A Survey of Foundation Models for IoT: Taxonomy and Criteria-Based Analysis

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Abstract

Foundation models have gained growing interest in the IoT domain due to their reduced reliance on labeled data and strong generalizability across tasks, which address key limitations of traditional machine learning approaches. However, most existing foundation model based methods are developed for specific IoT tasks, making it difficult to compare approaches across IoT domains and limiting guidance for applying them to new tasks. This survey aims to bridge this gap by providing a comprehensive overview of current methodologies and organizing them around four shared performance objectives by different domains: **efficiency**, **context-awareness**, **safety**, and **security & privacy**. For each objective, we review representative works, summarize commonly-used techniques and evaluation metrics. This objective-centric organization enables meaningful cross-domain comparisons and offers practical insights for selecting and designing foundation model based solutions for new IoT tasks. We conclude with key directions for future research to guide both practitioners and researchers in advancing the use of foundation models in IoT applications.

CCS Concepts

• **General and reference** → **Surveys and overviews**; • **Computing methodologies** → **Artificial intelligence**; • **Computer systems organization** → **Embedded and cyber-physical systems**.

Keywords

Foundation Model, Internet-of-Things, Survey, Critieria-Based Analysis

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Conference acronym 'XX, Woodstock, NY

ACM ISBN 978-1-4503-XXXX-X/2018/06
https://doi.org/XXXXXXX.XXXXXXX

ACM Reference Format:
Hui Wei, Dong Yoon Lee, Shubham Rohal, Zhizhang Hu, Shiwei Fang, and Shijia Pan. 2018. A Survey of Foundation Models for IoT: Taxonomy and Criteria-Based Analysis. In *Proceedings of Make sure to enter the correct conference title from your rights confirmation email (Conference acronym 'XX).* ACM, New York, NY, USA, 19 pages. https://doi.org/XXXXXXX.XXXXXXX

1 Introduction

Machine learning (ML) models have been widely adopted in IoT applications to enable more convenient, automated, and intelligent solutions across diverse domains (e.g., smart cities [108, 149], autonomous driving [15, 47, 57], smart agriculture [20, 95, 136], and precision health [64, 78, 135]). However, existing approaches that rely on traditional ML models (e.g., models trained on *task-specific* datasets [171]; deep learning models are also considered as traditional ML in this work) face two key limitations: **(C1) Dependence on Labeled data**: Most of proposed methods depend on supervised learning, which require large volumes of labeled data to achieve high performance [22, 25, 168]. However, IoT data are often not human-interpretable, making it difficult to obtain sufficient high-quality annotations. **(C2) Poor Generalization Across Contexts**: Even when labeled data are available, IoT data are highly heterogeneous. As a result, models trained in one context (e.g., specific environments or applications) often fail to generalize to others, limiting scalability and cross-domain applicability [32, 79, 172].

In order to address these two challenges, foundation models [23, 194] (e.g., large language models) have gained increasing attention and adoption in the IoT domain. First, foundation models (FMs) rely on self-supervised training instead of traditional supervised approaches, which addresses Challenge C1 by reducing the dependency on large labeled IoT datasets. Second, the training data for FMs typically span multiple domains and contexts, which allows FMs to learn generalizable, context-invariant representations, making them more adaptable to a wide range of downstream tasks. This mitigates Challenge C2.

To advance the field and guide future research, prior surveys [18, 21, 87, 133, 141, 171] have summarized FM-based approaches for IoT tasks, along with evaluation metrics and benchmark datasets, primarily from the perspective of *specific application domains* (e.g., healthcare, robotics, smart homes). However, our review of the cited papers reveals a key but previously overlooked insight: *while tasks* *within the same domain may require different techniques, similar techniques can often be applied across domains to address shared objectives* (e.g., reducing training time, personalizing outputs). Organizing the literature solely by application area obscures these cross-domain goals and the research opportunities they present. Moreover, proposed methods targeting the same objective are often evaluated on different tasks, without comparison to other approaches targeting the same objective. *This inconsistent evaluation makes it difficult to assess which approaches are most effective across different scenarios, providing limited insights for addressing the same objective in new tasks.*

To address the limitations identified above, this paper categorizes current research on FMs for IoT around four key performance criteria that serve as shared objectives across diverse application domains: (1) **Efficiency**, (2) **Context-awareness**, (3) **Safety** (different from Security in this paper. Please see Section 5 for more details), and (4) **Security and privacy**. By organizing the literature around these common objectives rather than specific tasks, we aim to provide a clearer understanding of how foundation models are being leveraged across the IoT landscape. This approach enables the community to (i) identify shared performance objectives across diverse IoT tasks, (ii) facilitate meaningful cross-domain comparisons, and (iii) promote the design of more generalizable and effective solutions. To support this goal, we address the following research questions:

(1) What *methodologies* have been proposed to improve each performance criterion?
(2) What *metrics* are used to evaluate these criteria?
(3) What *evaluation strategies* are commonly adopted when applying FMs to IoT tasks?

Finally, based on our analysis, we identify additional gaps in the literature and suggest future research directions to further advance the field.

The structure of this paper is as follows: Section 2 introduces three fundamental paradigms and frameworks for applying foundation models to IoT tasks, providing essential background for readers new to the field. Sections 3 through 6 examine the four key performance criteria along with commonly used approaches to improve each. Section 7 reviews the evaluation metrics used in the current literature for each criterion and discusses the strategies employed to assess FM-based solutions in IoT applications. Finally, Section 8 discusses existing research limitations and outlines future directions. Figure 1 presents a taxonomy of this paper and representative techniques.

For readers who are already familiar with foundation models, we recommend proceeding directly to the sections of interest. For those who are familiar with IoT but new to foundation models, we encourage a thorough reading of the entire paper, with particular emphasis on Section 2, which introduces the essential background relevant to this emerging area.

2 Foundations of FMs for IoT

In this section, we categorize existing approaches that leverage foundation models into three core paradigms: *prompt-based methods*, *agent-based methods*, and *training-based methods*. These approaches are used to: (1) perform end-to-end processing by perceiving, reasoning over, and making decisions based on sensor data, currently the primary focus of most reviewed studies, and (2) support reinforcement learning (RL) to improve policy learning for IoT tasks (e.g., HVAC control [178], mobile health [82], beam management [56]), an area that remains relatively underexplored. We then compare these paradigms across key dimensions, highlight their respective strengths and limitations, and provide practical guidance for selecting the most appropriate approach for practitioners and researchers.

2.1 Paradigm I: Prompt-Based Methods

Prompt-based methods leverage commercial or open-source *pretrained large language models (LLMs)* (e.g., GPT-4 [4], LLaMA-2 [148], DeepSeek-V2 [98]) to perform IoT tasks through textual inputs without requiring additional training [103, 130]. These prompts typically serve as task-specific instructions (e.g., "You are a knowledgeable IoT expert. Please classify the human activity described by the following IMU data."), which the model interprets to generate a response in the specified format [103, 130] (please refer to the example prompt for using LLMs to address the IoT task in Appendix A). Because prompt-based approaches rely solely on pretrained models, they enable rapid prototyping and deployment, particularly in settings with limited computational resources.

Prompt-based methods offer several advantages for applying foundation models to IoT tasks: (1) **Efficiency**: Unlike training-based methods that require substantial labeled data and computational power to update model parameters (see Section 2.3), prompt-based approaches leverage already trained LLMs which exhibit strong few-shot learning capabilities [24, 143], eliminating the need for fine-tuning or retraining. This significantly reduces deployment costs and time. (2) **General Knowledge**: LLMs trained on large-scale web data possess extensive general and domain-relevant knowledge, which can be leveraged to interpret IoT data and support tasks (e.g., human activity recognition from IMU signals) [12, 13, 32, 36, 39, 69, 79, 116, 142, 167]. (3) **Enhanced Reasoning**: Prompting techniques like chain-of-thought (CoT) [160] and program-of-thought (PoT) [31] can activate commonsense reasoning abilities in LLMs and improve their ability to interpret complex or ambiguous IoT data. This has been shown to significantly boost performance in tasks such as human activity recognition, industrial monitoring, and sensor data analysis [87, 165]. (4) **Flexibility with Heterogeneous Data**: Prompt-based methods can accommodate both structured (e.g., tabular sensor readings) and unstructured data (e.g., geospatial graphs) by explicitly specifying input and output formats in the prompt [51, 197]. This flexibility makes them well-suited to the diverse data types found in IoT systems. (5) **Natural Language Interfaces**: LLMs can serve as intuitive interfaces for querying or controlling IoT systems using natural language. This lowers the barrier to entry for non-experts and enhances system usability and accessibility. (6) **Interpretability**: Language-based outputs, especially when coupled with reasoning prompts (e.g., "Explain your answer in a few sentences."), enhance transparency by revealing the model's reasoning process. This allows users to verify the outputs and increases trust in the system, unlike many traditional ML models that operate as black boxes [37]. (7) **Real-Time Insights**: Prompted LLMs are capable of processing large

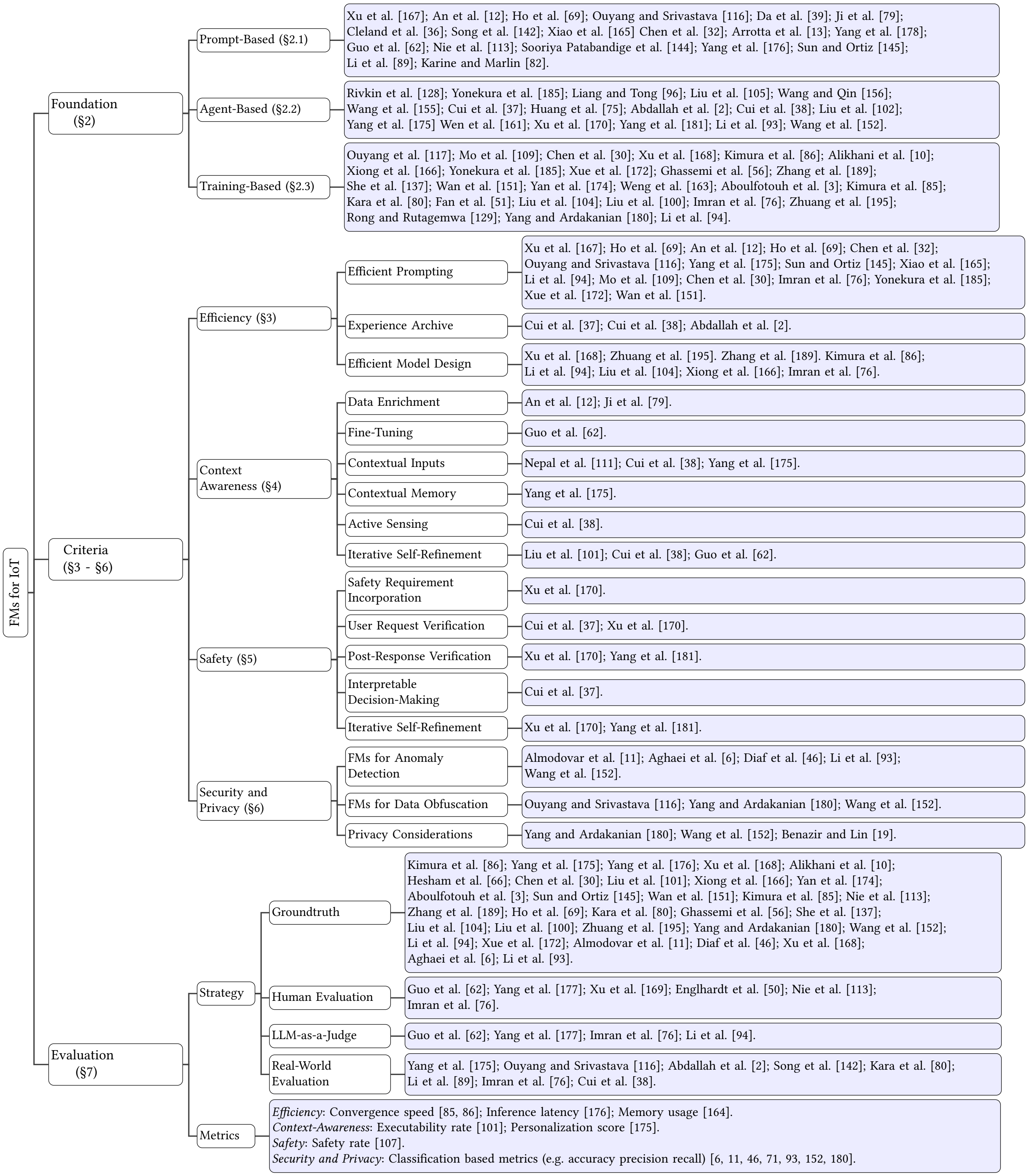

Figure 1: Taxonomy of Foundation Models for IoT. The structure of this paper is as follows: Section 2 introduces three fundamental paradigms and frameworks for applying foundation models to IoT tasks, providing essential background for readers new to the field. Sections 3 through 6 examine the four key performance criteria along with commonly used approaches to improve each. Section 7 reviews the evaluation metrics used in the current literature for each criterion and discusses the strategies employed to assess FM-based solutions in IoT applications. Finally, Section 8 discusses existing research limitations and outlines future directions.

streams of sensor data and producing actionable responses in real time, making them suitable for rapid prototyping and deployment in dynamic IoT environments [197].

2.2 Paradigm II: Agent-Based Methods

While prompt-based methods leveraging pretrained LLMs offer a lightweight and accessible way to address IoT tasks, they face several inherent limitations stemming from the constraints of the underlying pretrained models:

(1) **Hallucination and Knowledge Limitations**: Despite being trained on large-scale internet data, LLMs still suffer from hallucination (i.e., generating responses that are factually incorrect or nonsensical [73]). This issue arises from outdated or inaccurate information in the pretraining corpus and is particularly problematic in the IoT domain, where LLMs are rarely trained on sensor data or task-specific information. As a result, they may struggle to interpret some real-world signals and make accurate decisions in high-stakes applications (e.g., healthcare or autonomous driving) [5, 8, 48, 84, 153]. While embedding domain-specific knowledge into prompts can help, it is often incomplete and difficult to scale or adapt to dynamic user needs. Without access to accurate, up-to-date external knowledge, prompt-based methods remain fundamentally limited.

(2) **Lack of Specialized Capabilities and Active Perception**: Although LLMs demonstrate strong zero- and few-shot generalization, they often underperform relative to specialized modules on complex, domain-specific tasks (e.g., object detection, wireless resource allocation, numerical reasoning) [2, 37]. Furthermore, LLMs lack the ability to actively gather additional information when input data is ambiguous or incomplete, limiting their ability to resolve uncertainty and optimize task performance. This passivity contrasts significantly with the dynamic nature of many IoT environments.

(3) **Limited Reasoning and Planning for Complex Tasks**: Many IoT applications require multi-step reasoning and decision-making beyond basic question-answering. For instance, predictive maintenance in smart factories may involve interpreting sensor data, diagnosing failures, ordering components, and scheduling repairs. Solving such tasks requires the ability to decompose problems into subtasks, reason about their dependencies, and interact with external tools or systems [2, 37]. While prompt-based methods with manually embedded task decompositions offer partial solutions, they lack the adaptability and autonomy needed for real-time reasoning and planning across diverse scenarios, ultimately limiting the system's generalizability and effectiveness.

To overcome the limitations of prompt-based methods, LLM agents [106, 154, 162], which augment pretrained language models with additional modules: *external memory*, *tool integration*, and *planning capabilities*, are gaining increasing adoption across various IoT domains (e.g., smart homes [128, 185], industrial monitoring [96, 105, 156], autonomous driving [37, 75, 155]). These agents retain the strengths of prompt-based approaches while addressing their key shortcomings:

(1) **Access to External Knowledge**: By integrating external memory or online search tools, LLM agents can retrieve up-to-date, task-relevant information beyond what is stored in their static model parameters [88, 192]. This significantly mitigates hallucination and improves decision-making accuracy, especially in fast-evolving or safety-critical IoT applications.

(2) **Advanced Reasoning and Task Execution**: LLM agents can autonomously decompose complex tasks into subtasks [7, 74, 91, 159], perform multi-step reasoning [53, 121, 160, 183, 191], and invoke specialized tools or hardware systems as needed [126, 138]. This enables them to handle sophisticated IoT workflows (e.g., predictive maintenance or adaptive control) that go beyond the capabilities of purely prompt-driven models.

(3) **Adaptive Learning and Feedback Integration**: Through the use of external memory and feedback loops, LLM agents can store and recall prior experiences to improve performance over time. They can also adjust their outputs in response to real-time feedback from humans or the environment, allowing them to learn and adapt without retraining the base model [2, 37, 38].

By integrating the generalization capabilities of LLMs with domain-specific knowledge, real-time interactivity, and advanced reasoning, LLM agents offer a more robust and scalable solution for building intelligent, adaptable, and context-aware IoT systems, particularly for addressing complex tasks, that exceed the capabilities of prompt-based methods.

2.3 Paradigm III: Training-Based Methods

Although prompt-based and agent-based methods demonstrate promise in addressing IoT tasks, their effectiveness is limited by the constraints of pretrained LLMs, which typically lack task- and environment-specific knowledge [94, 109]. In contrast, training-based methods can update model parameters using domain-specific data, enabling higher accuracy and better adaptation to the target IoT application.

Training-based methods of foundation models for IoT tasks include two stages: *pretraining* and *fine-tuning*.

Pretraining involves training a large model (often not limited to language models) on extensive volumes of unlabeled data collected from diverse devices and environments. In the IoT context, this includes raw sensor data (e.g., vibration, acoustic, temperature signals) collected from many devices and environments [30, 80, 85, 86, 94, 109, 117, 163, 168, 174, 185]. The objective is to learn general, environment-invariant representations that are robust to variations in deployment conditions and noise levels. In practice, pretraining may not need to be performed from scratch if task-relevant pretrained models are already available (e.g., LIMU-BERT [168] for IMU data or VibroFM [85] for vibration signals).

Fine-tuning involves adapting the pretrained model to a specific application by updating all or part of its parameters using a smaller, labeled dataset relevant to the target task (e.g., fall detection within a specific building). This process tailors the general representations learned during pretraining to the unique characteristics of the application domain, sensor setup, or environmental context [66, 76, 86, 104, 166].

Compared to prompt-based and agent-based methods that rely on pretrained LLMs, training-based methods offer significant performance improvements on IoT tasks by updating model parameters and directly learning from raw sensor data. Also, unlike LLM-based approaches, they do not depend on converting numerical sensor data into natural language tokens. This tokenization process can introduce information loss or misinterpretation due to internal LLM limitations (e.g., inconsistent tokenization) [12, 190] or prompt engineering constraints (e.g., downsampling or quantization of long sensor inputs) [69, 109, 167]. Additionally, training-based methods can effectively leverage both labeled and unlabeled data, continuously improving through exposure to new domain-specific inputs by updating their internal representations.

2.4 Method Comparison

In this section, we compare the three most commonly used frameworks for applying foundation models to IoT tasks: *prompt-based methods*, *agent-based methods*, and *training-based methods*, as well as *traditional supervised learning methods*. The comparison is made across six dimensions: *computation requirement* (CR), *error rate on specific tasks* (ER), *task specificity* (TS), *development time* (DT), *labeled data requirement* (LDR), and *unlabeled data requirement* (UDR). For training-based methods, we focus on models after *fine-tuning*. Task specificity refers to the breadth of tasks a method can address; a lower specificity indicates broader applicability. Based on this comparison, we highlight the strengths and weaknesses of each method and offer practical guidance to help researchers and practitioners choose the most appropriate approach for their specific IoT applications.

Table 1 summarizes the comparison results, highlighting the strengths and limitations of each method. *Prompt-based methods* offer rapid development, low computational and data requirements, and easy adaptability to new or evolving IoT tasks. However, they typically yield higher error rates on complex or domain-specific tasks, which are limited by the fixed knowledge of the underlying LLM, and cannot improve over time through additional data exposure. *Agent-based methods* extend prompt-based approaches by enabling more complex, multi-step, and multi-device workflows, often achieving higher accuracy for orchestrated tasks without requiring the computational demands of full model training. Nonetheless, like prompt-based methods, they remain constrained by the static knowledge of the base LLM and cannot learn from new data. *Training-based methods* achieve the high accuracy and robustness for domain-specific IoT tasks, particularly when handling heterogeneous or noisy data. They can evolve through exposure to new data via pretraining and fine-tuning. However, they are the most resource- and time-intensive, requiring large volumes of unlabeled and labeled data, substantial computational resources, and longer training times. Compared to traditional ML methods, they often require less labeled data due to their ability to leverage generalizable knowledge from pretraining. *Traditional ML methods* are efficient for narrow, well-defined tasks with sufficient labeled data and offer low inference costs. However, they lack the flexibility and adaptability of FM-based approaches.

In conclusion, we offer the following practical guidance for selecting methods based on task requirements and resource constraints: use *prompt-based methods* for rapid prototyping or when computational resources and labeled data are limited; adopt *agent-based methods* for complex, multi-step IoT workflows requiring tool orchestration; apply *training-based methods* when high accuracy and robustness are critical, especially in domain-specific or mission-critical settings with abundant unlabeled data; and rely on *traditional ML approaches* for simple, well-defined tasks with sufficient labeled data and low computational demands. We also provide a decision tree for method selection based on the evaluated dimensions in Appendix B.

Note: The comparison in Table 1 does not account for security and privacy constraints. We assume that all pretrained LLMs are deployed in the cloud, computational resources are solely considered from the user's perspective, and inference costs on the cloud side are ignored. Additionally, we assume low time requirements are supported by high-speed network access. If these assumptions do not hold, the comparison results may differ. For instance, in privacy-sensitive applications (e.g., involving personal data), data may not be allowed to leave local devices [165]. In such cases, LLMs must be deployed locally, increasing the computational burden on edge devices and raising the resource requirements for prompt-based methods to a moderate level.

3 Criterion I: Efficiency

In the context of IoT tasks, efficiency in foundation models encompasses several key objectives: (1) *reducing inference time*, (2) *decreasing computational resources (e.g., memory) and energy consumption*, and (3) *lowering network load*.

Improving the efficiency of foundation models for IoT applications is essential due to their unique constraints of these environments. First, many IoT tasks (e.g., fall detection and autonomous driving) demand fast inference to ensure real-time responsiveness and prevent harmful delays [35, 40, 81, 110, 112, 173]. Second, most IoT devices have limited memory and battery capacity, requiring models to be both lightweight and energy-efficient [55, 119]. This constraint becomes even more critical when data must be processed locally on edge devices due to privacy and security concerns (e.g., in hospital settings where uploading sensitive patient data to the cloud is not viable) [165]. Finally, even when cloud processing is allowed, limited bandwidth in edge devices can introduce significant upload delays, further increasing overall inference latency [9, 131]. These challenges underscore the importance of developing efficient foundation models tailored to the IoT context.

To improve the efficiency of foundation models for IoT tasks, four common strategies are identified in the surveyed literature: *efficient prompting*, *experience archive*, and *efficient model architecture design*.

Efficient Prompting. Efficient prompting refers to minimizing prompt length without significantly compromising the critical information it conveys when using LLM-based methods, which rely on prompts as input. This is particularly important in IoT applications. When the LLM is hosted in the cloud, longer prompts increase token count, leading to higher network load and longer transmission times, which is an issue for IoT devices usually with limited bandwidth, ultimately slowing inference. When the LLM is deployed locally, processing longer prompts demand more memory due to the Transformer-based architecture of current models. However, edge devices typically have constrained memory and cannot efficiently process lengthy inputs. Therefore, efficient prompting is

Table 1: Comparison of Different Approaches. The first three methods apply foundation models, while the last represents traditional machine learning models with supervised learning. CR: computation requirement; ER: error rate; TS: task specificity; DT: development time; LDR: labeled data requirement, UDR: unlabeled data requirement. For training-based methods, we focus on models after fine-tuning.

Methods	CR	ER	TS	DT	LDR	UDR
Prompt-based	Low	High	Moderate	Low	Low	Low
Agent-based	Moderate	Moderate	Low	Moderate	Low	Low
Training-based	High	Low	High	High	Moderate	High
Traditional ML (supervised)	Moderate	High	Low	Moderate	High	Low

essential to ensure low-latency, resource-aware performance in IoT environments.

When LLMs are used for sensor data analysis and reasoning, which is the primary focus of most of the reviewed papers, the sensor data itself forms part of the prompt. However, as previously discussed, IoT devices can only support prompts with a limited number of tokens, which poses a major scalability challenge. For example, long-term monitoring tasks (e.g., tracking an individual's activity over two weeks at one-minute intervals) can generate numeric values far exceeding the input capacity of most LLM-based methods. Similarly, large-scale spatiotemporal data (e.g., those from air quality monitoring networks) also surpass the manageable prompt length [116]. These limitations restrict the direct application of LLMs to many real-world IoT scenarios that involve continuous or high-dimensional sensor streams.

To address the challenge of scaling LLMs to large-scale sensor data, researchers have proposed several strategies to reduce the volume of sensor data included in the prompt while preserving inference efficiency and performance. In the following sections, we review five key approaches that address this issue. For strategies focused on optimizing other components of the prompt (e.g., such as instructions or chain-of-thought (CoT) demonstrations [160]), please refer to surveys such as Chang et al. [28].

Downsampling and Quantization. Downsampling (i.e., resampling at a lower rate) and quantization (i.e., reducing data precision, such as rounding to integers or two decimal places) are commonly used to shorten the numerical sensor data [69, 167]. Quantization is effective because floating-point numbers with many decimal places are often split into multiple tokens by tokenization algorithms (e.g., Byte Pair Encoding [54, 134]). Lowering precision reduces the number of tokens generated by such decimal expansions [12]. However, quantization should be applied carefully, as discarding high-precision values may eliminate information crucial to the target task. Similarly, downsampling must preserve critical features to retain data utility [69]. For example, R peaks in ECG data must be retained if the goal is to detect cardiovascular diseases based on this feature.

Sliding Window. For long sensor data sequences, a common strategy is to divide the data into smaller windows for sequential processing. However, this segmentation can lead to the loss of important contextual information found before and after each window. Preserving context is crucial for accurate interpretation of sensor data. To mitigate this issue, overlapping sliding windows are often used, allowing each segment to retain some information from adjacent windows [32, 116].

Data Summarization. To reduce input volume, raw sensor data can be summarized before being passed to the model. Three common approaches are used for summarizing numerical sensor data. The first relies on external tools (e.g., calculators or Python scripts) to extract *high-level statistical features* (e.g., mean, variance, or FFT-based metrics) [12]. This method is particularly effective when these features are directly relevant to downstream tasks (e.g., an elevated average body temperature may indicate fever, suggesting a potential health concern). The second approach leverages LLMs or lightweight language models (e.g., DistillBert [132]) to generate *natural language summaries* of raw sensor data [116]. These models have shown strong capabilities in identifying and articulating key numerical patterns (e.g., trends and state changes) and these summaries are typically much shorter than the original data while preserving essential information. The third approach uses task specific modules (e.g., rule-based methods or lightweight ML models) to extract *task related information* (e.g., identifying individuals from vibration data or recognizing activities from audio signals) [116, 145, 175]. Only the extracted outputs are passed to the LLM when these simpler models are insufficient for completing the task [116]. This approach reduces the LLM's computational burden, allowing it to focus on high-level reasoning and user interaction.

Critical Information Incorporation. The information contained in the sensor data is often sparse, making it possible to significantly reduce input length by including only components containing task-relevant information. For example, in human activity recognition, sensor readings frequently remain unchanged for long durations (e.g., when a person is not present in a room). To eliminate redundancy, prompts can be constructed using only state-change events (i.e., time steps where sensor values change) [32]. In multi-modal settings involving numerous sensor types, an initial summary capturing sensor types, data formats, and the first and last readings of each type can be used to prompt the LLM. The model can then perform commonsense reasoning to identify which sensors are most relevant to the downstream task, allowing only the data from those critical sensors to be included in the final prompt [165].

Sensor Data Encoding. When fine-tuning is permitted, large-scale sensor data can be efficiently compressed using a lightweight neural encoder (e.g., an RNN for temporal data or a GNN for spatial data). The encoder transforms the raw sensor input into one or more compact embeddings, which are treated as special tokens and concatenated with textual tokens in the prompt. These combined representations are then input into the trainable LLM, with both the encoder and the LLM jointly optimized during training [30, 76, 94, 109, 151, 172, 185]. This approach addresses limitations associated with treating numerical sensor data as textual input, which can lead to information loss or misinterpretation due to internal LLM constraints (e.g., inconsistent tokenization) or prompt engineering challenges (e.g., downsampling or quantization of lengthy sensor sequences).

Experience Archive. The experience archive serves as an external memory (e.g., a database or cache) that stores historical interactions between the LLM-agent and the user, including past plans, tool and executor outputs, error messages from failed executions, and prior contextual information and decisions [2, 37, 38]. By enabling the agent to retrieve relevant past decisions and responses for similar scenarios or user queries, the experience archive reduces the need for repeated reasoning, planning, or replanning. This significantly improves decision-making efficiency by minimizing redundant computation and inference time.

Efficient Model Architecture Design. Efficient model architectures are essential for applying foundation models to addressing IoT tasks, since foundation models often contain a vast number of parameters to encode general knowledge across large-scale diverse datasets. This complexity results in high computational costs and prolonged inference time, making such models impractical for deployment on typical IoT devices or in scenarios requiring real-time responsiveness. In the following sections, we review several techniques aimed at improving the architectural efficiency of foundation models.

Efficient Transformer Architecture. The Transformer architecture [150] has been widely adopted in the IoT domain to build foundation models (e.g., IoT-LM [109] and LIMU-BERT [168]). However, Transformers are known for their high computational complexity, driven by three key factors: (1) *the self-attention mechanism*, which scales quadratically with input length; (2) *a deep multilayer architecture* with unshared trainable parameters across different layers; and (3) *fully-connected feedforward layers*, which contain the majority of the model's parameters.

To address the computational challenges of self-attention, sparse attention mechanisms [33, 34, 68, 146, 158] can be employed. Rather than allowing each token to attend to all others, sparse attention restricts attention to a limited set of positions, significantly reducing computational complexity. Additionally, attention mechanisms can be optimized for hardware-specific constraints, such as GPU memory and I/O throughput [41, 42]. To mitigate the overhead of multi-layer architectures, LIMU-BERT [168] introduces cross-layer parameter sharing, where only the first encoder layer is trained and its parameters are reused across all subsequent layers. This approach drastically reduces the total number of parameters, improving efficiency and enabling deployment on resource-constrained devices. Finally, to reduce the computational cost of fully connected layers, Mixture-of-Experts (MoE) architectures [26] can be used. MoE layers employ sparse gating to activate only a small subset of expert sub-networks per token, rather than processing each token through all experts. This design enables models to scale to billions of parameters while maintaining efficient training and inference. Recent work such as LiteMoE [195] further enhances the efficiency of MoE-based architectures for the on-device deployment.

Architecture with Linear Complexity. To further address the quadratic complexity of the self-attention mechanism and also a large amount of parameters in the Transformer model, new architecture has been proposed which has linear complexity, such as TNL [124], HGRN2 [125], cosformer [123], and Mamba [58]. Those new architectures have already been applied in the IoT field. For example, MambaReID [189] uses Mamba architecture to address Multi-modal object re-identification task. Their experiments demonstrates that their Mamba based model can achieve the similar accuracy on the person and vehicle re-identification tasks but consuming much less memory.

Adapter Layers. Adapter layers are parameter-efficient methods during the fine-tuning [70]. In this method, only adapter layers, which are simple added structures to the backbone foundation model and have much smaller parameters than the backbone foundation models, are updated during the fine-tuning, which saves a lot of memory and time compared to fine-tuning the whole models [86, 94, 104, 166]. Also low-rank adaptation (LoRA) [72], which is the low-rank approximation architecture for the fully connected adapter, can also be used to further reduce the number of parameters of the adapter (e.g., used in LLM4WM [104], LLaSA [76]).

4 Criterion II: Context Awareness

Context awareness refers to a system's ability to dynamically adapt its behavior based on situational factors relevant to a specific task [45, 120]. In the context of applying FMs to IoT tasks, contextual factors typically fall into two key categories: (1) *environmental context*, which includes physical conditions (e.g., time, location, room brightness, available IoT devices) [32, 38, 62] and virtual settings (e.g., accessible software applications) [101]; and (2) *user-specific context*, which accounts for individual preferences, schedules, backgrounds, and personalities.

Context awareness is critical for effectively applying FMs to IoT tasks. First, it enables FMs to accurately interpret raw sensor data, which typically consists of unstructured numerical values. Since these values reflect real-world physical states, understanding their meaning requires contextual metadata (e.g., sampling rate, sensor placement, and measurement units). Without this information, FMs struggle to infer the true significance of the data, impairing reasoning and decision-making [12]. Second, since FMs are pre-trained on broad datasets to capture general patterns, they often overlook context-specific cues essential for task performance in real-world environments [122, 186]. For instance, LLMs may generate overly generic outputs when they lack grounding in environmental context (e.g., availability of physical objects or tools), which limits their ability to produce actionable, situation-appropriate responses. Third, context-aware foundation models can dynamically adapt to diverse IoT scenarios without requiring separate models for each specific case. This adaptability is especially valuable in IoT environments, where tasks are inherently context-dependent and conditions frequently change. By enabling a single model to generalize across varying situations, context awareness enhances system flexibility and automation, while also reducing the burden of developing and maintaining multiple specialized models. Finally, incorporating user-specific context (e.g., location, activity, or preferences) allows FM-based IoT systems to personalize services and interactions. This not only improves usability but also enhances user engagement and satisfaction [175].

The collected papers propose various methods to enable context awareness in foundation models for IoT applications, which we summarize below.

Data Enrichment. Data enrichment involves augmenting formatted and encoded sensor inputs with additional contextual information to help foundation models more accurately interpret the underlying physical meaning behind the data. Critical background details (e.g., units of measurement, sampling rate, and device placement) are essential, as identical sensor readings can have vastly different meanings depending on the context [12, 79]. For instance, sequences of the same length may reflect different durations depending on sampling rates, and identical values could represent entirely different phenomena (e.g., movement speed vs. body temperature) based on the measurement unit. Without this contextual information, foundation models may misinterpret the data and make suboptimal decisions. Therefore, such metadata should be included alongside raw sensor inputs when using prompt-based, agent-based, or training-based approaches.

Fine-Tuning. One of the most effective ways to achieve context awareness in foundation models, originally trained on general-purpose datasets, is to fine-tune them using data specific to the target environment, user, and task. This process adjusts the model's parameters to capture context-specific patterns while preserving the general knowledge gained during pretraining. Fine-tuning significantly improves the model's ability to interpret and respond to contextual cues. For instance, Guo et al. [62] fine-tuned an LLM for an augmented reality (AR) system using user interaction and feedback data, enabling the model to generate virtual scenes more closely aligned with individual user preferences.

Contextual Inputs. While fine-tuning can significantly enhance the context awareness of foundation models, it often requires substantial computational resources and large volumes of training data. A more lightweight alternative when applying prompt-based or agent-based methods is to incorporate environmental and personal context directly into the model inputs as textual prompts. For example, Nepal et al. [111] personalize a journaling system by embedding user context, such as current mood, stress level, and summaries of daily behavior (e.g., screen time, walking duration), into the prompt before passing it to the LLM for reasoning. Similarly, LLMind [38] incorporates user profiles (e.g., background and experience) into the system prompt and leverages the LLM's role-playing capabilities [29] to generate tailored responses.

However, implementing context-aware personalization may raise significant privacy concerns. Developers must be careful of these issues and avoid intrusive practices (e.g., collecting personal information from users' social media without explicit consent) [175].

Contextual Memory. Contextual information can also be stored in external memory to enhance the context awareness when applying agent-based methods. This external repository should be updated in real time or at regular intervals to remain adaptive to contextual changes.

Several studies have proposed storing environmental or personal data in such memory structures. For example, Yang et al. [175] uses an LLM to extract persona-related information (e.g., personal interests, experiences, and background) from conversations and stores it in a persona database at the end of each interaction. For new conversational partners, the extracted persona are directly registered into the memory. For known users or previously encountered partners, they use the LLM to check for existing persona in the database. If no conflicting or redundant information is found, the extracted new persona are added. If the persona are semantically similar to existing entries, they are merged. If contradictions are detected, the old information in the database are replaced by the new ones. The stored personal information can then be integrated into the LLM's reasoning, either by accessing it through external memory during inference or by incorporating relevant context into prompts, enhancing the model's adaptability to individual users.

Active Sensing. In addition to *passively* receiving environmental data (e.g., sensor data) or user information (e.g., through user interactions), agent-based methods can also *actively* query physical IoT devices (e.g., sensors, robots) to gather additional information when the current context is insufficient for high-level reasoning or decision-making. This is referred to as the *active sensing* capability. For example, in the LLMind [38] paper, an agent-based check-in and security system can prompt a robot to approach and identify a person when the system cannot recognize them from low-resolution images captured by a ceiling-mounted camera or due to occlusion.

Iterative Self-Refinement. For methods based on LLMs, due to their non-deterministic nature, incorporating contextual information into prompts does not always guarantee fully executable responses or complete satisfaction of personalization requirements. To address this, iterative self-refinement mechanism are proposed to transforms LLMs into a closed-loop system [38, 62, 101]. Specifically, the LLM's output (e.g., a plan generated by an LLM-agent) receives feedback from the environment or the user if the response is not executable, possibly due to overlooked environmental or user-specific factors. The LLM is then reprompted with information about the execution error or user feedback, generating a revised response. This process repeats until the generated response fully meets the environmental and personalization requirements.

5 Criterion III: Safety

Safety in IoT systems refers to preventing the system and its components from causing physical harm or posing threats, and to protecting the surrounding environment from such risks [14]. It is worth noting that in other related surveys (e.g., Ma et al. [107]), safety may also encompass security, which refers to protecting models from external threats such as adversarial, jailbreak attacks. In this survey, we consider them *differently* as Shi et al. [140] and address security separately in Section 6.

Safety is a critical concern in FM-based IoT systems, particularly when model outputs can directly control or influence physical devices (e.g., industrial robots, medical equipment, vehicles, or infrastructure). First, malfunctions, misuse, or insufficient safeguards of FMs may lead to serious consequences, including accidents, equipment failure, or environmental damage. Second, due to their probabilistic nature, FMs may generate outputs that fail to consistently adhere to safety protocols [170, 181]. This risk increases when task goals are specified at runtime by untrained users, whose instructions may unintentionally conflict with implicit safety constraints. Third, FMs may generate overly general or context-agnostic responses that ignore critical environmental factors, potentially leading to harmful or catastrophic outcomes in the target task, even though the same responses would be safe in other environments or applications.

All studies reviewed in this survey focus on enhancing the safety of *LLMs*; therefore, we summarize the commonly used techniques for improving LLM safety in the context of IoT integration.

Safety Requirement Incorporation. Embedding safety requirements into LLM inputs, typically via system prompts, is a key strategy for promoting safety awareness [170]. This approach requires developers and domain experts to proactively identify potential risks and define appropriate constraints and mitigation strategies prior to deployment. In agent-based systems, where external information can be retrieved dynamically from online sources or databases, environment- and task-specific safety requirements can also be automatically incorporated into the prompt to ensure context-aware and adaptive safety compliance.

User Request Verification. When presented with a task from user requests, an LLM should reason over both the request and the current environmental context to assess whether the task is safe and compliant with predefined safety constraints. Context-aware reasoning is essential, as high-level instructions may not be safe to execute across all situations [37, 170]. For example, the model should recognize and reject unsafe user requests, such as driving at 200 miles per hour (322 km/h) on a snowy road.

Post-Response Verification. After the LLM generates the response, it is crucial to verify that the output adheres to both general and task-specific safety constraints, either manually or automatically. Manual verification, however, can be time-consuming, especially when domain expertise and complex reasoning are required. Therefore, automated verification methods are essential. For example, Xu et al. [170] utilizes the Z3 Python API to check safety constraints formulated as first-order logic (FOL) against LLM-generated plans, which are expressed in formal languages such as Linear Temporal Logic (LTL) [170, 181]. Alternatively, responses can be validated through simulations to ensure safe and correct execution before deployment in real-world environments.

Interpretable Decision-Making. When the LLM makes the decisions or operates the physical devices, especially in the high-stake scenarios (e.g., healthcare, autonomous driving), interpretability of the final decision is very important. This means being able to provide not only the final decision, but also the reasoning procedure explicitly (e.g., reasoning chain in Chain-of-Thought). This can help humans identify if the generated decision is correct and avoid catastrophes if the LLM intermediate reasoning steps violates the safety rules [37].

Iterative Self-Refinement. If an LLM output violates safety constraints, the model should be reprompted and required to regenerate the output iteratively, guided by feedback from either human reviewers or automated verification systems, until the generated response satisfies all predefined safety requirements [170, 181].

6 Criterion IV: Security and Privacy

Security and privacy refer to the protection of systems and data from malicious attacks (e.g., jailbreak attacks, adversarial attacks, PAII attacks) that may lead to unauthorized access, loss of system control, or data leakage [14, 27]. As discussed in Section 5, we distinguish security from safety, which pertains to preventing harmful outputs generated by the system. Notably, in this survey, security and privacy are considered from the perspective of *external* attackers, whereas safety concerns arise from the foundation model's *internal* probabilistic behavior. Therefore, *even if an FM-based IoT system is secure and private, it may still be unsafe.*

Security and privacy are critical for IoT systems for several reasons. First, the number of IoT devices is growing exponentially, and attacks targeting these systems are becoming increasingly frequent and sophisticated [93]. Second, IoT devices and networks often collect and transmit sensitive data (e.g., personal health information, location details, and business-critical metrics). Unauthorized access to or manipulation of this data can result in serious consequences, including identity theft, financial loss, and operational disruptions [6, 11, 46, 152]. Finally, because IoT devices are typically networked, compromising a single device can jeopardize the security of the entire system.

In this section, we summarize approaches to enhancing IoT security and privacy with foundation models in two contexts: (1) using foundation models to protect the security and privacy of IoT systems without directly participating in downstream tasks (e.g., human activity recognition, robot control), and (2) securing FM-based IoT systems where the foundation model plays a central role in downstream tasks.

FMs for Anomaly Detection. To enhance security and privacy, LLMs have been employed to detect potential anomalies, such as unusual activities in system or network logs and malicious sensor data-sharing requests. LLMs are commonly used for anomaly detection due to their ability to estimate the likelihood of a sentence or paragraph based on their training data. Specifically, an LLM can be trained on text-based datasets containing normal activity logs or benign user requests. When the model encounters abnormal behavior or malicious requests, it assigns a low probability to these inputs, indicating potential anomalies [6, 11, 46].

However, defining normal activities or requests in IoT systems based on pre-collected datasets is challenging, particularly in dynamic and heterogeneous environments where "normal" behavior can evolve over time. As a result, LLMs trained on static datasets may misclassify newly emerged benign activities as malicious. Such misclassifications can deny service to legitimate users, reducing system usability and potentially leading to financial losses.

To address this challenge, LLM agents are used to safeguard IoT systems in dynamic environments due to their reasoning and planning capabilities, as well as their ability to search and retrieve relevant information from external sources (e.g., external memory or the internet). These updatable resources allow the system to adapt to previously unseen intrusion patterns, such as zero-day attacks [93, 152].

FMs for Data Obfuscation. In addition to detecting and identifying abnormal behavior, FMs can also protect security and privacy of IoT systems through *data obfuscation*, particularly for protecting sensitive personal information.

Data obfuscation is a technique that transforms sensitive data into a less meaningful or recognizable form to prevent unauthorized access and ensure compliance with data protection regulations [16]. FMs can support data obfuscation in several ways: (1) identifying and masking sensitive information, such as personally identifiable information (PII) [116]; (2) summarizing raw sensor data into natural language descriptions [116]; (3) synthesizing realistic but non-identifiable sensor data [180]; and (4) enabling LLM agents to generate privacy-preserving data transformation pipelines (e.g., face blurring in video) by selecting tools from a library and planning multi-step workflows [152].

When leveraging FMs for data obfuscation, two key considerations must be addressed: (1) *Privacy–utility trade-off*: Excessive obfuscation can make transformed data significantly different from the original, making it difficult to recover critical information. This degradation can negatively impact the performance of downstream tasks [152, 180]. (2) *Personalization*: Rather than applying uniform rules (e.g., masking biometric identifiers or common activity types), obfuscation should account for individual user preferences regarding what information can be shared. This user-controlled privacy level, known as *privacy preference*, guides the filtering of data based on specific needs [19, 152, 180]. Supporting personalized privacy settings enhances system usability and can be achieved through techniques discussed in Section 4.

Privacy Considerations for FM-based IoT system. Two techniques are commonly used by the literature to protect privacy in FM-based IoT systems: (1) *Using less interpretable data modalities*: Selecting data types that are difficult for humans to interpret, such as vibration data instead of video for tasks like human activity monitoring, can improve privacy [175]. However, this approach requires foundation models capable of understanding such non-human-interpretable data, which is more challenging due to the limited availability of labeled training datasets. (2) *Data obfuscation in edge–cloud architectures*: When the edge-cloud collaboration system [147, 182] is leveraged, data should be obfuscated on *local devices*, using rule-based methods, machine learning models, or lightweight foundation models, before being transmitted to the cloud [19, 116, 187]. The cloud hosts more powerful FMs for task-specific reasoning, but transmitting raw data increases exposure to privacy risks during transit and in cloud environments, where broader access makes data more vulnerable to attacks.

7 Evaluation

In this section, we examine how foundation models are evaluated for IoT tasks. We review the metrics used for both downstream task performance and the four key performance criteria discussed earlier. Additionally, we summarize common evaluation strategies, outlining their applicable scenarios, relevant criteria, and associated advantages and limitations.

Metrics. Most evaluation metrics depend on the specific downstream task. We categorize them into four groups and summarize the commonly used metrics for each: (1) *Classification tasks* (e.g., beam prediction [10, 104, 139], human activity recognition [3, 32, 36, 79, 117, 145, 163, 166, 174]): Accuracy, F1 score, precision, recall, and specificity. (2) *Regression tasks* (e.g., channel prediction [52, 99, 100, 104], air quality forecasting [51]): Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Normalized MSE (NMSE). (3) *Complex IoT tasks involving LLM agents* (e.g., wireless network management): Success rate, which measures the proportion of tasks successfully completed, indicating whether the final objective was achieved [2, 101, 181]. (4) *Sensor QA tasks* (e.g., sensor summarization, ECG report generation) [30, 76, 94, 109, 151, 172, 185]: Natural language processing (NLP) metrics such as BLEU [118], ROUGE [97], and METEOR [17].

We also summarize specific evaluation metrics from the reviewed papers for each performance criterion discussed in this work: (1) *Efficiency*: Convergence speed (e.g., number of epochs to convergence) assesses the training efficiency of fine-tuning-based methods [85, 86]. Inference latency measures the time required for the FM-based IoT system to complete a downstream task during inference [176]. Memory usage measures the amount of memory consumed during inference [164]. (2) *Context-Awareness*: Executability rate evaluates how likely the model's response can be executed in a specific environment [101]. Personalization score assesses how well the response is tailored to an individual's unique characteristics (e.g., persona, background, schedule) [175]. (3) *Safety*: Safety rate quantifies the likelihood that a model's response violates predefined safety constraints [107]. (4) *Security and Privacy*: For security, the common task is anomaly detection and the corresponding metrics are classification based metrics (e.g., F1, precision, recall) [6, 11, 46, 71, 93]. For privacy, evaluation typically involves the attack accuracy, which measures how accurately an adversarial model can recover sensitive information that is intended to be protected [152, 180].

Strategies. Common evaluation strategies for foundation models in IoT tasks include: (1) ground-truth comparison, (2) human evaluation, (3) LLM-as-a-judge, and (4) real-world evaluation. We describe each approach in detail below.

Ground-Truth Comparison. The most common approach to evaluating foundation models for IoT tasks is to compare their outputs against ground-truth labels using explicitly annotated datasets for specific downstream tasks. Evaluation tasks typically fall into two categories: (1) *Closed-ended tasks*: These tasks have unique ground-truth labels. Common examples include classification (e.g., human activity recognition [3, 32, 36, 79, 117, 145, 163, 166, 174], beam prediction [10, 104, 139], disease detection [69]) and regression tasks (e.g., PM2.5 prediction [51]). Performance is measured using metrics such as accuracy for classification, or MAE and RMSE for regression, which quantify the difference between the model's predictions and the true labels. (2) *Open-ended tasks*: These are typically found in question-answering scenarios (e.g., "Please summarize the trend of the sensor signal" or "Please generate a report for the ECG."), where multiple valid responses may exist due to the inherent variability in natural language [30, 76, 94, 109, 151, 172, 185]. In such cases, natural language generation metrics like BLEU [118] and ROUGE [97] are used to assess the semantic similarity between the model's output and a reference response, which serves as the ground-truth.

Among the performance criteria discussed in this survey, ground-truth comparison is most commonly used in evaluating *security and privacy*. This is because their tasks often involve classification, such as determining whether a behavior is malicious or benign using foundation models. In contrast, ground-truth comparison is less frequently used for evaluating context awareness and safety, as these tasks are more subjective and influenced by individual preferences and real-world variability, making it difficult to define universally applicable labels.

Human Evaluation. Human evaluation is typically employed in the following scenarios when addressing IoT tasks: (1) *Open-ended generation tasks*: As noted earlier, open-ended tasks can have multiple valid responses, while datasets usually provide only a single reference answer. Relying solely on automated comparison with a reference may result in incomplete or biased evaluation. Human evaluation serves as the gold standard in these cases, allowing assessment across multiple dimensions (e.g., fluency, coherence, and relevance). It also enables qualitative judgments in situations where evaluation criteria cannot be easily formalized mathematically. Humans may either compare different outputs or assign scalar satisfaction scores to individual responses [76, 113]. (2) *Real-world deployment evaluation*: In practical IoT applications, FM-based systems are often validated in real-world environments where ground-truth labels are unavailable [50, 113, 177]. To benchmark performance in such settings, human judgment is essential. (3) *Usability evaluation*: Human evaluation is also critical for assessing the usability of FM-based IoT systems, particularly in personalized applications (see Section 4) [62, 113]. User feedback and experience play a key role in iterative development and refinement of these systems.

Among the performance criteria discussed in this survey, human evaluation is most commonly used to assess *context-awareness* and *safety*. These aspects are inherently subjective and heavily influenced by human experience, as well as situational nuances. For example, in an urban setting, a "safe" action might involve abrupt braking to avoid hitting a pedestrian, while on a highway, such behavior could increase the risk of a collision and be considered unsafe. The appropriate response depends on factors like speed, traffic density, and road conditions. Due to this complexity, single-label quantitative evaluations are often insufficient, making automated assessment challenging and highlighting the need for human judgment in evaluating these criteria.

However, human evaluation is generally slower and more costly than automated methods, especially when complex reasoning or expert knowledge is required (e.g., in disease diagnosis). Furthermore, to ensure meaningful and reliable results, evaluators must establish clear annotation guidelines, evaluate inter-rater reliability, ensure demographic diversity among annotators, and monitor consistency throughout the evaluation process [63, 65].

LLM-as-a-Judge. To address the high cost and slow turnaround of human annotation and evaluation, LLMs have gained popularity as automated judges for open-ended tasks and real-world scenarios. Trained on vast and diverse real-world data, LLMs possess broad general and domain-specific knowledge, allowing them to perform evaluations across a range of domains without task-specific fine-tuning. This makes LLM-based evaluation significantly more scalable and cost-effective [59, 90]. Moreover, LLM agents, augmented with reasoning and planning capabilities, have recently emerged as even more powerful evaluators [196]. In addition, many state-of-the-art commercial LLMs have been aligned with human preferences through reinforcement learning (e.g., RLHF [115]) or alternative methods such as Direct Preference Optimization (DPO) [127], making them more representative of human judgment. Thus, *context-awareness* and *safety* can also be assessed by LLM judges.

Despite these advantages, using LLMs as judges comes with inherent limitations and biases, including position bias, length bias, and output instability (e.g., flipping between responses) [157, 184, 193]. These issues must be carefully measured, mitigated, and monitored to ensure fair and reliable evaluation outcomes. Addressing these concerns is crucial for producing trustworthy evaluations that can guide the development and deployment of foundation models in real-world applications.

Real-World Evaluation. Real-world evaluation is essential for training and deploying foundation models in IoT applications, as these systems are ultimately intended for use in practical settings such as smart homes, cities, transportation, and healthcare. Testing in real-world environments allows researchers and developers to identify system limitations across diverse scenarios and iteratively improve performance.

During real-world evaluation, it is critical to assess not only the performance criteria outlined in this survey, but also key properties such as generalization (scalability), robustness, and usability in varying levels of complexity. Moreover, *such evaluations must be conducted in a carefully controlled manner to ensure safety for both humans and the environment.*

8 Discussion

In this section, we discuss the limitations of current approaches and propose future directions for more effective application and evaluation of foundation models in IoT tasks.

Insufficient Evaluation. Current FM-based approaches for IoT tasks often suffer from insufficient evaluation. Below, we highlight this issue from both the *general* perspective as well as the specific perspective from *security and privacy.*

Lack of Cross-Domain Comparison. As discussed in the Introduction (section 1), cross-domain comparisons are largely lacking in current research. Many studies evaluate their proposed methods only against simple baselines, neglecting comparisons with more advanced techniques from other IoT domains. This limits our ability to assess the relative strengths and weaknesses of different approaches and hampers practitioners in choosing the most suitable methods for new tasks. Additionally, no existing work evaluates *all* the performance criteria identified in this survey, which are essential for deploying foundation models in real-world IoT applications. To address these gaps, we propose the following: (1)*Cross-Domain Comparisons*: Researchers should benchmark their methods not only against basic baselines but also against advanced techniques from other IoT subfields, particularly those highlighted in this survey. (2) *Generalization Evaluation and Leaderboard Creation*: A standardized evaluation framework should be established, incorporating the performance criteria, methodologies, datasets, and sensor types commonly used across IoT domains. Developing a shared leaderboard would promote transparent, comprehensive comparisons and help identify the most effective methods for specific criteria, tasks, and sensor modalities.

Lack of Fine-Grained Evaluation. Many components in FM-based IoT systems lack fine-grained evaluation. For example, agent-based methods often involve multiple modules (i.e., tool use, memory, and plan generation) but evaluations typically focus only on the overall system performance. This overlooks critical questions (e.g., whether the agent selects the most appropriate tools, generates accurate plans, or retrieves relevant knowledge for specific tasks and user queries). Without fine-grained evaluation, it is difficult to identify system bottlenecks or guide meaningful improvements. Moving forward, component-level assessments using dedicated metrics are essential to understand each module's contribution to overall performance and to inform more effective system design.

Lack of Real-World Evaluation. Many studies fail to evaluate their methods in real-world environments using the full set of performance criteria outlined in this survey. This is a significant limitation, as IoT systems operate in complex and variable deployment settings that cannot be fully captured through simulation. Without real-world validation, it is difficult to assess the generalizability, reliability, and robustness of FM-based IoT solutions. In the future, we strongly recommend evaluating complete FM-based IoT systems in real-world settings using the full set of criteria defined in this survey. This is essential for identifying practical limitations, informing future improvements, and guiding the development of robust, deployable IoT solutions.

Lack of Security and Privacy Evaluation for FMs. While the methods discussed in Section 6 leverage foundation models (e.g., LLMs, diffusion models [179]) to defend against security and privacy threats (e.g., personal information inference attacks), the models themselves are inherently vulnerable [1, 107]. Consequently, using FMs in IoT security applications introduces additional risks. However, the real-world impact of these vulnerabilities in IoT settings remains largely unexplored, and current research offers limited guidance on mitigating such risks. Future work should include more comprehensive evaluations and the development of benchmark datasets to assess security and privacy threats arising from both pretrained and newly proposed FMs in IoT contexts.

Advanced FM Techniques for IoT. Advanced techniques in foundation models remain underexplored in the context of IoT. In this section, we highlight four such techniques related to LLMs and LLM agents that have not been widely applied to IoT tasks: *large reasoning models*, *multi-agent system*, *human preference alignment*, and *new model architecture and training objective*.

Large Reasoning Model (LRM). LRMs (e.g., OpenAI's o1 [77], o3 [114], and DeepSeek-R1 [60]) are a class of LLMs designed specifically for complex reasoning and planning, going beyond the instruction-following and question-answering capabilities of traditional LLMs. Many IoT applications—particularly those involving complex environments or high-stakes scenarios (e.g., healthcare or autonomous driving) require strong contextual reasoning and decision-making. LRMs, which emphasize logical inference over surface-level statistical patterns, hold significant promise for addressing these challenges more effectively.

Multi-Agent System. A multi-agent system based on LLMs [61, 92] consists of multiple LLM agents, each equipped with distinct capabilities defined by their roles, tools, and memory modules.

Compared to single-agent systems (as discussed in Section 2.2), LLM-based multi-agent systems are better suited for complex and dynamic IoT environments due to their enhanced scalability, adaptability, fault tolerance, and collaborative capacity. First, multi-agent systems integrate diverse skills and perspectives, making them well-suited for interdependent IoT scenarios that require coordination and negotiation (e.g., smart cities or supply chain management). Second, they can dynamically reallocate resources, adapt to new devices, and respond in real time to changing conditions. These capabilities that are difficult to achieve with a single agent make them more effective in unpredictable IoT settings. Third, agents can cross-validate each other's outputs, reducing the risk of errors and hallucinations, which is an especially valuable feature for safety-critical applications. Finally, multi-agent systems can distribute complex or lengthy tasks across agents, preserving coherence over time and across devices, thus overcoming the context window limitations of single LLMs.

However, effective multi-agent deployment requires careful task decomposition. Specifically, it is essential to determine how to partition the overall task into non-overlapping subtasks that align with each agent's strengths. Additionally, designing mechanisms for inter-agent communication and collaboration is crucial for achieving coherent and coordinated outcomes. These communication strategies should be compatible with the distributed and hierarchical nature of IoT networks, where each node may host a distinct agent, and agents communicate over the network via node-to-node connections.

Human Preference Alignment. Advanced human preference alignment techniques (e.g., Reinforcement Learning from Human Feedback (RLHF) [83, 115] and Direct Preference Optimization (DPO) [127]) have not yet been widely applied to personalize LLMs for IoT tasks. These alignment methods not only enhance personalization, enabling the model to better reflect individual user preferences, but also help embed socially and ethically appropriate behaviors. For example, teaching a model to prioritize waiting for an elderly person to cross the street rather than proceeding immediately can significantly improve the safety and trustworthiness of LLM-based IoT systems operating in real-world environments.

New Model Architecture and Training Objective. Current FMs used in training-based methods for IoT tasks are primarily based on the Transformer architecture [150]. However, Transformers may not be the most effective or efficient choice for processing sensor data, even for time-series data [43, 188], despite their popularity in this domain. This highlights the need for novel architectural designs and training strategies tailored specifically to the characteristics of IoT data. Below, we outline several key considerations for developing such models.

Designing FMs for IoT applications requires careful consideration of the unique characteristics of sensor data. Key considerations include: (1) *Architecture choice*: model architecture should be tailored to the unique properties or structures of sensor data. For example, in geo-spatial applications like air quality monitoring [49, 67], graph neural networks instead of Transformer may better capture spatial dependencies. (2) *Heterogeneous sensor types*: IoT networks often involve diverse sensor modalities. Designing models that can extract and integrate multi-modal information remains an open challenge. (3) *Sparse but salient signals*: Sensor data frequently contain sparse but crucial patterns. Incorporating selective attention or filtering mechanisms may help models focus on high-value segments. (4) *Metadata utilization*: Contextual information (e.g., sampling rates and device placements) should be explicitly encoded and included alongside raw sensor inputs to improve model understanding of the data collection process. How to encode them effectively into the model architecture is an open problem. (5) *Efficiency and robustness*: Models should be computationally lightweight for deployment on edge devices and robust to common issues like missing or noisy data. (6) *IoT-specific Training Objective*: Many existing pretraining tasks are directly adapted from NLP (e.g., masked token prediction [44]), but these may not suit the continuous, multi-modal nature of sensor data. There is a urgent need to develop IoT-specific unsupervised learning objectives.

9 Conclusion

In this survey, we provide a comprehensive overview of research leveraging foundation models for IoT tasks. We identify four shared performance criteria across diverse IoT applications, outline three key paradigms for applying foundation models, and examine current evaluation strategies for both general performance and individual criteria. Based on this analysis, we highlight several open research challenges and propose future directions. Our work offers guidance for more systematic evaluation, enables cross-domain comparisons, and provides valuable insights for applying and assessing foundation models in emerging IoT scenarios.

Acknowledgments

This research is supported by a UC Merced Spring 2023 Climate Action Seed Competition Grant, CAHSI-Google Institutional Research Program Award, and F3 R&D GSR Award funded by the US Department of Commerce, Economic Development Administration Build Back Better Regional Challenge.

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A Example Prompt for Human Activity Recognition Based on IMU Data

System Prompt

You are an IoT domain expert specializing in human activity recognition (HAR) using inertial measurement unit (IMU) sensor data. Your goal is to accurately determine whether the input IMU data corresponds to a specific human activity, based on provided data and context.

The task involves:

- Understanding the sensor data (acceleration and gyroscope) collected from wearable IMU devices.
- Using domain knowledge and context (e.g., units, sampling rate, placement) to interpret sensor patterns.
- Applying expert reasoning to infer human activity based on motion patterns.

You will follow these **decomposed steps**:

(1) Analyze the time series patterns from the accelerometer and gyroscope.
(2) Use context information to interpret the movement (e.g., high acceleration with oscillation = running).
(3) Match the interpreted signal to the target activity class.
(4) Provide the answer in the requested format.

You will be given a prompt that includes:

- A task description
- IMU data input
- Data collection context
- In-context demonstrations
- Output format constraints

You must **strictly follow the output format** provided in the user prompt. Do not include any explanation, justification, or additional content in your output.

User Prompt

Task: Determine whether the person is *running* based on the provided IMU data segment.

Data Collection Context:

- IMU Device: Worn on the right ankle
- Sampling Rate: 50 Hz (i.e., 50 samples per second)
- Duration: 10 seconds
- Sensors:
  - Accelerometer (X, Y, Z) in m/s^2
  - Gyroscope (X, Y, Z) in deg/s
- Units: All values are floating point with 2 decimal places
- Format: Each row corresponds to one timestamp

In-Context Demonstration #1

```
Task: Is the person running?
IMU Segment:
Time | Acc_X | Acc_Y | Acc_Z | Gyro_X | Gyro_Y | Gyro_Z
-----|-------|-------|-------|--------|--------|--------
0.00 | 0.20  | 9.81  | 0.10  | 0.01   | 0.02   | 0.00
...  | ...   | ...   | ...   | ...    | ...    | ...
[brief burst of high-frequency, high-magnitude motion]
Answer: Yes
```

In-Context Demonstration #2

```
Task: Is the person running?
IMU Segment:
Time | Acc_X | Acc_Y | Acc_Z | Gyro_X | Gyro_Y | Gyro_Z
-----|-------|-------|-------|--------|--------|--------
0.00 | 0.01  | 9.80  | 0.00  | 0.00   | 0.01   | 0.01
...  | ...   | ...   | ...   | ...    | ...    | ...
[mostly flat and stable readings over time]
Answer: No
```

Your Task

```
Task: Is the person running?
IMU Segment:
Time | Acc_X | Acc_Y | Acc_Z | Gyro_X | Gyro_Y | Gyro_Z
-----|-------|-------|-------|--------|--------|--------
0.00 | 0.03  | 9.79  | 0.01  | 0.01   | 0.00   | 0.01
0.02 | 0.05  | 9.82  | 0.03  | 0.01   | 0.01   | 0.00
0.04 | 0.04  | 9.78  | 0.02  | 0.00   | 0.02   | 0.01
...  | ...   | ...   | ...   | ...    | ...    | ...
```

Output Format:
Please **only respond with** `Yes` or `No`. **Do not** include any explanation or additional content.

B Method Selection

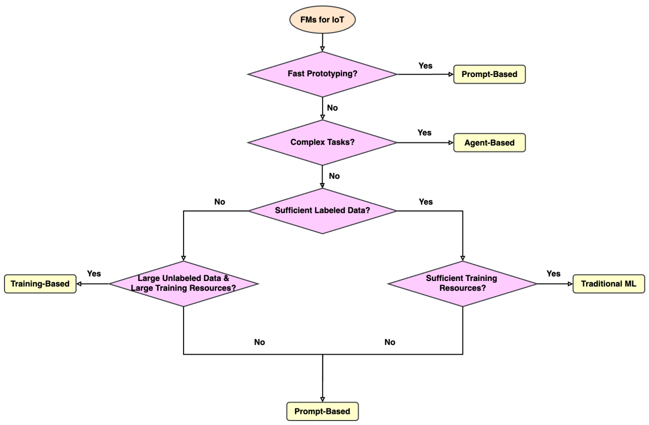

Figure 2: Method selection decision tree. The decision tree considers the three most commonly used frameworks for applying foundation models to IoT tasks: *prompt-based methods*, *agent-based methods*, and *training-based methods*, as well as *traditional supervised learning methods*. The selection is guided by six key dimensions introduced in Section 2.4 computation requirement (CR), error rate on specific tasks (ER), task specificity (TS), development time (DT), labeled data requirement (LDR), and unlabeled data requirement (UDR). While the decision tree provides general guidance, practitioners and researchers should adapt it to specific scenarios, particularly when additional constraints such as security and privacy are involved.