ICRA2026 Late Breaking Results Poster presented at
2026 IEEE International Conference on Robotics and Automation (ICRA 2026)
June 1-5, 2026. Vienna, Austria

The RoboAtlas: Mapping the Global Robotics Landscape

Jiacheng Zhang[1,2,†], Shuo Sun[1,3,†,*], Vasiliki Charisi[1,3,†], Xinru Wang[1,3],
Xinyue Chen[1,2], Zhexuan Ma[1,2], Alok Prakash[1,3], Thomas W. Malone[1,3]

Abstract— **Structured, model-level information on the world's robot systems remains scarce: existing reports often provide aggregated market statistics, while industry directories typically stop at company- or application-level information. In this work, we present an LLM-assisted, web-grounded analysis pipeline for studying the global robotics landscape at the robot-model level. The method combines company discovery, iterative verification, and model-level extraction of robot type, target industries, release year, and task descriptions from open-web evidence. Applying this pipeline, we study 8,229 robot models associated with 1,062 companies across 50 countries and 6 continents. Our findings reveal strong geographic concentration in the United States, China, and Japan, rapid growth after 2017, and substantial diffusion of robotics beyond manufacturing into logistics, healthcare, education, and household settings. Interestingly, this analysis revealed 24,585 tasks. Our work illustrates both the promise and certain limitations of LLM-assisted web analysis for large-scale robotics landscape mapping.**

I. INTRODUCTION

Robotics is expanding across manufacturing, logistics, healthcare, professional services, and household environments. However, there is still no widely available, model-level view of the global robotics landscape that consistently links robot systems to capabilities, target industries, release timing, and geography. This absence limits empirical research on technology diffusion, capability evolution, and the structure of the global robotics ecosystem.

Existing sources remain valuable but incomplete for in-depth research on robot applicability. The International Federation of Robotics (IFR) annual reports provide high-quality aggregate indicators for industrial and service robots, but not model-level product records and their respective robot capabilities [1], [2]. Company directories, such as The Robot Report, provide useful discovery coverage, but are primarily organized around company-level listings rather than robot-model-level [3]. Academic research often focuses on benchmark performance rather than commercial product landscapes. This work addresses this gap through an LLM-assisted pipeline that gathers and verifies open-web information to support analysis of robot-model trends worldwide.

This extended abstract makes three contributions: (i) an LLM-assisted pipeline for large-scale robot-model analysis from open-web evidence, (ii) an empirical characterization of geographic, temporal, morphological, industrial, and task-level patterns in global robotics, and (iii) a discussion of the opportunities and limitations of using LLM-assisted web analysis for robotics landscape studies.

[1]Singapore-MIT Alliance for Research and Technology.
[2]National University of Singapore.
[3]Massachusetts Institute of Technology.
[†]These authors contributed equally.
[*]Corresponding author.

II. PIPELINE OVERVIEW

Our method is implemented using a GPT model with web search support provided through the OpenAI tool interface [4], [5]. It implements a three-stage pipeline for extracting structured observations about robot models from open-web evidence.

Stage 1: Web Search. The input is a candidate company record from merged company-source data. The system performs web-grounded search to extract canonical company information, preferring official sources when available. The output is a structured company profile containing company name, official website, address, city, country, and continent.

Stage 2: Review. The input is the Stage 1 company profile. A review agent checks whether the extracted fields are supported by web evidence and identifies inconsistencies or weak support. When necessary, it provides corrective feedback and triggers iterative refinement. The output is a reviewed company profile with validated information.

Stage 3: Model Extraction. The input is the reviewed company profile from Stage 2. Using web evidence, the system identifies distinct robot models associated with the company and extracts structured attributes for each model, including model website, model image, release year, robot type, application industries, and tasks. The pipeline produces structured robot-model attributes for downstream descriptive analysis.

Quality mechanisms. Extraction reliability is improved through schema-constrained generation, evidence-aware review, and rule-based post-processing. Company-level outputs retain supporting web evidence, while geographic fields are normalized using ISO 3166-1 alpha-2 country codes [6]. In model extraction, industries are mapped to a fixed ISIC vocabulary [7], while robot types and tasks are normalized, invalid non-robot outputs are excluded, and release-year uncertainty is explicitly recorded. These choices improve the consistency of the extracted observations and the reliability of the downstream analysis.

III. EMPIRICAL FINDINGS

For this study, we identified approximately 7,000 robotics companies worldwide. After filtering for companies that produce autonomous robotic systems, we ended up with 1,062 companies to be included in the analysis. Additional results are forthcoming, and a comprehensive landscape analysis (covering approximately 50,000–60,000 distinct robot models) will be presented at the conference.

A. Geographic structure

The United States accounts for the largest share in our analysis with 2,245 models (27.3%), followed by China with 1,474 (17.9%), Japan with 794 (9.6%), Germany with 582 (7.1%), and France with 325 (3.9%). These top five countries account for 65.9% of all models, indicating a substantial concentration of robot-model production in a small number of countries. At the continental level, however, Asia (2,812, 34.2%), Europe (2,681, 32.6%), and North America (2,533, 30.8%) are nearly equally represented, collectively accounting for 97.6% of models. Europe has the widest country diversity, while Asia combines coverage with strong representation in industrial and mobile robotics.

B. Temporal dynamics

The time series shows modest activity before 2010, then rapid acceleration after 2017. Notably, the earliest robot model identified in our dataset can be traced back to 1959, highlighting the long historical span captured by the analysis. Annual counts peak at 843 models in 2024, with 2025 also remaining elevated. The pattern is consistent with the recent expansion of warehouse automation, delivery robotics, service robots, and AI-enabled platform.

C. Type landscape

Industrial robot arms are the largest canonical category with 1,701 models (20.7%). They are followed by AMRs with 1,015 (12.3%), drones/UAVs with 821 (10.0%), cleaning robots with 688 (8.4%), inspection robots with 632 (7.7%), and AGVs with 539 (6.6%). The long tail includes humanoids, exoskeletons, cobots, laboratory robots, autonomous forklifts, underwater robots, and other specialized systems, underscoring the morphological diversity of the robotics market.

D. Industry diffusion

Manufacturing remains the dominant target sector with 3,635 assignments (44.2% of models), followed by Transportation and Storage with 1,911 (23.2%). However, the analysis shows substantial breadth beyond traditional factory settings: Professional, Scientific and Technical Activities (18.2%), Education (13.5%), Human Health and Social Work (12.4%), and Public Administration and Defence (11.8%) each appear in more than one-tenth of all models.

E. Task capabilities

Across the analyzed robot models, we identified 45,623 task mentions spanning 24,585 unique task descriptions after normalization, providing a granular view of what robots actually do. The most common tasks emphasize navigation, obstacle avoidance, pick-and-place operations, transport, inspection, and recording. Grouping tasks by leading verb reveals a macro-capability structure led by *Transport/Deliver*, *Navigate/Move*, *Pick&Place*, *Capture/Record*, and *Inspect/Monitor*. This pattern highlights the importance of material handling, mobility, sensing, and operational monitoring across modern robot products.

IV. DISCUSSION

This study yields three broad conclusions. First, the study reveals a robotics landscape that is both concentrated and diverse: a small set of countries dominates volume, but the long tail of robot types, industries, and task descriptions is substantial. Second, release-year uncertainty is itself an informative market property, since sparse disclosure practices vary across firms and product segments. Third, the analysis reveals a large set of robotic tasks in a detailed and nuanced way that shows not only the expansion of the areas of application but also the diversity of tasks performed by specific robot models. In addition, this work provides a methodological contribution. Iterative multi-agent review improves extraction reliability relative to single-pass prompting because it makes contradictions explicit and forces correction before downstream model extraction.

Important limitations remain. The present analysis is based on web-observed robot-model information and does not constitute an exhaustive census of global robotics. Coverage is shaped by source-directory selection, web visibility, and uneven public documentation across firms and regions. Human validation remains essential for estimating residual error rates and refining edge-case taxonomy decisions.

V. CONCLUSION AND NEXT STEPS

The RoboAtlas highlights what recent robot-model evidence reveals about concentration, growth, diffusion, and capability structure across the global robotics ecosystem. In addition, this study shows that LLM-assisted web analysis can support large-scale empirical mapping of the global robotics landscape. Future work will focus on strengthening data validation, expanding dataset coverage, and enabling longitudinal tracking of changes over time.

VI. ACKNOWLEDGMENT

This research is supported by the National Research Foundation, Prime Minister's Office, Singapore and the Mens, Manus and Machina (M3S) research group of the Singapore–MIT Alliance for Research and Technology center.

REFERENCES

[1] International Federation of Robotics, *World Robotics 2024 – Service Robots*, 2024.

[2] International Federation of Robotics, *World Robotics 2024 – Industrial Robots*, 2024.

[3] The Robot Report, *Robotics and Intelligent Systems Company Database*, [Online]. Available: `https://search.therobotreport.com/`. Accessed: 2026-04-10.

[4] OpenAI, *Responses API Reference*, OpenAI Platform Documentation, 2026. [Online]. Available: `https://developers.openai.com/api/reference/resources/responses`

[5] OpenAI, *Web Search*, OpenAI Platform Documentation, 2026. [Online]. Available: `https://developers.openai.com/api/docs/guides/tools-web-search`

[6] International Organization for Standardization, *ISO 3166-1:2020 Codes for the representation of names of countries and their subdivisions – Part 1: Country code*, 2020.

[7] United Nations Statistics Division, *International Standard Industrial Classification of All Economic Activities (ISIC), Rev. 4*, 2008.