A SURVEY OF EMBODIED ARTIFICIAL INTELLIGENCE DATA ENGINEERING

Xuan Xia[1], Haoran Tong[1], Xing He[1], Bo Yu[1], Ning Ding[1], Xue Liu[2], Shaoshan Liu[2]
1.Shenzhen Institute of Artificial Intelligence and Robotics for Society, Shenzhen, China
2.Mohamed bin Zayed University of Artificial Intelligence, Abu Dhabi, United Arab Emirates
{xiaxuan, tonghaoran, hexing, boyu, dingning, shaoshanliu}cuhk.edu.cn
Steve.liu@mbzuai.ac.ae

ABSTRACT

Embodied Artificial Intelligence (EAI) Data Engineering represents a transformative shift in the field of AI, focusing on developing systematic, standardized, scalable and goal-driven technical frameworks to meet the data requirements of EAI systems. This comprehensive overview explores the concept of EAI data, its production systems, standardization, production technologies, and optimization directions in data engineering for EAI. It highlights the importance of addressing data bottlenecks such as cost inefficiency, data silos, and evaluation void. The key components of EAI data engineering are outlined, including the design of data production systems, establishment of data standards, real-world data collection technologies, and simulation data generation technologies. The deployment and application of EAI data engineering in various fields such as manufacturing, mining, and the service industry are also explored. By providing an in-depth analysis of the current state of EAI data engineering and offering insights into its future optimization directions, this survey aims to serve as a valuable resource for researchers and practitioners in the field.

Keywords Embodied Artificial Intelligence Data Engineering Data Collection Data Generation Teleopration Simulation

1 Introduction

Embodied Artificial Intelligence (EAI) represents a transformative shift in AI, where intelligence is not just computed but enacted—emerging through perception, interaction, and continuous adaptation in the physical world [1]. A key trait of EAI systems is that they must operate in dynamic, uncertain, and multi-modal environments. This fundamental difference places unprecedented demands on data: it must be temporally coherent, sensorily rich, causally structured, and behaviorally relevant. The success of embodied agents hinges not merely on model architectures, but on the depth, diversity, and structure of the data they are trained on [2]. Meanwhile, with a total addressable market size over $10 tillion, data engineering has become a critical enabler of both scientific progress and economic impact [3, 2].

Scaling laws [4, 5] offer a guiding principle for the development of EAI: intelligence emerges from data. However, unlike the vast amounts of data already accumulated in fields such as Natural Language Processing (NLP) and autonomous driving, the data required when robots enter homes, warehouses, and factories is fundamentally different—it is data of physical interaction. The acquisition of such data, including motion trajectories, collision feedback, haptic sensations, lighting conditions, and friction, faces exponentially increasing difficulty and cost. Even tens of thousands of hours of real-world robotic interaction data fall far short of the scale seen in Large Language Models (LLMs). While LLMs consume trillions of tokens, the interaction data currently available for robots amounts to only a tiny fraction—equivalent to just one in a hundred thousand of what LLMs process.

Therefore, the demand for EAI data has driven the rapid development of technology in this field in recent years. As shown in Fig. 1, The current EAI data production exists in various modes, each with its own advantages and disadvantages in terms of equipment costs, labor costs, scene limitations, and computational consumption. More importantly, current methods are fragmented, unsustainable, and inconsistencies in data quality and universality, led

Figure 1: Current EAI data production methods are fragmented, unsustainable, and inconsistencies in data quality and universality, led to the current EAI data bottlenecks. EAI data engineering represents a significant shift from opportunistic EAI data production to next generation EAI data production to solve EAI data bottlenecks.

to the current EAI data bottlenecks (which will be detailed in Section 2.3). Solving these bottlenecks requires the use of systematic engineering methods to design new EAI data production pipelines. Therefore, we argue that data engineering is no longer a support task, but the foundation upon which scalable and generalizable EAI will be built. By mapping the current landscape and identifying methodological and infrastructural gaps, this survey aims to establish EAI data engineering as a first-class research frontier. We advocate for a shift from opportunistic EAI data production to systematic, standardized, scalable and goal-driven EAI data production, so as to unlock new opportunities for reproducible research, robust generalization, and inclusive innovation in EAI.

1.1 Concept of Embodied Artificial Intelligence Data

The concept of EAI originated in Alan Turing's seminal 1950 paper, "Computing Machinery and Intelligence."[6] In this paper, Turing envisioned two potential paths for the development of artificial intelligence: one focused on abstract computational intelligence (e.g., playing chess), and the other involving equipping machines with sensors to enable interaction with the physical world, humans, and their environment through a physical presence, hence achiving scalability [7, 8]. The latter approach constitutes what we now refer to as EAI.

EAI data refers to the multimodal sensory inputs and behavioral outputs that enable intelligent agents to perceive and interact with their environments. This data encompasses both physical-world observations collected by robotic sensors (e.g., LiDAR, cameras, force-torque sensors) and synthetic data generated through simulation platforms. The uniqueness of EAI data lies in its embodiment characteristics - it must capture spatiotemporal relationships between agents' actions and environmental changes. Physical agents produce real-world operational data through task execution, while digital agents generate simulated interaction data with programmed environments. Both data types share common structuring requirements for temporal alignment, action-effect pairing, and contextual annotation, but differ in fidelity and collection scalability. EAI data serves as the foundational resource for developing embodied cognition models, bridging the gap between abstract intelligence and physical/digital embodiment.

1.2 Related Surveys in the Field of Embodied Artificial Intelligence Data

As shown in Table 1, recent years have seen a surge in the publication of surveys related to EAI data. These surveys cover a wide range of topics, from teleoperation techniques [10, 12] to the Simulators [9, 11] and datasets [16, 17]. Notable contributions include comprehensive reviews on the use of internet video data for robot learning [14], task planning and code generation [15], and the integration of generative artificial intelligence [20]. These reviews highlight the rapid advancements and increasing complexity of data in the EAI field.

Table 1: Related Surveys in the Field of EAI Data

Title	Year	Publication	Data Engineering Related Content
Toward next-generation learned robot manipulation [9]	2021	SCIENCE ROBOTICS	Data and simulation of manipulation
Teleoperation methods and enhancement techniques for mobile robots: A comprehensive survey [10]	2021	Robotics and Autonomous Systems	Teleoperation enhancement techniques
A Survey of Embodied AI: From Simulators to Research Tasks [11]	2022	IEEE TETCI	Simulation platform and embodied question answering data
Teleoperation of Humanoid Robots: A Survey [12]	2023	IEEE Transactions on Robotics	Teleoperation systems for humanoid robots
Multiple Mobile Robot Task and Motion Planning: A Survey [13]	2023	ACM Computing Surveys	Task and Motion Planning
Towards Generalist Robot Learning from Internet Video: A Survey [14]	2024	ArXiv	Learning from internet video data
Real-world robot applications of foundation models: a review [15]	2024	ADVANCED ROBOTICS	Task planning and code generation
A Survey of Imitation Learning: Algorithms, Recent Developments, and Challenges [16]	2024	IEEE TRANSACTIONS ON CYBERNETICS	Datasets of imitation learning
Robot learning in the era of foundation models: a survey [17]	2025	Neurocomputing	Datasets of manipulation, navigation, planning, and reasoning
A Survey of Robotic Navigation and Manipulation with Physics Simulators in the Era of Embodied AI [18]	2025	ArXiv	Simulators and benchmark datasets of navigation and manipulation
A Survey of Interactive Generative Video [19]	2025	ArXiv	Task planning and policy learning via generative simulation
Generative Arti cial Intelligence in Robotic Manipulation: A Survey [20]	2025	ArXiv	Data, image, code, policy generation for manipulation

foundation for the production, management, and utilization of data in EAI. By proposing EAI Data Engineering, we can address the unique challenges and opportunities in this interdisciplinary eld more effectively. A dedicated survey would not only synthesize the latest advancements and trends but also identify gaps and future directions, facilitating more ef cient and effective research and development efforts.

1.3 Embodied Arti cial Intelligence Data Engineering

As shown in Fig. 2, EAI data originates from various sources, ranging from the broadest category of internet data, to the intermediate layer of simulation data (including synthetic data), and nally to the rarest real-world data, forming the EAI data pyramid. Different EAI technological approaches have varying requirements for these types of data. EAI data engineering refers to a systematic technical framework designed to address the data requirements of EAI, encompassing the entire lifecycle of data production from design and development to management. Its core objective is to establish high-quality, multimodal datasets through standardized data collection and generation. Speci cally, this engineering discipline covers the following key components:

Design of EAI Data Production Systems: The design of data production systems for EAI involves planning and constructing a framework capable of ef ciently and accurately acquiring multimodal data tailored to the needs of robots. This design must comprehensively consider factors such as sensor con gurations, data types, data collection frequency and precision, as well as data storage and preprocessing methods [21, 22].

Establishment of EAI Data Standards: EAI data standards refer to a set of norms and guidelines formulated to ensure the quality, consistency, and interoperability of data within EAI. These standards cover aspects such as data formats, annotation methods, quality control, privacy protection, and the integration of multimodal data, aiming to provide a uni ed framework for data collection, generation, storage, and sharing [23, 24]. By establishing clear data standards, the usability and reliability of data can be improved, fostering data sharing and collaboration across different systems and platforms.

Development of Real-World EAI Data Collection Technologies: They involve methods for directly acquiring multimodal data from physical environments using sensors, cameras, microphones, and other devices. These technologies capture information such as the robot's visual, auditory, tactile, and motion, as well as environmental objects, scenes, and human behaviors, providing realistic data support for EAI models [25, 26, 27].

Development of Simulation EAI Data Generation Technologies: They involve creating high- delity, diverse virtual environments and task scenarios through virtual simulation platforms to generate multimodal data. Leveraging advanced 3D modeling, physics engines, and generative arti cial intelligence, these technologies can rapidly produce large volumes of high-quality training data, simulating various interactions and dynamic changes in the real world [28, 29, 30].

Application and Optimization: They involve designing and implementing data production solutions tailored to the speci c needs of industries or domains such as healthcare, industrial manufacturing, and education. By continuously

Figure 2: The components of EAI data engineering and the outline of this survey

optimizing data collection processes and systems, this approach aims to improve data quality, reduce costs, and enhance data availability and real-time performance [31, 32, 33].

This survey will introduce the content of EAI data engineering in the above order. Speci cally, Section 2 begins with an overview of the foundations of EAI data engineering, Section 3 discusses EAI data production systems, Section 4 explores EAI data standards, Section 5 examines real-world EAI data collection technologies, Section 6 delves

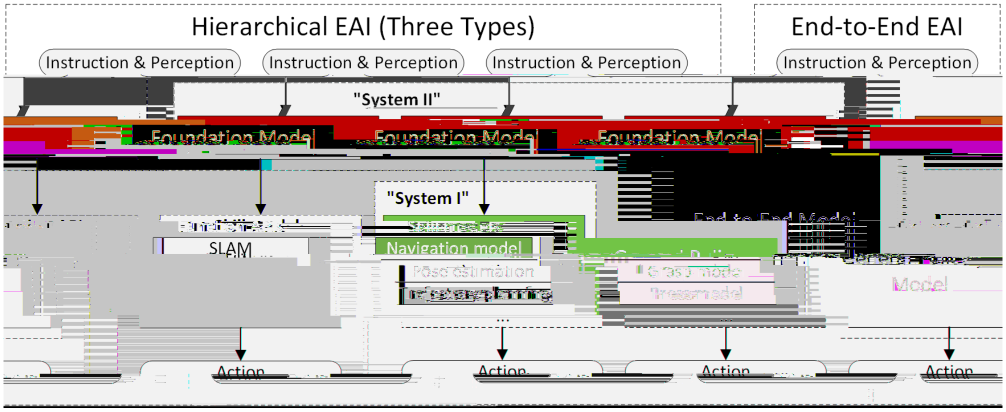
Hierarchical EAI (Three Types)
End-to-End EAI
Instruction & Perception
Instruction & Perception
Instruction & Perception
Instruction & Perception
"System II"
"System I"
Navigation model
SLAM
Action
Action
Action
Action

Table 2: Overview of Training Methods, Data Types, Typical Datasets, and Typical Models of Data Demanders

Data demanders	Foundation Models	Skill Models	General Policy Models	End-to-End Models
Training Methods	GP, SFT, RLHF, DPO, .etc.	RL, IL, .etc.	RL, IL, GP, SFT, .etc.	GP, SFT, RLHF, DPO, RL, IL, .etc.
Data Types	Internet data,			

the design, manufacturing, and purchasing of data collection devices. They also cover robot adaptation, site maintenance, and long-term human resource investment. Although some video demonstration data reduces the cost of real-world data collection, and simulation and synthetic data provide signifcant supplementation, the cost of collecting high-quality teleoperation data is still prohibitive. Reducing this cost requires further technological innovation and optimization of data collection processes.

- Data Silos The use of various data collection devices and technologies makes it diffcult to gather data in a unifed format across diverse scenarios, tasks, and robot bodies. As a result, EAI datasets are isolated from each other. This makes it diffcult to share and integrate data across different systems. The absence of EAI models that can generalize across different robot bodies means that datasets will continue to exist in isolated states. Building more universal and compatible EAI models and data standards is necessary to break down these data silos and enhance data sharing and utilization effciency.
- Evaluation Void There is a lack of standards and theoretical guidance in the data collection process. It is hard to assess whether the collected data effectively enhances the value of the dataset. This leads to blind data collection, redundant construction, and waste of resources. Developing more scientifc and reasonable evaluation metrics and standards is essential to improve data quality and promote the healthy development of EAI data engineering.

The cost ineffciency, data silos, and evaluation void are the three data bottlenecks in EAI. The purpose of EAI data engineering is to collect high-quality human demonstration and robot perception at a low cost across as many scenarios, tasks, and robot bodies as possible, in order to construct high-quality EAI datasets. EAI data engineering is designed to address these three bottlenecks

3 Data Production Systems Design for EAI

The frst step in conducting EAI data engineering is to design an EAI data production system. EAI data production consists of two aspects: real-world data collection and simulation data generation. Real-world data collection involves robots interacting directly with the external environment through sensors in actual settings to gather operational data and environmental feedback. This method can provide authentic and direct data. Simulation data generation refers to creating data through computer simulations or generative models. The primary advantage of this method is the ability to rapidly produce large amounts of data, thereby reducing costs.

The design of data production systems is crucial for addressing the EAI data bottleneck of cost ef ciency Effective EAI data engineering must strike a balance between high-fdelity real-world data collection, which provides invaluable insights but can be resource-intensive, and scalable, diverse simulation generation, which offers fexibility and scalability at a potentially lower cost. By integrating these two approaches, data production systems can optimize the trade-offs between data quality, cost, and scalability, thereby enhancing the overall effciency and effectiveness of EAI data engineering.

3.1 Real-World Data Collection Systems

Real-world data collection systems can be categorized into teleoperation-based data collection systems (tele-DCS) and teaching-based data collection systems (teach-DCS), depending on the different methods of data collection. A more detailed classifcation and introduction of real-world data collection technologies will be provided in Section 5. Here, a brief introduction to their system architecture design will be given to help readers understand the basic principles of system operation.

3.1.1 Teleoperation-Based Data Collection Systems

As shown in Fig. 4, the basic hardware architecture of tele-DCS mainly consists of fve major components. Teleoperation devices are used to output control parameters and receive feedback data, including control devices (such as joysticks for robot movement and direction control), display devices (such as monitors or virtual reality headsets), and a computing unit for processing operator inputs and feedback data. Communication devices are responsible for

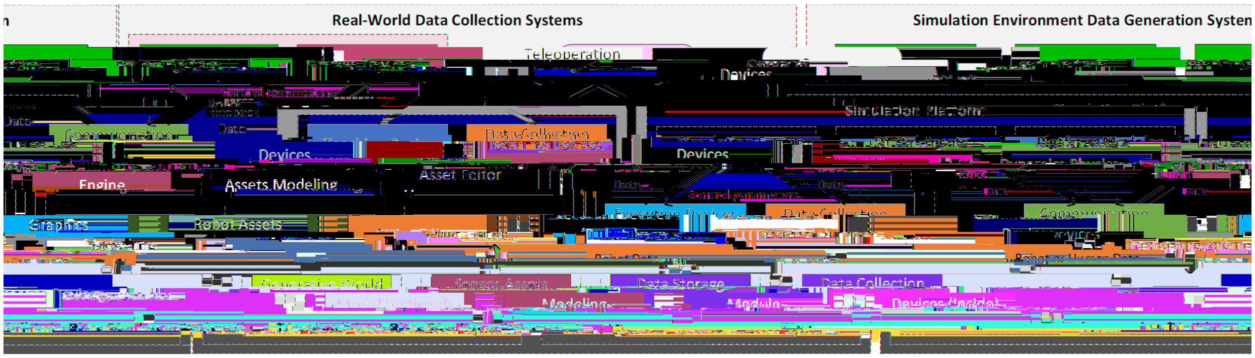

Figure 4: The basic architecture of real-world data collection systems and simulation data generation systems

3.1.2 Teaching-Based Data Collection Systems

Teach-DCS are used to record the teaching actions of human. The core purpose of teaching is to record the movements, postures, and environmental interaction information from robot (directly) or human (indirectly). Fig. 4 illustrates the hardware structure of a teach-DCS. It is more simplifed compared to tele-DCS. Teaching devices can be categorized into three types, with the specifc choice depending on factors such as task requirements, operational precision, environmental adaptability, and cost: (1) The robot itself as the teaching device, where operators directly manipulate the robot to complete the teaching tasks; (2) A part of the robot as the teaching device, such as the end effector of a robotic arm or a specifc sensor module; and (3) Teaching devices or teaching data separate from the robot, where operators collect human teaching data using external devices, such as cameras or motion capture systems.

3.2 Simulation Data Generation Systems

Simulation data generation systems (SDGS) are tools used to simulate robot behavior in virtual environments and generate multimodal data. Compared to real-world data collection systems, they are pure software systems that omit the hardware part in development, offering advantages such as low cost and ease of use.

Generally speaking, SDGS do not exist in isolation but are part of a robot simulation system. In addition to data generation functions, a robot simulation system may also include functions for training, testing, and deploying models of robot perception, decision-making, control, and more. This section will not introduce the entire robot simulation system but will focus solely on the data generation aspect. As shown in the Fig. 4, the system is composed of multiple hierarchical key components.

3.2.1 Simulation Engine

The simulation engine is the core of the entire system, responsible for simulating the behavior of robots in a virtual environment. It includes a dynamics physics engine that simulates the physical behavior of robots interacting with the environment, including various forces such as gravity, friction, elasticity, and inertia, and their effects on the robot's motion state, ensuring that the physical phenomena in the simulation conform to real physical laws. Additionally, it features a graphics rendering engine that converts three-dimensional models 249(a)-250(graph252(tools)-5)15(xterno)-253 conditions such as forces, motion, and acceleration. Sensor assets modeling aims to generate a mathematical model that accurately refects the relationship between sensor inputs and outputs, including the functional relationships between mechanical behavior, displacement, strain, stress, or vibration characteristics and the measured quantities. These models can simulate the working principles of devices such as cameras, radar, and force sensors, as well as their interactions with robots or other objects.

3.2.3 Platform Modules

The construction of a simulation platform requires the addition of various platform modules. Here, only three core modules are introduced. Other non-core modules, such as the graphical user interface and communication modules, are not discussed here. The asset editor allows users to create, edit, and manage digital assets in an intuitive manner. The script editor allows users to write and edit scripts that control the behavior of the simulation. These scripts can defne the actions of robots, dynamic changes in the environment, responses of sensors, etc. The data storage module saves various data generated during the simulation process.

3.2.4 System Interfaces

The simulation platform only provides a general digital modeling platform, and a SDGS can only be constructed by designing corresponding interfaces on its basis. These interfaces serve as the bridge for interaction between the system and external models, environments, or users. The User Interface allows the simulation platform to exchange data with external systems or users, defning the rules and protocols for data transmission to ensure that different systems or applications can be interconnected and exchange data, achieving data sharing and information interoperability. The Agent Interface enables the simulation platform to integrate various types of agents, such as robots controlled by LLMs, thereby achieving automated and intelligent processing of complex tasks, including path planning, high-level semantic understanding, long-range reasoning, and more. The Policy Interface can be connected to various robot policy models and algorithms, allowing users to control the behavior of robots or agents based on specifc models, rules, or conditions, such as path planning under a specifed policy or bimanual coordination under a specifed trajectory generation policy.

4 Standardization for EAI Data

The standardization of EAI data is crucial for addressing the EAI data bottlenecks of data silos and evaluation void. In the intricate tapestry of EAI ecosystems, where diverse data sources and formats often lead to fragmented and incompatible datasets, standardization acts as the unifying thread. It harmonizes data structures, facilitates seamless interoperability, and ensures that datasets from various origins can be integrated and utilized cohesively [56]. Moreover, standardization provides a common framework for evaluating data quality and utility, thereby flling the evaluation void and enabling more reliable and consistent assessments of EAI models. The standardization of data in EAI can be divided into multiple aspects. This section will frst introduce the classifcation of EAI datasets. Subsequently, it will propose standardization directions for EAI datasets.

4.1 Classi cation of EAI Datasets

EAI datasets can be classifed as shown in Fig. 5. Among these, demonstration datasets and embodied question-answering (EQA) datasets can be used for training EAI models or agents. The former is primarily utilized for training the "System I", while the latter is used for training the "System II". Both types of datasets can also be combined for end-to-end model training. On the other hand, benchmark datasets are generally not involved in the training of EAI models but are instead used more for evaluating the performance of agents.

4.1.1 Demonstration Datasets

Demonstration datasets typically consist of a series of operational or movement examples that robots can learn from to acquire the skills needed to complete tasks. These can be further divided into manipulation demonstration datasets and locomotion demonstration datasets. The former focuses on robots learning how to perform tasks by observing human or robot manipulation behaviors, while the latter is centered on robots learning how to move and perform actions in space. Table 3 and Table 4 present statistical information on common demonstration datasets currently in use, respectively.

- Manipulation Demonstration Datasets (MDD). Manipulation refers to a series of actions performed by humans or robots on objects, such as grasping, moving, rotating, placing, or adjusting the posture and position of objects to complete specifc tasks. MDD usually contain a series of manipulation videos or action sequences

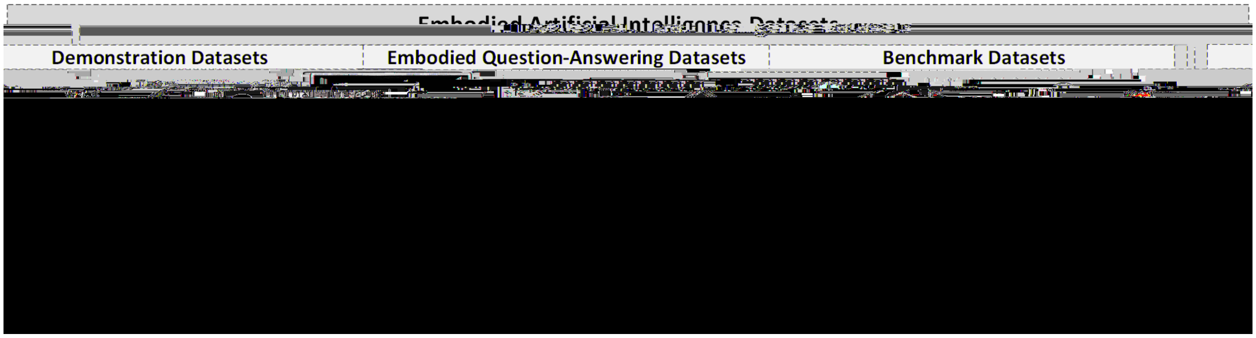

Figure 5: EAI datasets classifcation

Table 3: Common Manipulation Demonstration Datasets

Dataset	Data Form	Data Scale	Data Modality	Year
GraspNet-1Billion[57]	Real	97,280 images and 1.2B grasping	RGB-D	2020
RoboNet[58]	Real	162k trajectories and 15 million frames	Color Images	2020
ACRONYM[59]	Simulated	17.7M parallel grasping pairs	Point Cloud	2021
BridgeData[60]	Real	7,200 demonstrations	RGB-D	2021
AKB-48[61]	Real	100K generated RGB-D images	RGB-D	2022
BC-Z[48]	Real	25k demonstrations and 18k human video	RGB	2022
RT-1[62]	Real	130k robot demonstrations	RGB	2022
Grasp-Anything[63]	Simulated	1M samples and 600M grasping	Text / Image	2023
GAPartNet[64]	Simulated	8,489 instances	Point Cloud / RGB-D	2023
ManiSkill2[65]	Simulated	4M demonstration frames	Point Cloud / RGB-D	2023
ARNOLD[66]	Simulated	10,080 demonstrations	Text / RGB-D	2023
DexArt[67]	Simulated	6K point clouds for each object	Point Cloud	2023
BridgeData V2[51]	Real	60,096 trajectories, 50,365 teleoperation demonstrations, 9,731 deployments	RGB-D, Audio, Text and Haptic	2023
Open X-Embodiment[23]	Real	22 types of robots, over 1 million trajectories, 527 skills	Force Sensing Information / Point Cloud / RGB-D	2023
RH20T[68]	Real	147 tasks, 42 skills, 10,000 robot operation sequences and 110,000 corresponding human demonstration videos	RGB, Depth, Binocular Infrared, Haptic, Audio	2024
DROID[69]	Real	76k trajectories and 350 hours of interaction	RGB-D	2024
ARIO[24]	Real & Simulated	258 series and 321,064 tasks	RGB-D, Audio, Text and Haptic	2024
RoboMIND[70]	Real & Simulated	55,000 robot trajectories, 279 tasks, 61 types of objects	Text / RGB-D	2024
AgiBot World[71]	Real	Over 1 million trajectories of over 100 robots, over 100 scenes in fve domains	RGB-D, Haptic	2025

carried out by humans or robots. These actions are meticulously recorded and annotated so that robots can analyze and learn how to execute these actions through machine learning algorithms. Since most manipulations are based on grasping, some MDD may exclusively contain grasping data.

- Locomotion Demonstration Datasets (LDD) LDD focus on recording and providing full-body motion control data of robots or organisms when performing movement tasks, such as walking, running, jumping, crawling, and their variants under different environments and conditions. By capturing and recording key frames, joint angles, velocities, accelerations, and other information during the movement process, LDD provide the foundation for robots to learn how to move in three-dimensional space and maintain balance. Most current LDD are used for humanoid robots to meet specifc task requirements.

The construction of MDD is a systematic process. It begins with defning clear manipulation tasks, then designing corresponding experimental scenarios in the real world or simulation environments. Data on robot-environment interactions are collected using teleoperation technologies, among others. These data are subsequently labeled and analyzed to extract key features and interaction patterns, ultimately being organized into a comprehensive dataset that includes information on environmental states, robot actions, object properties, and task outcomes. The sources of motion data in LDD mainly come in three forms: motion capture data, video-based human motion estimation, and synthetic data.

Table 4: Common Locomotion Demonstration Datasets

Dataset Dataset	Year	Data Source	Data Scale	Modalities
Human3.6M[72]	2014	Motion capture	3.6 million frames of 3D human pose data	2D and 3D skeletal joint positions, depth images, and video sequences
KIT Motion-Language Dataset[73]	2016	Motion capture	3,911 actions with 6,278 natural language annotations	3D skeletal joint positions, text
AMASS[74]	2019	Motion capture	Over 300 subjects and more than 11,000 movements	3D skeletal joint positions
HumanAct12[75]	2020	Synthetic	1,191 3D motion clips, totaling 90,099 poses	3D skeletal joint positions
HumanML3D[76]	2022	Motion capture & Synthetic	14,616 actions and 44,970 descriptions	3D skeletal joint positions, text
Humanoid-X[77]	2024	Pose estimation	163,800 action samples	Videos, text descriptions, 3D human poses,

Table 6: Common Benchmark Datasets

Dataset	Year	Type	Data Form	Agent	Sensors	Supported Tasks

Figure 6: The entire lifecycle of EAI data and its corresponding three standardization phases

Figure 7: The classi cation of real-world data collection technologies for EAI

silos cannot be eliminated solely through improvements in RWDCT. Synchronized development of general models and robot bodies is also required to achieve this goal.

RWDCT for EAI can be categorized into teleoperation-based and teaching-based data collection. As shown in Fig. 7, these categories can be further divided into various speci c methods. All technologies discussed in this section essentially involve the construction of the demonstration datasets introduced in Section 4.1.1.

5.1 Teleoperation-based Data Collection Technologies

Teleoperation, or telerobotics, refers to a method where a human operator controls a robot or mechanical system from a distance. The pre x "tele-" implies remote operation, allowing the operator to manipulate the robot's actions from a distant location. As shown in Fig. 7, teleoperation can be categorized into three types.

5.1.1 Pose-based Teleoperation Technologies

Pose-based teleoperation refers to the method where a human operator remotely controls a robot using devices that directly record pose data. These devices convert pose signals into control signals for the robot's movements. Among remote operation devices, pose-based systems are the most diverse. They can range from simple handheld controllers to wearable devices such as gloves, motion capture suits, or exoskeletons, and isomorphic teleoperation robots that form a master-slave structure with the controlled robot. Therefore, as shown in Fig. 7, these technologies can be further subdivided into three categories.

- Handle-based Teleoperation Typically, such devices feature a simple structure and transmit the pose parameters of the end effector to the robot solely through a joystick-like device, such as HATO [107].
- Wearable Teleoperation Such devices are generally presented in the form of exoskeletons and offer greater intuitiveness and naturalness, as it allows operators to directly control the robot through their own body movements, such as AirExo [108] and ACE[109].
- Isomorphic Teleoperation Isomorphic teleoperation refers to the real-time replication of movements between two identical robots, such as Mobile ALOHA [45], GELLO [110], and HOMIE [111]. This involves setting one

robot as the master (operator) device and the other as the subordinate device. Since the dynamic structures of the two robots are identical, the complexity of control and motion replication is significantly reduced.

5.1.2 Visual-based Teleoperation Technologies

Visual-based teleoperation refers to the process of capturing an operator's movements using visual sensing technologies (such as RGB-D cameras) and then converting these movements into control commands to manipulate a robot. This method directly maps human actions to robot actions, allowing operators to easily and intuitively control robotic systems. It is suitable for cost-saving scenarios with lower precision requirements, such as DexPilot[112], AnyTeleop [113], HumanPlus[114], and DIME[2].

5.1.3 Optical-Inertial Teleoperation Technologies

Optical-inertial teleoperation is a sophisticated approach that integrates optical motion capture systems with inertial measurement units (IMUs) to remotely control robots. This method leverages the respective advantages of wearable teleoperation and vision-based teleoperation technologies to achieve more accurate, reliable, and continuous tracking of the operator's movements. Typical optical-inertial teleoperation systems include motion capture systems, virtual reality (VR)-based teleoperation platforms, and other integrated forms, such as Bunny-VisionPro[115], OmniH2O[114], and Mobile-TeleVision[116].

5.2 Teaching-Based Data Collection Technologies

Teaching-based data collection refers to the process where a human operator performs a task or a series of tasks, and the teaching data is then used to guide the robot in performing similar tasks. As shown in Fig. 7, teaching-based data collection methods can be divided into two categories.

5.2.1 Direct Teaching Technologies

Direct teaching, also known as hand-guided teaching, is characterized by its intuitive operation, making it suitable for simple teaching tasks. It does not require additional hardware, resulting in lower costs. However, its drawbacks include low teaching efficiency and limited applicable scenarios. Specific implementations of direct teaching include the following:

- Drag Teaching Physically manipulates the robot's joints or end-effector to desired positions through manual guidance. It has been widely applied in various industrial robotic arms and assistive robotic arms.
- Teach Pendant Teaching Allowing operators to directly control or program the robot via a handheld teach pendant, such as buttons, knobs, and touchscreens.

In terms of usage, teach pendant teaching is somewhat similar to handheld-based teleoperation. However, there are key differences. Teach pendant teaching is suited for programming setups and scenarios requiring precise control, with operators interacting directly and in close proximity to the robot. In contrast, handheld-based teleoperation emphasizes flexibility and safety, enabling remote, real-time control of the robot by the operator. A more intuitive distinction is that teach pendants are typically specialized devices manufactured according to robot vendor specifications, while handheld-based teleoperation devices are usually third-party, general-purpose tools, adhering to different interface standards and communication protocols.

5.2.2 Indirect Teaching Technologies

In indirect teaching, operators no longer directly manipulate the entire robot. In the field of data collection for EAI, three common indirect teaching methods exist:

- End-Effector Teaching It involves operators completing teaching tasks by controlling the robot's end-effector, such as UMI [26] and Fast-UMI [117]. They transform the end-effector into a universal manipulation interface, enabling humans to hold it independently for data collection. Compared to using the entire robot for data collection, using only the end-effector allows for convenient data acquisition in various open environments. As a result, this technique is also referred to as "in-the-wild" data collection.
- Motion Capture Teaching It refers to the process where an operator wears motion capture devices (such as data gloves [27] and motion capture suits [118]), and the system records the operator's movements to serve as teaching data for robots.

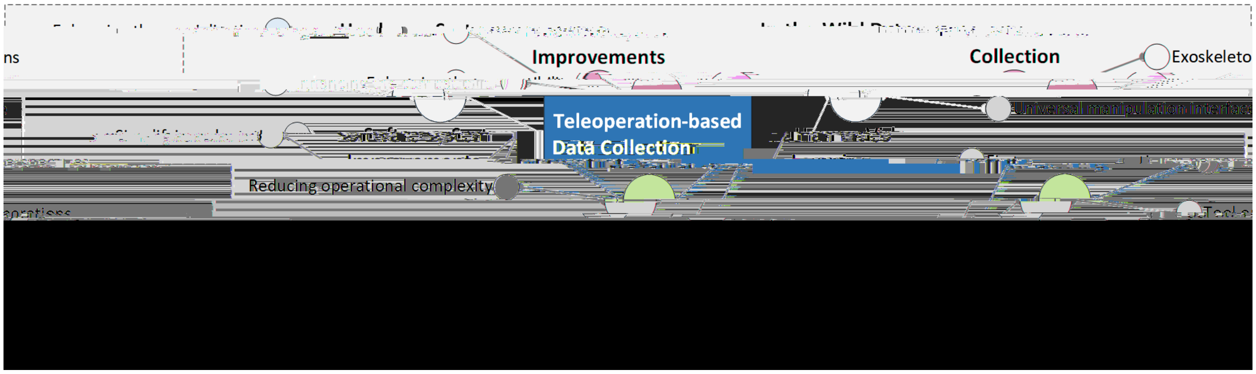

Figure 8: The improvement directions in real-world data collection technologies

- Human Video Teaching: It is an emerging robotic learning method aimed at completing complex tasks by imitating human behavior, without the need for manual programming or extensive robot data collection. The core of this approach lies in using human video demonstrations as a source of knowledge, enabling robots to understand and execute tasks while demonstrating strong generalization capabilities [119, 120]. This technology may be more cost-effective than expert demonstrations performed by robots [121, 122].

There is an essential difference between the data collected through indirect teaching and teleoperation: Indirect teaching collects human data, while teleoperation collects robot data. Indirect teaching data may not precisely correspond to robot movements and may not guarantee the usability of the collected data. For example, the range of motion in indirect teaching data may exceed the robot's workspace, or lacks tactile data. In contrast, teleoperation directly maps human actions to the robot and it can obtain all robot data.

It should be noted that the above technical classifcations are not absolute. A data collection system can integrate multiple collection technologies (for example, HOMIE is an integration of wearable teleoperation and isomorphic teleoperation). In practice, people need to make comprehensive choices for the optimal data collection methods based on various aspects such as the adopted technical approach, collection effciency, and cost.

5.3 Improvement Directions in Real-World Data Collection Technologies

5.3.1 Improvement Directions in Teleoperation-based Data Collection Technologies

Teleoperation is the most widely used method for data collection, directly producing robot data with signifcant research focus on its improvement. As shown in Fig. 8, improvements can be categorized into three main directions:

Hardware System Improvements aim to enhance the specialization and compatibility of teleoperation hardware systems. Specialization focuses on better adaptation for specifc robot types, such as bimanual robots [123], quadruped robots [124], grippers [125], dexterous hands [126, 127], and humanoid robots [128, 129]. Compatibility improvements aim to work with various robot types [130, 131]. Software System Improvements are dedicated to simplifying teleoperation software adaptation and reducing user operational complexity. Examples include integrating multiple human-machine interaction interfaces [132, 133], improving device compatibility [134], and incorporating built-in motion mapping strategies to avoid singularities [135]. Interaction Strategy Improvements aim to address the inherent unreliability of human movements, which can introduce delays, jitter, and errors in teleoperation. To collect high-quality data, various strategies have been proposed: Policy assisting humans involves using existing policy models to autonomously perform repetitive actions during data collection or correct unreliable human teleoperation behaviors online, requesting human input only when uncertain [136, 137, 138]. Humans assisting policy leverages policy models to perform repetitive actions, with humans correcting and updating the model when it produces unreliable behaviors [139, 140, 141, 142, 143]. Bidirectional assistance combines these two modes, and may even incorporate adversarial strategies [144, 145, 146, 147].

5.3.2 Improvement Directions in teaching-based Data Collection Technologies

Teaching, especially indirect teaching, offers greater fexibility as it is not constrained by the robot's physical form. The focus of its improvement lies in leveraging this advantage while ensuring data quality. As shown in Fig. 8, improvements can be categorized into three main directions:

In-the-Wild Data Collection aims to develop affordable, lightweight, and user-friendly hardware devices for effcient data collection in open environments, such as exoskeletons and universal manipulation interface. The former focus on lightweight design [148] and wider variety compatibility of dexterous hands [149, 150]. The later focus on developing more versatile hardware and software systems, such as lighter structures [151], tactile supporting [152, 153, 154, 155], dexterous hands supporting [156, 157], join policy assistance [158], and adaptability to other robot forms [159, 160]. Human Video Learning

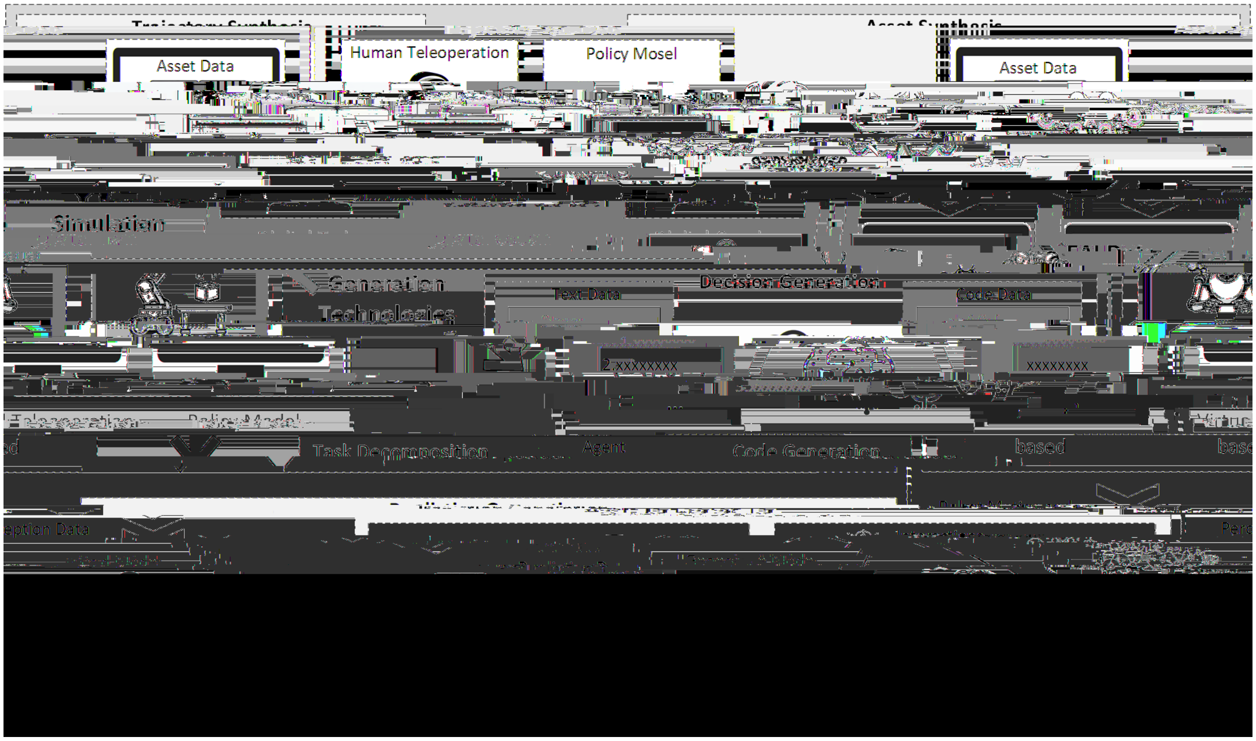

Figure 9: The classifcation of simulation EAI data generation technologies

allows operators to directly generate demonstration data within simulation environments, which can serve as seeds for subsequent large-scale data generation, such as MimicGen [28].

- Policy Model-Based: Compared to manually synthesizing trajectory data through virtual teleoperation, using an existing policy model to automatically synthesize large amounts of data in a simulator offers signifcant effciency improvements and can construct a powerful data fywheel, such as DexMimicGen[177].

6.2.2 Asset Synthesis

It refers to the creation of virtual scenes and objects, particularly interactive objects in simulation environments, using generative AI and related technologies to support the training, simulation, and evaluation of robots. Asset synthesis is typically based on real-world scenes or objects to avoid generating arbitrary assets that deviate from reality. It often involve the processing of 3D reconstruction or 3D generation technologies, suche simologoationhiatioadianc

- Task DecompositionIt is a prerequisite for executing complex tasks, which involves breaking down task goals into a series of actionable sub-goals. This usually requires the use of LLM to perform reasoning and analysis based on input information and to formulate specifc action plans in conjunction with a task planning module, such as COWP [182] and EAIB [183].

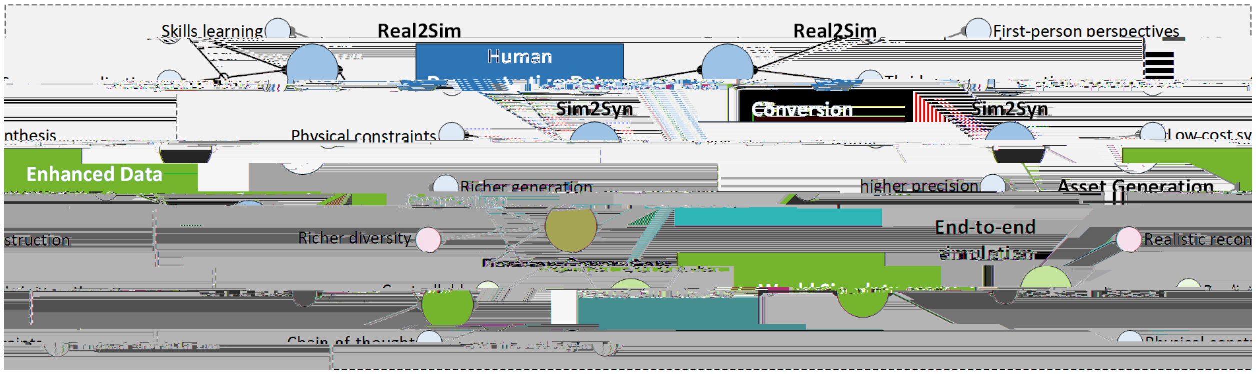

Figure 10: The improvement directions in simulation data generation technologies

real world. This asymptotic approximation may also be subject to scaling laws, implying that the cost of achieving higher fdelity in simulations could increase disproportionately. Consequently, merely enhancing simulation precision may not suffce to bridge the gap. A more effective strategy might involve constructing a world model that incorporates the sim2real gap as a learnable component, enabling the use of simulation outcomes to predict real-world behaviors more accurately.

The decision of whether to employ simulation data, and if so, determining the appropriate scale and proportion for its integration, remains an open and complex question within the feld. These questions necessitate a multifaceted approach, involving the coordinated development and maturation of various technologies over an extended period. Only through such efforts can we hope to arrive at well-informed and effective solutions that balance the benefts and limitations of simulation data in relation to real-world applications.

7 The Application and Optimization of EAI Data Engineering

The application of EAI Data Engineering can be delineated into three distinct phases: the analysis of data requirements within specifc application domains, the selection of appropriate data production methods, and the optimization of concrete deployments. Accordingly, this section will unfold discussions from these three perspectives, offering guidance to practitioners in the feld.

7.1 Data Requirement Analysis of Industry and Service Industry

As shown in Table 7, applications in different felds have varying requirements for the core capabilities of EAI, and thus their most prioritized data needs also differ. This section defnes the industrial feld as covering four sectors: manufacturing, mining, utilities (including electricity, heat, gas, and water production and supply), and construction. Robots in these four felds are referred to as industrial robots. Generally, manufacturing robots are distinguished from robots in the other three subfelds, which are collectively referred to as special robots.

Manufacturing robots have specifc capability requirements to meet the demands of modern production processes. They need to possess autonomous learning and adaptability, enabling them to automatically adjust their operational processes in response to changes in tasks. In precision manufacturing sectors, such as electronics and semiconductor production, high-precision motion control capabilities are essential. Additionally, manufacturing robots must be able to quickly switch between production tasks to minimize changeover time.

Special robots, on the other hand, face unique challenges that require different capabilities. They need to have high environmental adaptability to operate in extreme conditions, such as high temperatures, high pressures, and toxic or hazardous environments. These robots must also be capable of executing complex tasks with higher uncertainty, such as disaster rescue, power inspection, and space exploration. Furthermore, special robots must prioritize safety and reliability to ensure stable operation in hazardous environments [216].

As listed in the Characteristics in Table 7, the industrial feld is characterized by the fact that centuries of development have standardized the scenarios, tools, objects, and operations as much as possible. The remaining challenge is how to use EAI to generalize to the parts that are not standardized. Therefore, the application of EAI data engineering should focus on goal-driven producing the corresponding prioritized data according to the

Table 7: Goal-Driven Data Requirement Analysis of Industry and Service Industry

Field	Sub eld		Characteristics	Core Capability Requirements	Most Needed Data
Industry	Manufacturing		Standardized scenarios, tools, objects, and operation	Production line adaptability, high-precision motion control	Domain knowledge data, manipulation data, and asset data
	Special feld	Mining	Non-standardized scenarios, tools, objects, and operations	High environmental adaptability, safety and reliability	Domain knowledge data, manipulation and locomotion data
		Utilities	Non-standardized scenarios, but standardized tools, objects, and operation	High safety and reliability, customization, autonomous decision-making	Domain knowledge data, manipulation data, locomotion data, and asset data
		Construction	Standardized scenarios and tools, but non-standardized objects and operation	High environmental adaptability, safety and reliability	Domain knowledge data, manipulation data, locomotion data, and asset data
Service Industry	-		Highly diverse and dynamic, with different sub-sectors having varying requirements for robot capabilities	Strong perception,precise motion control, autonomous decision-making, emotion recognition, continuous learning and adaptation	Common sense data, manipulation and locomotion data, decision-making data, human-robot interaction and empirical data

characteristics and core capability requirements of different industrial elds, and improve the corresponding production effciency.

The application felds of service industry include wholesale and retail trade, transportation, storage and postal services, accommodation and catering services, education, health and social work, culture, sports and entertainment, and healthcare. In the service industry, which is highly diverse and dynamic, with different sub-sectors having varying requirements for robot capabilities, the demands for the dynamics performance of robots and the intelligence of EAI models are both very high. As a result, the need for all types of data is almost equally important. To this end, data production in the service industry needs to be closely synchronized with the development of robot bodies and EAI models, and progress in tandem within the loop of "production-training-testing-improvement-reproduction".

7.2 Selection of EAI Data Production Methods

The choice of EAI data production methods is pivotal for the effciency and effectiveness of data acquisition, as illustrated by the comparative analysis in Table 8. Each method presents unique advantages and challenges across various parameters such as equipment cost, labor cost, computational cost, application scope, productivity, data availability, and diversity. Understanding these attributes is fundamental for goal-driven selecting the most appropriate method for specifc EAI applications.

Table 8: Comparison of characteristics of different EAI data production methods when producing the same amount of data

Technical type	Real-World Data Collection	

capabilities, covering system design, data standardization, collection, generation, and application. The challenges inherent in EAI Data Engineering, while formidable, present opportunities for innovation and improvement. The development of systematic EAI data production platforms, scalable standards, integration of data and model, real-sim collaborative, goal-driven production, and open data trading platforms are identifed as key directions for future progress. These advancements are poised to enhance the effciency, quality, and applicability of EAI data, thereby propelling the feld forward.

To realize the full potential of EAI, the industry must shift from opportunistic data use to systematic, standardized, scalable and goal-driven EAI data engineering. As we look to the future, the continuous evolution of EAI Data Engineering will be instrumental in unlocking the full potential of embodied intelligence. By fostering collaboration across academia, industry, and government, and by leveraging cutting-edge technologies, we can surmount existing barriers and create more intelligent, adaptive, and human-centric robotic systems. The ultimate goal is to develop EAI systems that can seamlessly integrate into our daily lives, enhancing productivity, safety, and quality of life. This review serves as a testament to the dynamic and promising nature of EAI Data Engineering, inviting researchers and practitioners to contribute to this transformative journey.

9 Acknowledgments

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References

[1] Wang Fan and Shaoshan Liu. Putting the smarts into robot bodies. Communications of the ACM, 68(3):6–8, 2025.

[2] Shaoshan Liu. The value of data in embodied artifcial intelligence. Communications of the ACM, 2024.

[3] Shaoshan Liu. Shaping the outlook for the autonomy economy. Communications of the ACM, 67(6):10–12, 2024.

[4] Jared Kaplan, Sam McCandlish, Tom Henighan, Tom B Brown, Benjamin Chess, Rewon Child, Scott Gray, Alec Radford, Jeffrey Wu, and Dario Amodei. Scaling laws for neural language models. arXiv preprint arXiv:2001.08361, 2020.

[5] Tim Pearce, Tabish Rashid, Dave Bignell, Raluca Georgescu, Sam Devlin, and Katja Hofmann. Scaling laws for pre-training agents and world models. arXiv preprint arXiv:2411.04434, 2024.

[6] Alan M Turing. Computing machinery and intelligence. Springer, 2009.

[7] Shuang Wu, Bo Yu, Shaoshan Liu, and Yuhao Zhu. Autonomy 2.0: The quest for economies of scale. Communications of the ACM, 68(4):28–32, 2025.

[8] Shaoshan Liu and Shuang Wu. A brief history of embodied artifcial intelligence, and its future outlook. Communications of the ACM, 2024.

[9] Jinda Cui and Jeff Trinkle. Toward next-generation learned robot manipulation. Science robotics, 6(54):eabd9461, 2021.

[10] MD Moniruzzaman, Alexander Rassau, Douglas Chai, and Syed Mohammed Shamsul Islam. Teleoperation

[14] Robert McCarthy, Daniel CH Tan, Dominik Schmidt, Fernando Acero, Nathan Herr, Yilun Du, Thomas G Thuruthel, and Zhibin Li. Towards generalist robot learning from internet video: A survey. *arXiv preprint arXiv:2404.19664*, 2024.

[15] Kento Kawaharazuka, Tatsuya Matsushima, Andrew Gambardella, Jiaxian Guo, Chris Paxton, and Andy Zeng. Real-world robot applications of foundation models: A review. *Advanced Robotics*, 38(18):1232–1254, 2024.

[16] Maryam Zare, Parham M Kebria, Abbas Khosravi, and Saeid Nahavandi. A survey of imitation learning: Algorithms, recent developments, and challenges. *IEEE Transactions on Cybernetics*, 2024.

[17] Xuan Xiao, Jiahang Liu, Zhipeng Wang, Yanmin Zhou, Yong Qi, Shuo Jiang, Bin He, and Qian Cheng. Robot learning in the era of foundation models: A survey. *Neurocomputing*, page 129963, 2025.

[18] Lik Hang Kenny Wong, Xueyang Kang, Kaixin Bai, and Jianwei Zhang. A survey of robotic navigation and manipulation with physics simulators in the era of embodied ai. *arXiv preprint arXiv:2505.01458*, 2025.

[19] Jiwen Yu, Yiran Qin, Haoxuan Che, Quande Liu, Xintao Wang, Pengfei Wan, Di Zhang, Kun Gai, Hao Chen, and Xihui Liu. A survey of interactive generative video. *arXiv preprint arXiv:2504.21853*, 2025.

[20] Kun Zhang, Peng Yun, Jun Cen, Junhao Cai, Didi Zhu, Hangjie Yuan, Chao Zhao, Tao Feng, Michael Yu Wang, Qifeng Chen, et al. Generative artifcial intelligence in robotic manipulation: A survey. *arXiv preprint arXiv:2503.03464*, 2025.

[21] Kaiyuan Chen, Letian Fu, David Huang, Yanxiang Zhang, Lawrence Yunliang Chen, Huang Huang, Kush Hari, Ashwin Balakrishna, Ted Xiao, Pannag R Sanketi, et al. Robo-dm: Data management for large robot datasets. *arXiv preprint arXiv:2505.15558*, 2025.

[22] Xuan Xia, Bo Yu, Jialin Jiao, Xinmin Ding, Xing He, Haoran Tong, Yufei Lin, Tongyi Shen, Ning Ding, and Shaoshan Liu. Airspeed: An open-source universal data production platform for embodied artifcial intelligence.

[23] Abby O'Neill, Abdul Rehman, Abhinav Gupta, Abhiram Maddukuri, Abhishek Gupta, Abhishek Padalkar, Abraham Lee, and Acorn Pooley et al. Open x-embodiment: Robotic learning datasets and rt-x models. *ArXiv*, abs/2310.08864, 2023.

[24] Zhiqiang Wang, Hao Zheng, Yunshuang Nie, Wenjun Xu, Qingwei Wang, Hua Ye, Zhe Li, Kaidong Zhang, Xuewen Cheng, Wanxi Dong, Chang Cai, Liang Lin, Feng Zheng, and Xiaodan Liang. All robots in one: A new standard and unifed dataset for versatile, general-purpose embodied agents. *ArXiv*, abs/2408.10899, 2024.

[25] Zipeng Fu, Tony Zhao, and Chelsea Finn. Mobile aloha: Learning bimanual mobile manipulation with low-cost whole-body teleoperation. *ArXiv*, abs/2401.02117, 2024.

[26] Cheng Chi, Zhenjia Xu, Chuer Pan, Eric Cousineau, Benjamin Burchfel, Siyuan Feng, Russ Tedrake, and Shuran Song. Universal manipulation interface: In-the-wild robot teaching without in-the-wild robots. *ArXiv*, abs/2402.10329, 2024.

[27] Chen Wang, Haochen Shi, Weizhuo Wang, Ruohan Zhang, Fei-Fei Li, and Karen Liu. Dexcap: Scalable and portable mocap data collection system for dexterous manipulation. *ArXiv*, abs/2403.07788, 2024.

[28] Ajay Mandlekar, Soroush Nasiriany, Bowen Wen, Iretiayo Akinola, Yashraj S. Narang, Linxi Fan, Yuke Zhu, and Dieter Fox. Mimicgen: A data generation system for scalable robot learning using human demonstrations. In *Conference on Robot Learning*, 2023.

[29] Tianyuan Dai, Josiah Wong, Yunfan Jiang, Chen Wang, Cem Gokmen, Ruohan Zhang, Jiajun Wu, and Fei-Fei Li. Automated creation of digital cousins for robust policy learning. *ArXiv*, abs/2410.07408, 2024.

[30] Leonardo Barcellona, Andrii Zadaianchuk, Davide Allegro, Samuele Papa, Stefano Ghidoni, and Efstratios Gavves. Dream to manipulate: Compositional world models empowering robot imitation learning with imagination. *arXiv preprint arXiv:2412.14957*, 2024.

[31] Joey Hejna, Suvir Mirchandani, Ashwin Balakrishna, Annie Xie, Ayzaan Wahid, Jonathan Tompson, Pannag Sanketi, Dhruv Shah, Coline Devin, and Dorsa Sadigh. Robot data curation with mutual information estimators. *arXiv preprint arXiv:2502.08623*, 2025.

[32] Haozhuo Li, Yuchen Cui, and Dorsa Sadigh. How to train your robots? the impact of demonstration modality on imitation learning. *arXiv preprint arXiv:2503.07017*, 2025.

[33] [illegible]

[15]

[35] Fanqi Lin, Yingdong Hu, Pingyue Sheng, Chuan Wen, Jiacheng You, and Yang Gao. Data scaling laws in imitation learning for robotic manipulation.

[57] Fang Hao-Shu, Wang Chenxi, Gou Minghao, and Lu Cewu. Graspnet-1billion: A large-scale benchmark for general object grasping. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, pages 11444–11453, 2020.

[58] Sudeep Dasari, Frederik Ebert, Stephen Tian, Suraj Nair, Bernadette Bucher, Karl Schmeckpeper, Siddharth Singh, Sergey Levine, and Chelsea Finn. Robonet: Large-scale multi-robot learning. ArXiv, abs/1910.11215, 2019.

[59] Clemens Eppner, Arsalan Mousavian, and Dieter Fox. Acronym: A large-scale grasp dataset based on simulation. In 2021 IEEE International Conference on Robotics and Automation (ICRA), pages 6222–6227. IEEE, 2021.

[60] Frederik Ebert, Yanlai Yang, Karl Schmeckpeper, Bernadette Bucher, Georgios Georgakis, Kostas Daniilidis, Chelsea Finn, and Sergey Levine. Bridge data: Boosting generalization of robotic skills with cross-domain datasets. ArXiv, abs/2109.13396, 2021.

[61] L. Liu, Wenqiang Xu, Haoyuan Fu, Sucheng Qian, Yong-Jin Han, and Cewu Lu. Akb-48: A real-world articulated object knowledge base. 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pages 14789–14798, 2022.

[62] Anthony Brohan, Noah Brown, Justice Carbajal, Yevgen Chebotar, Joseph Dabis, and Chelsea Finn et al. Rt-1: Robotics transformer for real-world control at scale. ArXiv, abs/2212.06817, 2022.

[63] An Dinh Vuong, Minh Nhat Vu, Hieu Le, Baoru Huang, Huynh Thi Thanh Binh, Thieu Vo, Andreas Kugi, and Anh Nguyen. Grasp-anything: Large-scale grasp dataset from foundation models. In 2024 IEEE International Conference on Robotics and Automation (ICRA), pages 14030–14037. IEEE, 2024.

[64] Haoran Geng, Helin Xu, Chengyang Zhao, Chao Xu, Li Yi, Siyuan Huang, and He Wang. Gapartnet: Cross-category domain-generalizable object perception and manipulation via generalizable and actionable parts. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 7081–7091, 2023.

[65] Jiayuan Gu, Fanbo Xiang, Xuanlin Li, Z. Ling, Xiqiang Liu, Tongzhou Mu, Yihe Tang, Stone Tao, Xinyue Wei, Yuan Yao, Xiao Yuan, Pengwei Xie, Zhiao Huang, Rui Chen, and Hao Su. Maniskill2: A unifed benchmark for generalizable manipulation skills. ArXiv, abs/2302.04659, 2023.

[66] Ran Gong, J

[75] Chuan Guo, Xinxin Zuo, Sen Wang, Shihao Zou, Qingyao Sun, Annan Deng, Minglun Gong, and Li Cheng. Action2motion: Conditioned generation of 3d human motions. In *Proceedings of the 28th ACM International Conference on Multimedia*, 2020.

[76] Chuan Guo, Shihao Zou, Xinxin Zuo, Sen Wang, Wei Ji, Xingyu Li, and Li Cheng. Generating diverse and natural 3d human motions from text. In *2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 5142–5151, 2022.

[77] Jiageng Mao, Siheng Zhao, Siqi Song, Tianheng Shi, Junjie Ye, Mingtong Zhang, Haoran Geng, Jitendra Malik, Vitor Campanholo Guizilini, and Yue Wang. Learning from massive human videos for universal humanoid pose control. ArXiv, abs/2412.14172, 2024.

[78] Abhishek Das, Samyak Datta, Georgia Gkioxari, Stefan Lee, Devi Parikh, and Dhruv Batra. Embodied question answering. In *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 1–10, 2018.

[79] Cătălina Cangea, Eugene Belilovsky, Pietro Lio', and Aaron C. Courville. Videonavqa: Bridging the gap between visual and embodied question answering. *ArXiv*, abs/1908.04950, 2019.

[80] Xiaojian Ma, Silong Yong, Zilong Zheng, Qing Li, Yitao Liang, Song-Chun Zhu, and Siyuan Huang. Sqa3d: Situated question answering in 3d scenes. *ArXiv*, abs/2210.07474, 2022.

[81] Sinan Tan, Mengmeng Ge, Di Guo, Huaping Liu, and Fuchun Sun. Knowledge-based embodied question answering. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 45(10):11948–11960, 2023.

[82] Yi Chen, Yuying Ge, Yixiao Ge, Mingyu Ding, Bohao Li, Rui Wang, Rui-Lan Xu, Ying Shan, and Xihui Liu. Egoplan-bench: Benchmarking multimodal large language models for human-level planning. 2023.

[83] Arjun Majumdar, Anurag Ajay, Xiaohan Zhang, Pranav Putta, Sriram Yenamandra, Mikael Henaff, and Silwal et al. Openeqa: Embodied question answering in the era of foundation models. In *2024 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 16488–16498, 2024.

[84] Allen Ren, Jaden Clark, Anushri Dixit, Masha Itkina, Anirudha Majumdar, and Dorsa Sadigh. Explore until confdent: Effcient exploration for embodied question answering. *ArXiv*, abs/2403.15941, 2024.

[85] Vishnu Sashank Dorbala, Prasoon Goyal, Robinson Piramuthu, Michael Johnston, Reza Ghanadhan, and Dinesh Manocha. Is the house ready for sleeptime? generating and evaluating situational queries for embodied question answering. 2024.

[86] Emily Jin, Zhuoyi Huang, Jan-Philipp Fränken, Weiyu Liu, Hannah Cha, Erik Brockbank, Sarah A. Wu, Ruohan Zhang, Jiajun Wu, and Tobias Gerstenberg. Marple: A benchmark for long-horizon inference. *ArXiv*, abs/2410.01926, 2024.

[87] Min Zhang, Jianye Hao, Xian Fu, Peilong Han, Hao Zhang, Lei Shi, Hongyao Tang, and Yan Zheng. Mfe-etp: A comprehensive evaluation benchmark for multi-modal foundation models on embodied task planning. *ArXiv*, abs/2407.05047, 2024.

[88] Mengfei Du, Binhao Wu, Zejun Li, Xuanjing Huang, and Zhongyu Wei. Embspatial-bench: Benchmarking spatial understanding for embodied tasks with large vision-language models. In *Annual Meeting of the Association for Computational Linguistics*, 2024.

[89] Chen Gao, Baining Zhao, Weichen Zhang, Jinzhu Mao, Jun Zhang, Zhiheng Zheng, Fanhang Man, Jianjie Fang, Zile Zhou, Jinqiang Cui, Xinlei Chen, and Yong Li. Embodiedcity: A benchmark platform for embodied agent in real-world city environment. *ArXiv*

[96] Yue Fan, Winson X. Chen, Tongzhou Jiang, Chun ni Zhou, Yi Zhang, and Xin Eric Wang. Aerial vision-and-dialog navigation. In Annual Meeting of the Association for Computational Linguistics, 2022.

[97] Quanyi Li, Zhenghao Peng, Lan Feng, Qihang Zhang, Zhenghai Xue, and Bolei Zhou. Metadrive: Composing diverse driving scenarios for generalizable reinforcement learning. IEEE Transactions on Pattern Analysis and Machine Intelligence, 45(3):3461–3475, 2023.

[98] Matt Deitke, Eli VanderBilt, Alvaro Herrasti, Luca Weihs, Jordi Salvador, Kiana Ehsani, Winson Han, Eric Kolve, Ali Farhadi, Aniruddha Kembhavi, and Roozbeh Mottaghi. Procthor: Large-scale embodied ai using procedural generation. ArXiv, abs/2206.06994, 2022.

[99] Sriram Yenamandra, A. Ramachandran, Karmesh Yadav, Austin S. Wang, Mukul Khanna, ThØophile Gervet, Tsung-Yen Yang, Vidhi Jain, Alexander Clegg, John Turner, Zsolt Kira, Manolis Savva, Angel X. Chang, Devendra Singh Chaplot, Dhruv Batra, Roozbeh Mottaghi, Yonatan Bisk, and Chris Paxton. Homerobot: Open-vocabulary mobile manipulation. In Conference on Robot Learning, 2023.

[100] Chengshu Li, Ruohan Zhang, Josiah Wong, Cem Gokmen, and Sanjana Srivastava et al. Behavior-1k: A human-centered, embodied ai benchmark with 1, 000 everyday activities and realistic simulation. ArXiv, abs/2403.09227, 2024.

[101] Shubo Liu, Hongsheng Zhang, Yuankai Qi, Peifeng Wang, Yaning Zhang, and Qi Wu. Aerialvln: Vision-and-language navigation for uavs. 2023 IEEE/CVF International Conference on Computer Vision (ICCV), pages 15338–15348, 2023.

[102] Wayne Wu, Honglin He, Jack He, Yiran Wang, Chenda Duan, Zhizheng Liu, Quanyi Li, and Bolei Zhou. Metaurban: An embodied ai simulation platform for urban micromobility. In International Conference on Learning Representations, 2024.

[103] Hanqing Wang, Jiahe Chen, Wensi Huang, Qingwei Ben, Tai Wang, Boyu Mi, Tao Huang, Siheng Zhao, Yilun Chen, Sizhe Yang, Peizhou Cao, Wenye Yu, Zichao Ye, Jialun Li, Junfeng Long, Zirui Wang, Huiling Wang, Ying Zhao, Zhongying Tu, Yu Qiao, Dahua Lin, and Jiangmiao Pang. Grutopia: Dream general robots in a city at scale. ArXiv, abs/2407.10943, 2024.

[104] Jungdae Lee, Taiki Miyanishi, Shuhei Kurita, Koya Sakamoto, Daich Azuma, Yutaka Matsuo, and Nakamasa Inoue. Citynav: Language-goal aerial navigation dataset with geographic information. ArXiv, abs/2406.14240, 2024.

[105] Lingfeng Zhang, Yuening Wang, Hongjian Gu, Atia Hamidizadeh, Zhanguang Zhang, Yuecheng Liu, Yutong Wang, David Gamaliel Arcos Bravo, Junyi Dong, Shunbo Zhou, Tongtong Cao, Yuzheng Zhuang, Yingxue Zhang, and Jianye Hao. Et-plan-bench: Embodied task-level planning benchmark towards spatial-temporal cognition with foundation models. ArXiv, abs/2410.14682, 2024.

[106] Rui Yang, Hanyang Chen, Junyu Zhang, Mark Zhao, Cheng Qian, Kangrui Wang, Qineng Wang, Teja Venkat Koripella, Marziyeh Movahedi, Manling Li, Heng Ji, Huan Zhang, and Tong Zhang. Embodiedbench: Comprehensive benchmarking multi-modal large language models for vision-driven embodied agents. ArXiv, abs/2502.09560, 2025.

[107] Toru Lin, Yu Zhang, Qiyang Li, Haozhi Qi, Brent Yi, Sergey Levine, and Jitendra Malik. Learning visuotactile skills with two multifngered hands. ArXiv, abs/2404.16823, 2024.

[108] Hongjie Fang, Haoshu Fang, Yiming Wang, Jieji Ren, Jing Chen, Ruo Zhang, Weiming Wang, and Cewu Lu. Airexo: Low-cost exoskeletons for learning whole-arm manipulation in the wild. 2024 IEEE International Conference on Robotics and Automation (ICRA), pages 15031–15038, 2023.

[109] Shiqi Yang, Minghuan Liu, Yuzhe Qin, Runyu Ding, Jialong Li, Xuxin Cheng, Ruihan Yang, Sha Yi, and Xiaolong Wang. Ace: A cross-platform visual-exoskeletons system for low-cost dextero6-2501.-252.lo forop22 0 Td [(A

[113]

[133]

[154] Fangchen Liu, Chuanyu Li, Yihua Qin, Ankit Shaw, Jing Xu, Pieter Abbeel, and Rui Chen. Vitamin: Learning contact-rich tasks through robot-free visuo-tactile manipulation interface. arXiv preprint arXiv:2504.06156, 2025.

[155] Samuel Clarke, Suzannah Wistreich, Yanjie Ze, and Jiajun Wu. X-capture: An open-source portable device for multi-sensory learning. arXiv preprint arXiv:2504.02318, 2025.

[156] Tony Tao, Mohan Kumar Srirama, Jason Jingzhou Liu, Kenneth Shaw, and Deepak Pathak. Dexwild: Dexterous human interactions for in-the-wild robot policies. arXiv preprint arXiv:2505.07813, 2025.

[157] Chengyi Xing, Hao Li, Yi-Lin Wei, Tian-Ao Ren, Tianyu Tu, Yuhao Lin, Elizabeth Schumann, Wei-Shi Zheng, and Mark R Cutkosky. Taccap: A wearable fbg-based tactile sensor for seamless human-to-robot skill transfer. arXiv preprint arXiv:2503.01789, 2025.

[158] Kei Takahashi, Hikaru Sasaki, and Takamitsu Matsubara. Feasibility-aware imitation learning from observations through a hand-mounted demonstration interface. arXiv preprint arXiv:2503.09018, 2025.

[159] Huy Ha, Yihuai Gao, Zipeng Fu, Jie Tan, and Shuran Song. Umi on legs: Making manipulation policies mobile with manipulation-centric whole-body controllers. arXiv preprint arXiv:2407.10353, 2024.

[160] Mingyo Seo, H Andy Park, Shenli Yuan, Yuke Zhu, and Luis Sentis. Legato: Cross-embodiment imitation using a grasping tool. IEEE Robotics and Automation Letters, 2025.

[161] Simar Kareer, Dhruv Patel, Ryan Punamiya, Pranay Mathur, Shuo Cheng, Chen Wang, Judy Hoffman, and Danfei Xu. Egomimic: Scaling imitation learning via egocentric video. arXiv preprint arXiv:2410.24221, 2024.

[162] Haonan Chen, Cheng Zhu, Yunzhu Li, and Katherine Rose Driggs-Campbell. Tool-as-interface: Learning robot tool use from human play through imitation learning. ICRA 2025 Workshop: Beyond Pick and Place, 2025. , 2025.

[163] Arthur Allshire, Hongsuk Choi, Junyi Zhang, David McAllister, Anthony Zhang, Chung Min Kim, Trevor Darrell, Pieter Abbeel, Jitendra Malik, and Angjoo Kanazawa. Visual imitation enables contextual humanoid control. arXiv preprint arXiv:2505.03729, 2025.

[164] Nataliya Nechyporenko, Ryan Hoque, Christopher Webb, Mouli Sivapurapu, and Jian Zhang. Armada: Augmented reality for robot manipulation and robot-free data acquisition. arXiv preprint arXiv:2412.10631, 2024.

[165] Sirui Chen, Chen Wang, Kaden Nguo, Aug-

[174] Viktor Makoviychuk, Lukasz Wawrzyniak, Yunrong Guo, Michelle Lu, Kier Storey, Miles Macklin, David Hoeller, Nikita Rudin, Arthur Allshire, Ankur Handa, et al. Isaac gym: High performance gpu-based physics simulation for robot learning. arXiv preprint arXiv:2108.10470, 2021.

[175]

[212] Jiachen Lu, Ze Huang, Zeyu Yang, Jiahui Zhang, and Li Zhang. Wovogen: World volume-aware diffusion for controllable multi-camera driving scene generation. In *European Conference on Computer Vision*, pages 329–345. Springer, 2024.

[213] Yurui Chen, Junge Zhang, Ziyang Xie, Wenye Li, Feihu Zhang, Jiachen Lu, and Li Zhang. S-nerf++: Autonomous driving simulation via neural reconstruction and generation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2025.

[214] Ruili Feng, Han Zhang, Zhantao Yang, Jie Xiao, Zhilei Shu, Zhiheng Liu, Andy Zheng, Yukun Huang, Yu Liu, and Hongyang Zhang. The matrix: Infinite-horizon world generation with real-time moving control. *arXiv preprint arXiv:2412.03568*, 2024.

[215]