F1-Score (%)	Test Set F1-Score (%)
IMNTPU1	90.51	93.18	87.13	88.39
IMNTPU2	88.65	91.64	88.82	89.86
IMNTPU3	92.16	91.64	-	-

### Conclusions and Contributions

#### Conclusions:

The performance with data augmentation method (Double Redaction) in English dataset is superior than without data augmentation.

#### Contributions:

- The major contribution of the research is that data augmentation approach may help reduce imbalanced situation.
- We have developed a novel method for data augmentation technique, which is double redaction and translation approach, and can decrease the issue of imbalanced dataset.

#### ACKNOWLEDGMENTS

This research was supported in part by the Ministry of Science and Technology (MOST), Taiwan under grant number 110-2410-H-305-013-MY2, and National Taipei University (NTPU) under grant number 110-NTPU-ORDA-F-001, 111-NTPU-ORDA-F-001, and 111-NTPU-ORDA-F-003.

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NTCIR

2023

# NTCIR-17 Best Poster Presentation Award

## NTCIR-17 FinArg-1

NTCIR

IMNTPU at the NTCIR-17 FinArg-1  
Argument-based Sentiment Analysis and Identifying Attack and  
Support Argumentative Relations in Social Media Discussion Threads



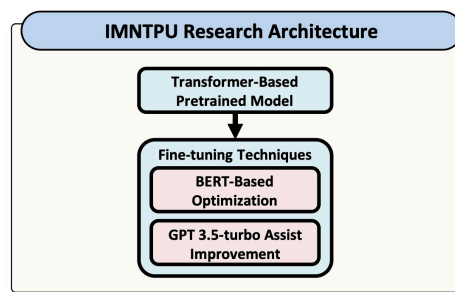
Chia-Tung Tsa<sup>1</sup>, Wen-Hsuan Liao<sup>1</sup>, Hsiao-Chuan Liu<sup>1</sup>, Vidhya Nataraj<sup>2</sup>, Tzu-Yu Liu<sup>3</sup>, Mike Tian-Jian Jiang<sup>4</sup> and Min-Yuh Day<sup>1,\*</sup>

\*myday@gm.ntpu.edu.tw

<sup>1</sup>Information Management, <sup>2</sup>Smart Healthcare Management, <sup>3</sup>Business Administration,  
National Taipei University, New Taipei City, Taiwan

<sup>4</sup>Zeals Co., Ltd. Tokyo, Japan

In recent years, there has been a surge of interest in argument-based sentiment analysis and the identification of argumentative relationships in social media. These tasks encompass **sentiment analysis of premises and claims**, as well as the **classification of argumentative relationships**. Within these tasks, we have developed a fine-tuning method for transformer models. To evaluate and showcase this concept, we established a comprehensive framework to test and display the performance of **BERT, RoBERTa, FinBERT, ALBERT, and GPT 3.5-turbo models** on financial data and social media texts. Ultimately, the experimental results of these sub-tasks validate the effectiveness of our strategies. The primary contribution of our research is our proposal of two key elements: fine-tuning predominantly with BERT models and employing GPT for generative classification, aiming to enhance the identification of argumentative classifications. Through fine-tuning techniques, the state-of-the-art models can achieve better performance than the baseline.



Hyperparameter Settings	
NTCIR-17 FinArg-1 Hyperparameter Settings	
Hyperparameter	Value
Learning Rate	1e-5, 5e-5
Max Length	128, 256
Batch Size	8, 16
Epochs	3, 4, 5

### Fine-tuning Techniques

- Our research in Natural Language Processing (NLP) explores deep learning models like **BERT, ALBERT, and RoBERTa** for sentence classification. RoBERTa, in particular, shows superior performance in NLP tasks due to more data and extended training, refining BERT's original training approach. The study used RobertaTokenizer for tokenization and RobertaForSequenceClassification for training and evaluation.
- A **5-fold cross-validation technique** was employed to fine-tune and assess model performance, involving dividing the dataset into five parts and using each in turn for validation. This ensures a stable and reliable performance evaluation. The study **also adjusted hyperparameters** such as sentence length, batch size, and training epochs to improve learning efficiency. For fair comparison, the same settings were applied to both RoBERTa and BERT models during fine-tuning.

### Performance

NTCIR-17 FinArg-1 Argument Unit Classification				
Model	Micro-F1	Macro-F1	Weight-F1	Accuracy
IMNTPU-1 (BERT-base)	75.44%	75.31%	75.40%	74.82%
IMNTPU-2 (RoBERTa-base)	<b>76.06%</b>	<b>76.05%</b>	<b>76.07%</b>	<b>75.64%</b>
IMNTPU-3 (GPT 3.5-turbo)	56.97%	56.82%	56.70%	55.08%

NTCIR-17 FinArg-1 Argument Relation Detection and Classification				
Model	Micro-F1	Macro-F1	Weight-F1	Accuracy
IMNTPU-1 (RoBERTa-base)	78.99%	47.36%	76.54%	78.55%
IMNTPU-2 (FinBERT)	<b>82.61%</b>	<b>52.97%</b>	<b>82.14%</b>	<b>79.13%</b>
IMNTPU-3 (BERT-uncased)	80.72%	50.73%	79.67%	78.55%

NTCIR-17 FinArg-1 Identifying Attack and Support Argumentative Relations in Social Media Discussion Threads			
Model	Micro-F1	Macro-F1	Weight-F1
IMNTPU-1 (Finetuned-Albert)	<b>52.88%</b>	<b>34.77%</b>	<b>48.73%</b>
IMNTPU-2 (RoBERTa-Large)	48.71%	24.64%	40.50%

### GPT Generation Strategies and Optimization

- In our study, we demonstrate the application of **OpenAI's ChatGPT API**, integrating deep learning with Natural Language Processing (NLP) for detailed text analysis. The technology is finely tuned to **classify sentences accurately as either "claim" or "premise"**, aiding researchers in identifying core arguments and their supporting reasons. This classification is part of a multi-step process, with specific sentiment labels providing clear targets for the model.
- The distinction between "claim" and "premise" is vital for understanding arguments and their justifications. Moreover, the method's scalability and adaptability make it versatile, suitable for not only basic sentiment analysis but also for more complex text analysis with additional classification labels.

### Conclusions and Contributions

- We combined fine-tuning BERT and RoBERTa with the innovative use of GPT 3.5 Turbo, effectively capturing subtle nuances in conversational texts while demonstrating significant performance in generative tasks.
- Our study offers a comprehensive solution to the Argument Unit Classification challenge, thoroughly evaluating various methods' pros and cons. Additionally, in the multi-class classification task of financial sentiment analysis, we've revealed deeper semantic aspects of texts by analyzing inter-sentential relationships.

**ACKNOWLEDGMENTS**  
 This research was supported in part by the National Science and Technology Council (NSTC), Taiwan, under grants MOST 110-2410-H-305-013-MY2, NSTC 112-2425-H-305-002-, and NSTC 112-2627-M-038-001-, and National Taipei University (NTPU), Taiwan under grants 112-NTPU-ORDA-F-003, 112-NTPU-ORDA-F-004, USTP-NTPU-TMU-112-01, NTPU-112A413E01, and NTPU-112A513E01.

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# NTCIR

# 2023

# NTCIR-17

# Best Poster

# Presentation

# Award

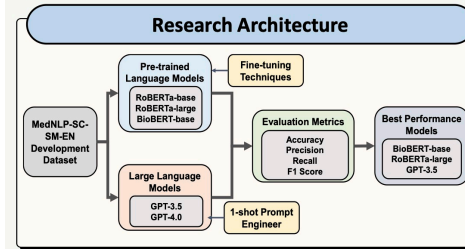
# NTCIR-17 Real MedNLP



Hsiao-Chuan Liu<sup>1</sup>, Vidhya Nataraj<sup>2</sup>, Chia-Tung Tsai<sup>1</sup>, Wen-Hsuan Liao<sup>1</sup>, Tzu-Yu Liu<sup>3</sup>, Mike Tian-Jian<sup>4</sup> Jang and Min-Yuh Day<sup>1,\*</sup>  
\*myday@gm.ntpu.edu.tw

<sup>1</sup>Information Management, <sup>2</sup>Smart Healthcare Management, <sup>3</sup>Business Administration, National Taipei University, New Taipei City, Taiwan  
<sup>4</sup>Zeals Co., Ltd. Tokyo, Japan

The IMNTPU team engaged in the NTCIR-17 RealMedNLP task, specifically focusing on Subtask1: Adverse Drug Event detection (ADE) and the challenge of identifying related radiology reports. This task is centered on harnessing methodologies that offer significant aid in real-world medical services, especially when training resources are limited. In our approach, we harnessed the power of pre-trained language models (PLMs), particularly leveraging models like the BERT transformer, to understand both sentence and document structures. Our experimentation with diverse network designs based on PLMs paved the way for an enlightening comparative analysis. Notably, BioBERT-Base emerged as a superior contender, showcasing commendable accuracy relative to its peers. Furthermore, our investigation made strides in the realm of one-shot learning for multiclass labeling, specifically with the GPT framework. The insights gathered emphasized the necessity for more specialized strategies, suggesting avenues for future research in multiclass labeling tasks.



### Prompt Engineer

#### One-shot Learning

- Analysis showed reduced accuracy in insight extraction from short, ambiguous tweets.
- GPT-3.5 labeled 929 instances, GPT-4.0 labeled 789, while the actual ground truth was 400.

#### Prompt

You are a medical expert analyzing tweets to check whether the user suffers adverse drug events.

**\*\*Scenario\*\*:** Because every text is from Twitter, the texts are short. Please consider this situation and annotate the text with proper labels to check whether the user suffers adverse drug events. For instance, users list the adverse drug effects rather than express personal experiences of adverse reactions.

**\*\*Your annotating steps are as follows: \*\***

- Check whether the user lists the adverse drug effects rather than expressing personal experiences of adverse reactions.
- Check whether this tweet's user suffers from adverse drug events.
- Check the symptoms in these 22 symptoms listed below.

**\*\*Your annotation should be in the following format:\*\***

- If the user suffers from the tweet's symptom instead of listing the adverse drug events, output with the corresponding label.
- If the user doesn't suffer from the symptom in the tweet, output with "None".

**\*\*Symptom Labels\*\*:**  
nausea, diarrhea, rash, stomatitis

**\*\*Here is some annotate example for you to base on.\*\***  
Text: I finished C due to side effects of the contrast dye. I was feeling kind of sick and nausea was getting worse, so I thought it would be tough, but this morning my chest hurts... I'm going to go to the hospital tomorrow, though I'm anxious because I have 2 hours left until the test results...  
Label: nausea, pain  
\*Other 22 samples for GPT to know.\*

### Fine-tuning Techniques

#### Hyperparameters

- Fine-tuned for multi-label text classification
- Max Epochs: 10
- Max Sequence Length: 512
- Learning Rate: 5e-5
- Batch Size: 16
- Loss Func.: BCEWithLogitsLoss

### Performance

Exact Accuracy of Test Dataset and Development Dataset			
Models	Development Dataset (#1,192)	Test Dataset (#1,993)	
BioBERT-Base (Submission Run 1)	0.92	0.82	
Roberta-Base	0.76	-	
Roberta-Large (Submission Run 2)	0.85	0.81	
GPT3.5 (Submission Run 3)	0.72	0.69	
GPT 4.0	0.62	-	

Subtask 1-SM-ADE-EN Binary and Per Label Performance Metrics							
Models	Score	Precision		Recall		F1 Score	
		ADE	NO ADE	ADE	NO ADE	NO ADE	
BioBERT-Base	Binary	0.74	0.91	0.78	0.89	0.76	0.90
	Per label	0.72	1.00	0.76	0.99	0.74	0.99
RoBERTa-Large	Binary	0.73	0.93	0.83	0.88	0.78	0.90
	Per label	0.71	1.00	0.77	0.99	0.74	0.99
GPT3.5	Binary	0.47	0.47	0.20	0.91	0.28	0.82
	Per label	0.42	0.98	0.18	1.00	0.25	0.99

Subtask 1-SM-ADE-EN Binary and Per Label Performance Metrics in Development Dataset							
Models	Score	Precision		Recall		F1 Score	
		ADE	NO ADE	ADE	NO ADE	NO ADE	
BioBERT-Base	Binary	0.90	0.97	0.93	0.96	0.92	0.97
	Per label	0.91	0.97	0.93	0.96	0.92	0.97
RoBERTa-Large	Binary	0.89	0.83	0.59	0.97	0.71	0.90
	Per label	0.85	0.99	0.49	1.00	0.62	0.99
BioBERT-Base	Binary	0.87	0.93	0.85	0.94	0.86	0.93
	Per label	0.84	0.99	0.77	1.00	0.81	1.00
GPT3.5	Binary	0.72	0.80	0.53	0.90	0.61	0.85
	Per label	0.62	0.99	0.57	0.99	0.60	0.99
GPT4.0	Binary	0.52	0.96	0.95	0.61	0.67	0.75
	Per label	0.48	1.00	0.92	0.98	0.63	0.99

Exact Match Accuracy Results in Development Dataset			
Models	Accuracy	Models	Accuracy
RoBERTa-Base	0.86	GPT3.5-1-shot	0.54
RoBERTa-Large	0.87	GPT3.5-scenario	0.69
BioBERT-Base	0.85	GPT4.0-1-shot	0.61
BioBERT-Large	0.86	GPT4.0-scenario	0.70
		GPT3.5-fintune	0.85

### Conclusions and Contributions

- Expanded dataset with GPT-3.5 boosts RoBERTa accuracy from 0.76 to 0.86.
- Refined prompts for tweets, increasing GPT4.0 accuracy to 0.70.
- BioBERT excels in drug event extraction; GPT one-shot learning shows limits.
- We proposed two critical elements, Prompt Engineer and Fine-Tuning Techniques. GPT-4.0 showing enhanced performance in ambiguous datasets.

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# Summary

- 1. Generative AI:  
Powering Digital Sustainability Transformation**
- 2. Generative AI and Large Language Models (LLMs):  
Popular Generative AI Applications**
- 3. Generative AI for Sustainable Development  
Innovative Applications**

# Acknowledgments: Research Projects

1. **Fintech Green Finance for Carbon Market Index, Corporate Finance, and Environmental Policies.**  
Carbon Emission Sentiment Index with AI Text Analytics
  - NTPU, 113-NTPU\_ORDA-F-003, 2023/01/01~2024/12/31
2. **Digital Support, Unimpeded Communication: The Development, Support and Promotion of AI-assisted Communication Assistive Devices for Speech Impairment (1/3).**  
**Multimodal Cross-lingual Task-Oriented Dialogue System for Inclusive Communication Support**
  - NSTC 112-2425-H-305-002-, 3 Years (2023/05/01-2026/04/30) Year 1: 2023/05/01~2024/04/30
3. **Research on speech processing, synthesis, recognition, and sentence construction of people with language disabilities.** **Multimodal Cross-lingual Task-Oriented Dialogue System**
  - NTPU, 113-NTPU\_ORDA-F-004, 2023/01/01~2025/12/31
4. **Metaverse AI Multimodal Cross-Language Task-Oriented Dialogue System**
  - ATEC Group, Fintech and Green Finance Center (FGFC, NTPU), NTPU-112A413E01, 3 Years (2023/05/01~2026/04/30)
5. **Generative AI-Driven ESG Report Generation Technology**
  - Industrial Technology Research Institute (ITRI), Fintech and Green Finance Center (FGFC, NTPU), NTPU-113A513E01, 2024/03/01~2024/12/31
6. **Establishment and Implement of Smart Assistive Technology for Dementia Care and Its Socio-Economic Impacts (2/3).** **Intelligent, individualized and precise care with smart AT and system integration**
  - NSTC, 112-2627-M-038-001-, 2023/08/01~2024/07/31
7. **Prospective longitudinal study on peri-implant bone loss associated with peri-implantitis**
  - USTP (NTPU, TMU), USTP-NTPU-TMU-113-03, 2024/01/01~2024/12/31

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## Q & A

# 生成式AI與永續發展的應用

## Generative AI and Sustainable Development Applications

2024/06/26 (Wed) 10:30 - 12:00

L703, Tainan University of Technology (TUT), Tainan, Taiwan

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