

From Language to Action: Employing Foundation Models in Autonomous Robots

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Abstract

001 Foundation models have demonstrated remark- 040
002 able capabilities in natural language processing 041
003 tasks, generating interest in their potential for 042
004 robotic applications. However, the existing liter- 043
005 ature lacks a transparent and comprehensive 044
006 synthesis of these advancements. This paper 045
007 utilizes the PRISMA framework to systemati- 046
008 cally review and explore the integration of found- 047
009 ation models in robotic applications. Through 048
010 an in-depth analysis of 76 studies, we investi- 049
011 gate current trends in models, modalities, and 050
012 experimental methods. Additionally, this study 051
013 maps the state-of-the-art applications of found- 052
014 ation models in robotics tasks, and illustrate 053
015 how these tasks are interconnected. Synthesiz- 054
016 ing these findings, we identified key challenges 055
017 and future direction. This study establishes a 056
018 benchmark and offers insights into future re- 057
019 search directions for developing safe and au- 058
020 tonomous embodied foundation models. All 059
021 data, and findings are available on the project 060
022 repository ¹.

1 Introduction

023 Foundation models are defined as large-scale Arti- 064
024 ficial Intelligence (AI) models trained on an exten- 065
025 sive and internet-scale dataset, capable of generaliz- 066
026 ing knowledge across a wide range of tasks. These 067
027 models utilize massive datasets in a self-supervised 068
028 manner to learn from unannotated data, allowing 069
029 them to be adapted to various downstream tasks 070
030 (Bommasani et al., 2021). Generalizing across 071
031 diverse tasks without tasks-specific fine-tuning 072
032 in models, such as GPT-4 (Achiam et al., 2023) 073
033 Llama-2 (Touvron et al., 2023) Gemini (Anil et al., 074
034 2023) Claude (Anthropic, 2023), have significantly 075
035 advanced the natural language processing (NLP) 076
036 field. Such strengths along with their adaptability 077
037 and ability to process multi-modal data (text, im- 078
038 age, sound) have drawn the attention of researchers 079
039

040 in various domains, ranging from the medical field 041
042 (Cho et al., 2023) to robotics (Xiao et al., 2023) 043
044 to bring cognitive capabilities of these models to 045
046 physical world applications. 047

048 To achieve a degree of autonomy in physi- 049
050 cal world, embodied agents or robots have been 051
052 utilized from many years ago (Smithers, 1997). 053
054 There are generally two broad solution categories 055
056 for automating these embodied agents: (1) pre- 057
058 programming robots for specific scenarios; (2) tele- 059
060 operating robots to leverage human cognitive abili- 061
062 ties (Saidi et al., 2016). The first category already 063
064 employed AI paradigms, such as reinforcement 065
066 learning (Delgado and Oyedele, 2022) and deep 067
068 learning (Karoly et al., 2021), to automate specific 069
070 labor-intensive and repetitive tasks (Bruun et al., 071
072 2022; Yu et al., 2009). While these robots can 073
074 deliver satisfactory precision in designated tasks, 075
076 their adaptability and generalizability are often lim- 076
077 ited due to training on narrowly focused datasets 077
078 designed for specific tasks. Consequently, man- 078
079 ual adjustments may be necessary to accommodate 079
080 even minor task variations in physical world appli- 080
081 cations (Cully et al., 2015). In contrast, the second 081
082 category involves tele-operated robots, which can 082
083 be remotely operated by experts, allowing them to 083
084 adapt to various tasks without the need for manual 084
085 reprogramming. However, their dependency on hu- 085
086 man operators has limited their performance and 086
087 productivity. For example, even slight connection 087
088 delays can significantly impede robot performance 088
089 in extraterrestrial physical worlds (Seo et al., 2024). 089

090 On the other hand, foundation models are trained 090
091 on vast amounts of data to exhibit adaptability, 091
092 generalizability, and overall performance across 092
093 a variety of domains (Chang et al., 2023). This 093
094 intrinsic feature can be seen as a solution to move 094
095 embodied agents and robots to a higher level of 095
096 autonomy for physical world applications. Conse- 096
097 quently, this study aims to: (1) systematically ex- 097
098 plore the current state of the art of tools, methods, 098
099

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and applications of foundation models in robotic applications; (2) investigate how foundation models have impacted the cooperation of cognitive and acting tasks in physical environments; (3) identify current challenges and provide future directions for future embodied foundation models. Therefore, this study can serve as a benchmark for other researchers to track progress toward future safe and fully autonomous embodied agents.

2 Autonomous Robot Components

Figure 1 illustrates essential components of a robot operating within a physical world. Autonomous robots are comprised of two main platforms: (1) the deliberation platform; and (2) the execution platform. The execution platform, which is influenced by the robot’s morphology, includes various actuators, motors, sensors, end effectors, and manipulators. Developments in this platform are beyond the scope of this study, as our primary focus is on the deliberation platform. This platform is responsible for receiving objectives and percepts (mostly from various sensors), processing them, and generating actionable commands or communication signals.

The deliberation platform employs two main modules: (1) the cognitive module, which is responsible for all cognitive processes in robots; and (2) the acting module, which translates cognitive outputs into fine-grained actionable commands. Reasoning is the highest-level cognitive process, inferring new information from existing signals. Mid-level processes include planning, which involves decision sequences to achieve goals, and decision-making, which selects actions based on percepts and predefined criteria. Human-robot interaction enables communication through speech recognition, natural language processing, and understanding gestures or facial expressions. Perception involves processing environmental information, including object recognition, scene understanding, SLAM, and gesture recognition. The acting module controls actuators for executing actions, navigating through environments with path planning and obstacle avoidance, and manipulating objects.

2.1 Related Studies

To date of drafting this manuscript, three studies have surveyed the application of foundation models in robotics. The first review paper by [Firoozi et al. 2023](#) surveyed the application of foundation models in robotics with an emphasis on future chal-

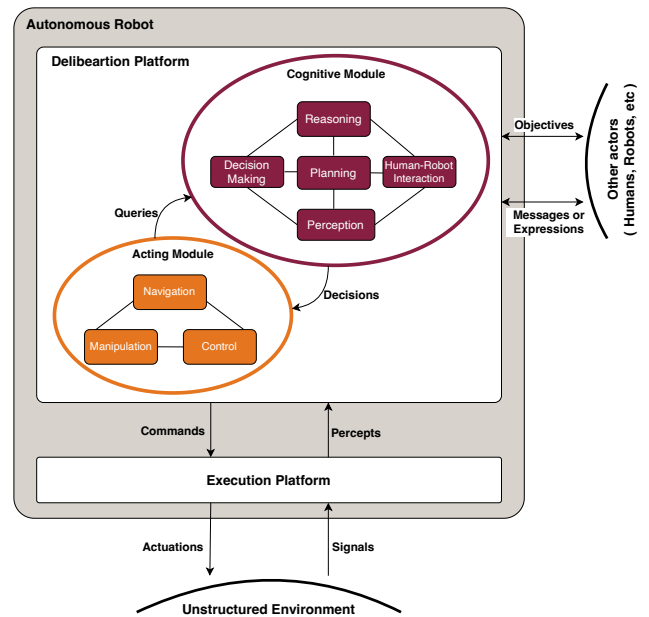


Figure 1: Conceptual view of robot in physical world applications

lenges and opportunities. The second review paper by [Xiao et al. 2023](#) explored existing studies focused on robot learning using foundation models to identify potential future areas. In the third review, [Hu et al. 2023](#) examined different studies relevant to foundation models and investigated how their application could be adapted to the robotics field.

These studies lack a transparent and reproducible approach for categorizing their findings and providing insights for future research. While they do categorize studies, they fail to accurately highlight the significance of each field, making it difficult to compare and analyze which applications need more attention from researchers. This method also falls short in identifying subtle research gaps that are not apparent through narrative categorization. Consequently, there is a lack of an objective benchmark in the field to track progress and ensure that studies are advancing safely and aligning with our goals. This study is distinguished from previous ones for the following reasons: (1) Our study builds an objective picture of the current state-of-the-art in employing foundation models for robotic applications. We map the impact of these models across different cognitive and acting tasks and explore the correlations between them. (2) The provided current state-of-the-art are synthesized to identify new challenges and potential future research directions, paving the way for a safe and autonomous future in the field. (3) Our study employs a transparent and

reproducible methodology, aiming to establish a clear and objective benchmark for future research.

3 Methodology

A systematic review approach has been selected for this study based on PRISMA framework (Page et al., 2021) to explore the embodiment of foundation models in physical worlds through robots.

3.1 Databases

Web of Science (WoS) and Scopus are two comprehensive databases serving as major tools for systematic review in the field of science, technology, engineering and mathematics (STEM) (Kandall, 2017; Visser et al., 2020). In addition to these, ArXiv is selected as the main source for preprint studies within the scope of our study because: (1) it serves as one of the main sources of studies related to foundation models from 2018 up to now (Gusenbauer and Haddaway, 2020); (2) it helps us to cover emerging ideas that are not yet published in journals due to the long process of publishing (Movva et al., 2023).

3.2 Search query

Query-based search is one of the most fundamental methods for identifying relevant studies in a field of research (Chen and Song, 2019). To maximize the potential of identifying relevant studies within our scope, we constructed two word-family blocks, containing keywords relevant to our targeted studies (see Figure 2). Within these blocks, keywords are connected with "OR" command to maximize the likelihood of retrieving relevant studies. Among these blocks, the word-family block for foundation models (left block) is connected with "AND" command to the word-family block for robotics (right block). Linking the left block with the right block generates a search query suitable for exploring the application of foundation models in robotics for physical world applications.

3.3 Screening

Figure 3 illustrates the process of identifying relevant studies for this survey. It should be noted that the number of studies at each step is dependent on the date of drafting this manuscript was drafted (March 2024). Initially, the search query was applied to identified databases, followed by the exclusion of duplicate studies. Subsequently, several eligibility refinements, such as language, date,

and study types were made to the search outputs to align them more closely with the study's scope. Noting that the first versions of foundation models emerged in 2018, we restricted the identified studies to the time frame of 2018 to 2024. In the next step, we established two set of screening criteria to ensure that the identified studies are relevant to our scope.

4 Results

This section aims to provide an objective picture of the current state-of-the-art in the applicability of foundation models for automating tasks in physical world using robots. To achieve this goal, all identified studies were subjected to a comprehensive whole-text content analysis. We extract a set of 20 features to have a detailed and complete overview of the recent trend.

These features can be categorized to two 10 feature groups: (1) general features: authors, title, published year, source title, DOI, link to paper, author affiliations, abstract, author and index keywords; (2) specific features: applications, foundation model use, applied tasks, domain, study objective, robot morphology, evaluation method, modalities, transformer architecture, and open source status. Due to the limited space, we present a subset of the features in the main paper while description and details of all other features are available under the open source licence ².

4.1 Foundation model usage trends

This section investigates the frequency of utilizing foundation models for robotic and physical world applications. As seen in Figure 4, the integration of foundation models into robotics is dominated by GPT-Based models, which account for over 44% of foundation model usage. GPT-3.5 is the most frequently used LLM, highlighting its applicability and ease of use. Although GPT-4 is located in third usage place, it should be noted that the usage of GPT-4 is rapidly growing.

Another interesting finding is that CLIP model is the most frequent used models among Visual Language Models (VLMs) and second place among all foundation model usages in robotic applications. CLIP is primarily utilized for bridging similarities between text, as the first source of receiving language instructions, and images, as the primary means of understanding environments. It has been

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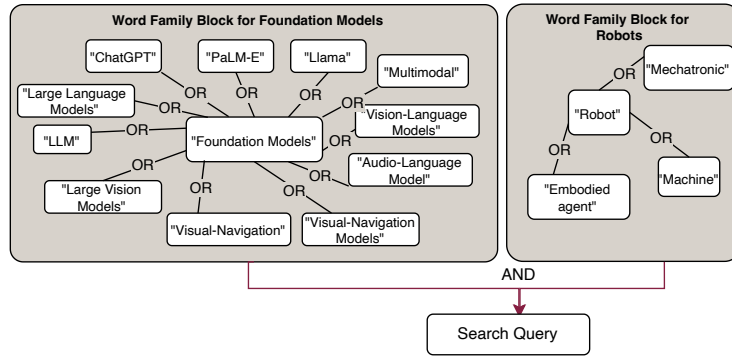


Figure 2: Process of building search queries

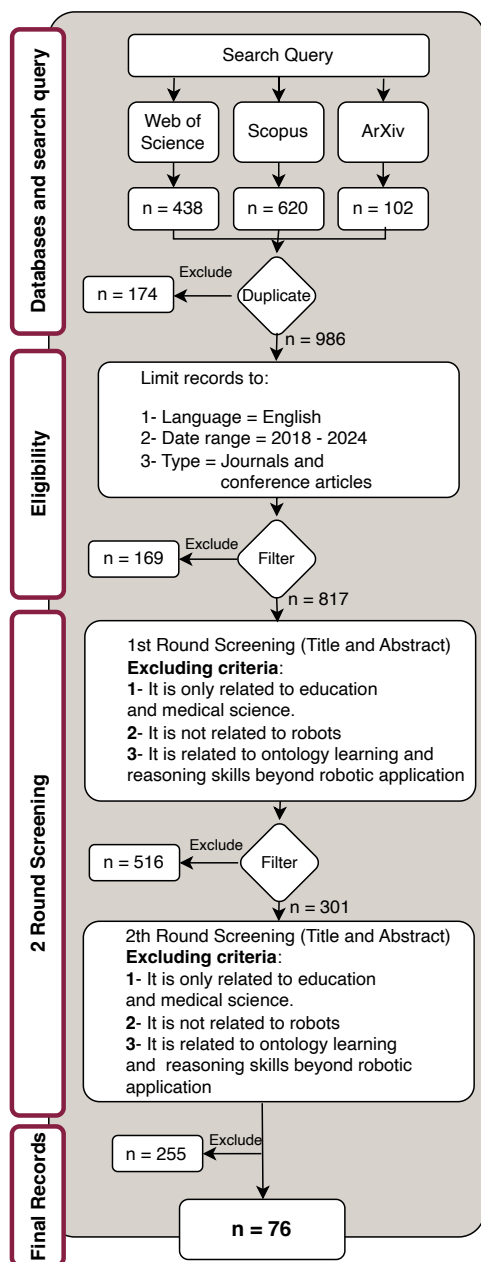


Figure 3: Process of identifying relevant records (PRISMA)

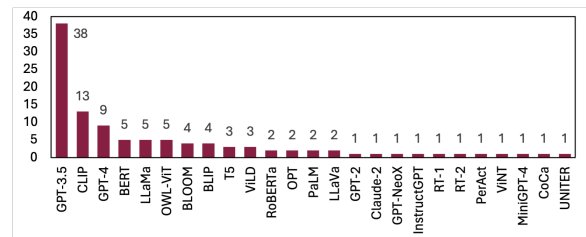


Figure 4: Frequency of using different foundation models in robotic field

used in various studies to perform Vision-Language Navigation (VLN) related tasks (Lan et al., 2023; Lin et al., 2022), as well as other manipulation tasks (Cui et al., 2022; Liao et al., 2023; Shridhar et al., 2021), and even high-level recognition tasks, such as reasoning (Kamath et al., 2023). As seen in Figure 4, the frequency of remaining models is five or fewer,

4.2 Modalities

As mentioned in Table 1, more than half of the identified studies utilize only text for developing their use cases. Although it indicates the early stages of studies in this field, 31% multimodal text and image models indicate the move toward more multimodal models. However, the number of studies using other modalities such as 3d and audio data is very limited. This lack of diversity in modalities may hinder the development of more comprehensive and robust robotic systems capable of perceiving and interacting with the real world, which is inherently multimodal.

4.3 Experiment method

Within the final records, %42 studies tested their findings through implementation in real-world experiments (see Table 2. However, this amount for

Status	Number	Percentage
Text	39	%51
Image	5	%6
Image and text	24	%31
3D data	1	%1
Audio	1	%1
Not available	1	%10

Table 1: Modalities of foundation models utilized in identified studies.

Experiment method	Number	Percentage
Real-world	32	%42
Simulation	10	%13
Dataset	7	%9
Not available	27	%36

Table 2: Experiment methods of foundation models utilized in identified studies.

simulation and dataset experiments are respectively %13 and %9. This indicates a gap that there is still a need for more comprehensive and diverse evaluation methods. Moreover, a considerable amount of studies (%36) are conceptual and doesn't validate their findings through experiments. Therefore, more studies are needed in this field to bridge the gap between theory and practice, and to thoroughly evaluate the performance and limitations of foundation models in realistic robotic applications.

4.4 Current State of the Art: Application of Foundation Models in Robotics

This section aims to provide a map of the current state of the use of different foundation models in robotic tasks. To achieve this, the identified records were labeled based on the foundation models used and the specific tasks to which these models were applied (foundation model use and applied tasks features). Figure 5 illustrates the flow of applying different foundation models for robotic tasks. This figure is organized across four analytical layers: foundation models, their categories, and categories of robotic tasks, and the specific robotic tasks.

Foundation model categories: Within the foundation model categories, Large Language Models (LLMs) contributed to 69% of foundation models utilized for robotic applications, indicating that most studies are exploring the text modalities and capabilities of this category for addressing classic challenges in robotic domains. For example, some studies utilize the capabilities of these foundation

models in understanding language and coding to generate robotics execution codes in industries (Fan et al., 2024; Yoshikawa et al., 2023). VLMs also contributed another 20% of foundation model applications in robotic tasks, helping to bridge language instructions with vision perception in various studies (Kawaharazuka et al., 2023). However, less attention has been given to the application of LVMs (%7) in the robotic domain, where further studies are needed. Moreover, a few studies have gone beyond text or image-based foundation models by creating robot transformers (Brohan et al., 2023; Stone et al., 2023), yet more studies, such as MiniGPT-3D (Tang et al., 2024), are felt necessary to build 3D foundation models as they can contribute more significantly to robot-specific tasks that require direct interaction with the 3D world.

Planning and perception tasks: When it comes to robotic tasks, foundation models are primarily (72%) utilized for cognitive tasks rather than acting tasks (28%). Within the cognitive domain, perception and planning are most common goal of using foundation models in many identified records. For example, studies utilized capabilities of ChatGPT in understanding text to change the traditional method of robot planning, by generating behavior-tree (Cao and Lee, 2023) or considering the current state of robots in plan generation (Xie et al., 2023). Furthermore, some studies focused on providing robots with better perception by utilizing foundation models in complex robotic tasks, such as scene anomaly detection (Obinata et al., 2023).

Human-Robot Interaction (HRI) is another important use case of foundation models in the robotics field. The use of foundation models in HRI can be categorized into three main streams. First, some studies utilize LLMs to improve HRI through better extraction of machine-understandable information from human instructions (Bimbatti et al., 2023; Tabone and Winter, 2023). Another group of studies uses foundation models to understand public perceptions toward robots (Brandtzaeg et al., 2023; Jangjarat et al., 2023; ?). The last group applies the capabilities of LLMs to generate human-like text to respond to humans and improve trust between humans and robots (Mishra et al., 2023; Ye et al., 2023; Sevilla-Salcedo et al., 2023).

Reasoning and decision-making tasks: In terms of reasoning, one mainstream application is the use of foundation models for providing commonsense knowledge to robots (Jain et al., 2023; Zhou et al., 2023b). Commonsense reasoning is

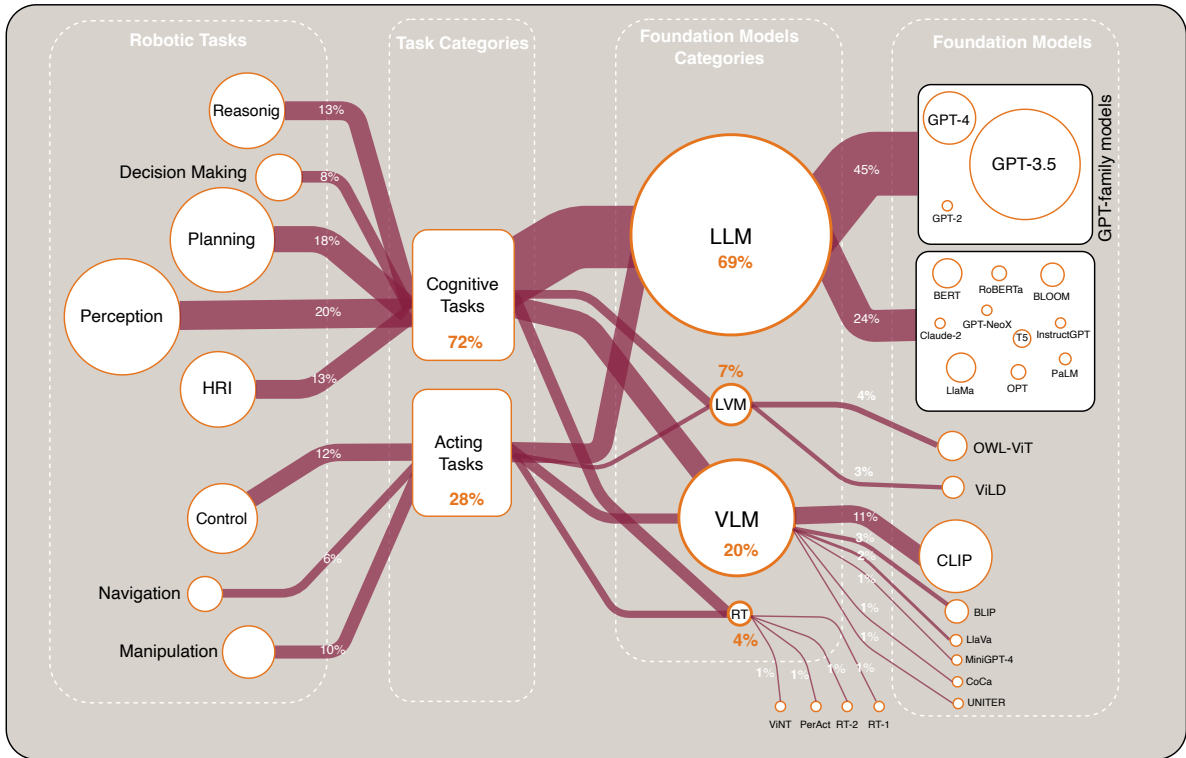


Figure 5: Flow diagram of foundation model applications in robotic tasks

a hard task for machines but it is crucial in many tasks. For example, Krause and Stolzenburg 2024 utilized LLM commonsense reasoning capabilities in the field of question answering (QA), which is one of the most important tasks of NLP. Ocker et al. 2023 found that LLMs are not sufficient enough on their own to provide commonsense reasoning but they are effective in synergy with formal knowledge representations. On the other hand, few studies investigate the decision-making abilities of LLMs in connection with different robotic tasks, such as planning (Ouyang and Li) and manipulation (Lew et al., 2023).

Control, manipulation, and navigation: Beyond cognitive tasks, the capabilities of foundation models in acting tasks are less explored. For example, some studies use language understanding of LLMs as a translation module between human and robot for controlling the simple motion of robots (Tanaka and Katsura, 2023; Kawaharazuka et al., 2023). Some other studies are providing innovative frameworks for improving spatial reasoning required in LLMs for robotic manipulation tasks (Shridhar et al., 2021; Jin et al., 2023). Navigation is another challenging tasks that recent foundation models are used to allow researchers to have semantic reasoning and go beyond conventional map-

based systems (Gadre et al., 2022; Yu et al., 2023). Despite these examples, acting tasks are usually come with other cognitive tasks such as planning, and perception. As a result, a network of connection between these tasks help us to achieve better interpretation of foundation model capabilities.

4.5 Robotic Task Integration

Robotic cognitive and acting tasks are utilized in studies in an interconnected manner to automate specific tasks. Accordingly, most identified records employ foundation models across a variety of cognitive and acting tasks in a interconnected manner to evaluate and validate their research. Consequently, there is a need for a network diagram that shows how foundation models are used to interconnect different robotic tasks. Figure 6 illustrates the co-occurrence network of robotic tasks, where cognitive and acting tasks are represented as nodes. The edges between nodes represent the co-occurrence of two tasks within a single study. The size of each node is proportionate to the number of its connections, indicating that larger nodes are more frequently utilized in conjunction with other tasks in studies. The thickness of the edges indicates the frequency of concurrent task usage in the studies.



Figure 6: Co-occurrence network of robotic tasks using foundation models

As illustrated in Figure 6, the most significant connection is the use of foundation models for HRI and Perception. This finding, coupled with the dominance of LLMs in foundation models, indicates that most studies leverage the text analytical capabilities of foundation models to extract both defined and undefined information for other significant robotics tasks, including planning, control, and manipulation.

The navigation node is smaller than other nodes, indicating that navigation tasks less frequently co-occur with other robotic tasks. This suggests that the majority of the field is interested in validating the capabilities of foundation models in cognitive tasks, and some acting tasks such as control and manipulation, rather than incorporating the complexity of moving in a 3D environment into their studies. Another interesting finding is that all edges leading to the decision-making node are thin, which indicates that this task is also overlooked in many studies. Despite the small size of the reasoning task node, there is a considerable connection between this node and the perception node. This represents a major category within this field, which involves utilizing reasoning capabilities to perceive situations where only a small amount of information is available, such as unseen scenes and undefined events (Ocker et al., 2023; Ren et al., 2023; Zhang et al., 2024)

5 Discussion: Challenges and future prospects

5.1 Situated Reasoning

Currently, more studies are focused on robotic cognitive tasks (see Figure 5), which can be attributed to the fact that the current architecture of most foundation models is designed for sequential tokens, making them better suited for cognitive tasks rather than acting tasks that require extensive situated reasoning and direct interaction with 3D data. One of the main challenges in utilizing foundation models for acting tasks is the scarcity of 3D data compared to text and image data. A potential solution to this challenge can be the use of Digital Twins as a source for training foundation models on 3D data.

5.2 Physical Laws

Furthermore, the generative models, such as Sora (Liu et al., 2024), can be leveraged to create simulations of real-world environments, providing a rich source of data for training and testing. However, a significant obstacle in expanding generative models for creating simulations is their current limitation in accurately modeling physical laws, such as gravity, collisions, and other laws that are crucial for realistic simulations and interactions with the physical world. Addressing this challenge is pivotal for enabling foundation models to reason effectively about the complex dynamics and constraints of the physical world.

5.3 Hallucination

A primary issue toward effective integration of robots and foundation models is the tendency of these models to "hallucinate," meaning they sometime generate outputs that are factually incorrect, logically inconsistent, or physically infeasible. This uncertainty becomes particularly critical when robots are expected to perform a broader range of general tasks in 3D environments, especially those rarely encountered in their mostly textual and image data. Despite retrieval-based and other related path toward addressing this issue, some studies seek methods that enable LLMs to ask for help in uncertain situations (Ren et al., 2023).

5.4 Error Handling

Furthermore, this uncertainty challenge can lead to error handling due to various potential to robot

493	action failures. These failures include: (1) execu-	542
494	tion failures, where the model understands the task	543
495	and environment correctly but fails to achieve the	544
496	expected outcome; (2) planning failures, where the	545
497	model generates an incorrect or infeasible sequence	546
498	of actions despite comprehending the task and en-	547
499	vironment; and (3) comprehension failures, where	548
500	the model misinterprets the context of the environ-	549
501	ment or task. To address these issues, several ap-	550
502	proaches have been proposed. Prompt engineering	551
503	methods allows the model to prompt itself with the	552
504	output plan and the latest environment observations	553
505	for potential corrections. Additionally, incorporat-	554
506	ing models with enhanced situated reasoning can	555
507	provide more accurate predictions of robot capabil-	556
508	ities in complex environments. Another effective	557
509	strategy is leveraging human feedback, which can	558
510	resolve various types of errors.	559
511	5.5 Model Biases	560
512	Recent studies highlight different biases in GPT-	561
513	family models (Rutinowski et al., 2023; Sinha,	562
514	2023; Toro, 2023). Considering that currently most	563
515	studies use GPT-based models (refer to Section	564
516	4.1), further research is needed to investigate the	565
517	biases of using single models or a combination of	566
518	different agents in more sensitive tasks, such as	567
519	human-robot interaction or decision-making. Ident-	568
520	ifying these biases is a critical challenge that is	569
521	crucial to tackle to ensure the safe and reliable in-	570
522	tegration of foundation models into robotic systems,	571
523	especially in applications involving direct interac-	572
524	tion with humans or decision-making processes.	573
525	5.6 Ethical considerations	574
526	While a comprehensive discussion of ethics goes	575
527	beyond the scope of this study and requires exten-	576
528	sive exploration of various ethical frameworks, it	577
529	is essential to encourage more researchers to en-	578
530	gage with this sensitive area. Key ethical considera-	579
531	tions include privacy, safety, responsibility, and the	580
532	moral behavior of robots, each of which warrants	581
533	thorough examination. As a potential approach to	582
534	addressing these issues, (Zhou et al., 2023a) have	583
535	proposed a framework that equips foundation mod-	584
536	els with the capability for moral reasoning, drawing	585
537	on diverse ethical theories. Such research is appro-	586
538	priate first-step as it advances the preparation of	587
539	robots for deeper integration into human-centric	588
540	environments, ensuring their actions are guided by	589
541	sound ethical principles.	590
	5.7 Toward unstructured environment	
	Most studies have tested the integration of founda-	
	tion models in organized and structured environ-	
	ments, such as housing settings. However, unstruc-	
	tured environments are in greater need of founda-	
	tion model capabilities due to the limitations of	
	traditional hard-coded approaches that are unsuit-	
	able for these settings. The flexibility and general-	
	izability inherent in foundation models can signifi-	
	cantly enhance performance and adoption in such	
	complex environments. Nonetheless, there are chal-	
	lenges in this endeavor. Unstructured environments	
	are difficult for real-world testing applications, and	
	we currently lack a simulation solution that accu-	
	rately represents the dynamic events and unpre-	
	dictability of these settings. A crucial first step is	
	to systematically identify inherent features in un-	
	structured environment tasks that hinder robotic	
	adoption. For instance, future studies can explore	
	how commonsense reasoning in foundation models	
	can aid robot decision-making in situations where	
	information is highly dynamic or scarce.	
	6 Conclusion	
	The integration of foundation models into robotics	
	is an emerging field with significant potential for	
	enabling advanced cognitive and acting capabilities	
	in physical world applications. While the current	
	research landscape is dominated by leveraging the	
	language understanding abilities of LLMs, there is	
	a growing interest in exploring multimodal and 3D	
	foundation models for more comprehensive scene	
	understanding and situated reasoning. However,	
	several key challenges need to be addressed, includ-	
	ing scarcity of 3D data, improving the modeling of	
	physical laws in simulations, mitigating hallucina-	
	tions, developing robust error-handling strategies,	
	and addressing ethical concerns surrounding the de-	
	ployment of embodied agents. Overcoming these	
	hurdles will be crucial for realizing the vision of	
	safe and fully autonomous embodied foundation	
	models capable of generalizing across a wide range	
	of unstructured environments and tasks.	
	7 Limitation	
	Despite the contributions of this study as discussed	
	before; all research studies have limitations, and	
	the present attempt is no exception to this rule. The	
	survey process only considered studies in English,	
	and used a particular set of keywords for search-	
	ing. Besides, the screening process of core studies	

can be considered subjective in nature, although the process was performed three separate times to minimize the error. In addition, all analyses are based on the data retrieved from WoS, Scopus, and Arxiv databases. Therefore, the findings may not fully reflect the entire available efforts and studies in the field.

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