ContextAgent: Context-Aware Proactive LLM Agents with Open-World Sensory Perceptions

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Abstract

Recent advances in Large Language Models (LLMs) have propelled intelligent agents from reactive responses to proactive support. While promising, existing proactive agents either rely exclusively on observations from enclosed environments (e.g., desktop UIs) with direct LLM inference or employ rule-based proactive notifications, leading to suboptimal user intent understanding and limited functionality for proactive service. In this paper, we introduce ContextAgent, the first context-aware proactive agent that incorporates extensive sensory contexts to enhance the proactive capabilities of LLM agents. ContextAgent first extracts multi-dimensional contexts from massive sensory perceptions on wearables (e.g., video and audio) to understand user intentions. ContextAgent then leverages the sensory contexts and the persona contexts from historical data to predict the necessity for proactive services. When proactive assistance is needed, ContextAgent further automatically calls the necessary tools to assist users unobtrusively. To evaluate this new task, we curate ContextAgentBench, the first benchmark for evaluating context-aware proactive LLM agents, covering 1,000 samples across nine daily scenarios and twenty tools. Experiments on ContextAgentBench show that ContextAgent outperforms baselines by achieving up to 8.5% and 6.0% higher accuracy in proactive predictions and tool calling, respectively. We hope our research can inspire the development of more advanced, human-centric, proactive AI assistants.

1 Introduction

Large Language Model (LLM) agents are revolutionizing our daily life [16], assisting users with complex tasks such as automated web navigation [12, 56, 9], software engineering [46, 51, 36], and healthcare services [4, 43, 25]. While LLM agents are receiving growing attention and adoption, most of them still function in a *reactive paradigm*: They can initiate tasks only upon explicit user instructions and yet lack the autonomy to perceive environments and offer proactive support for users.

To further reduce reliance on instructions and alleviate human cognitive workload, proactive agents emerge, which are capable of initiating tasks without explicit user queries [55, 24, 23, 52, 50]. For example, research on proactive agents have explored coding assistance [55, 24], conversation participation [23, 44], re-asking strategies to reduce ambiguity in user instructions [52], and multi-agent cooperation scenarios [50, 39]. However, their limited ability in open-world perceptions and restricted functionality for proactive service hinders their potential as personal companions.

Environmental Perception. When explicit user instructions are absent, environment perception is crucial for proactive LLM agents. Recent studies [24, 55] proposed proactive agents for programming

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assistance, while they require access to specific inputs such as computer screenshots or keyboard inputs. We argue that an ideal proactive agent should be able to perceive open-world environments in the user's daily life, utilizing wearable devices such as smart glasses and earphones. By sharing the same perception as the user, the agent can understand the user's intention and provide services automatically. Besides, the hands-free nature of these ubiquitous wearable devices aligns well with the mission of proactive agents, freeing both the user's hands and mind from additional workload.

Functionality for Proactive Services. Current personal assistants can deliver proactive notifications via wearables, yet remain limited by static, rule-based pipelines (e.g., alerts when rapid falling is detected [3]). Recent studies [24, 55, 44, 52] propose to build proactive agents with LLMs. However, these agents only provide direct answers during user interactions, without leveraging external tools, and remain limited to enclosed environments (e.g., desktop and keyboard inputs [24, 55]). Therefore, there remains a research gap in developing a context-aware proactive LLM agent that can exploit extensive sensory contexts to comprehensively understand user intentions, predict the necessity of proactive services, and automatically integrate external tools to deliver unobtrusive services as a personal companion.

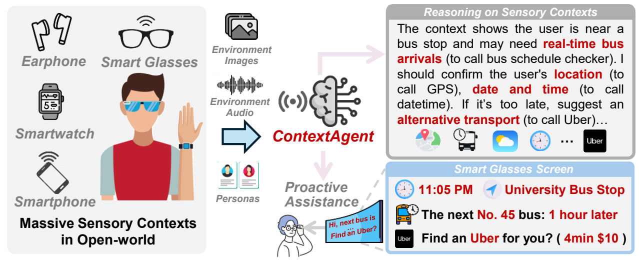


Figure 1: ContextAgent is a proactive AI assistant free of user explicit instructions. ContextAgent can continuously perceive environmental contexts (e.g., image and audio) to detect the necessity of proactive services, and provide assistance based on tool-augmented LLM reasoning.

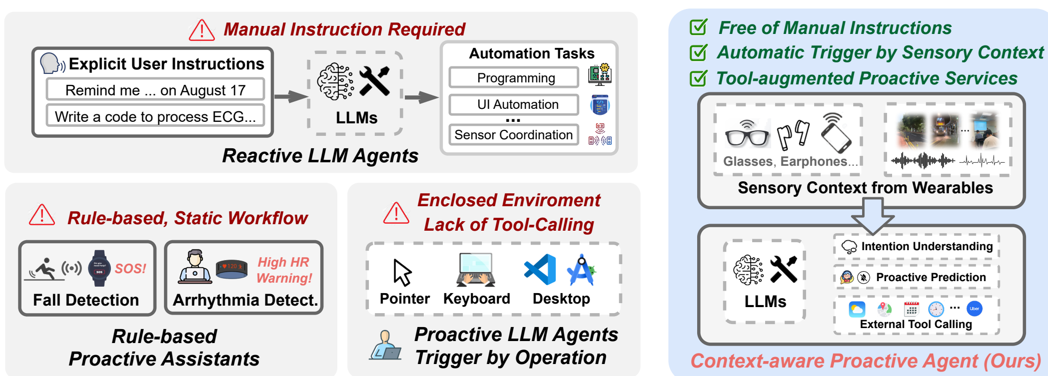


Figure 2: Comparison with existing works. Reactive LLM agents require explicit user instructions to initiate tasks. Prior proactive LLM agents focus on perceiving enclosed environments (e.g., desktop UIs) and may still require user operations (e.g., keyboard inputs) alongside direct LLM inference. In contrast, ContextAgent requires no manual instructions, harnesses massive sensory contexts from the open world, and employs tool-augmented LLM reasoning for enhanced proactive services.

In this paper, we introduce ContextAgent, the first context-aware proactive LLM agent that harnesses extensive sensory contexts for enhanced proactive services. ContextAgent first employs a proactive-oriented context extraction approach to derive both sensory and persona contexts from massive sensory perceptions such as egocentric videos and audio. We then develop a context-aware reasoner that integrates both sensory and persona contexts for reasoning, predicts the necessity of proactive services, and calls external tools when necessary. This reasoner is fine-tuned with reasoning traces distilled from advanced reasoning LLMs, enabling it to think before acting. Fig. 1 shows an example scenario where the user arrives at a bus stop just after the bus has left. ContextAgent can leverage this sensory context to proactively deliver useful services, such as real-time bus schedules, and determine whether alternative transportation is needed. By harnessing sensor perceptions from hands-free, egocentric wearables (e.g., smart glasses and earphones), along with tool-augmented LLM reasoning, ContextAgent moves closer toward a more ubiquitous and proactive AI assistant.

To better examine ContextAgent, we further introduce a new benchmark, ContextAgentBench, for the comprehensive evaluation of context-aware proactive LLM agents. ContextAgentBench contains 1,000 samples covering nine daily life scenarios, such as working and chitchat, and includes twenty external tools. We conduct comprehensive evaluations, comparing ContextAgent to six baselines and testing on 10 LLMs. Results show that ContextAgent achieves the state-of-the-art performance in proactive predictions and tool calling. We summarize the contributions of this work as follows.

- We first raise the research problem of context-aware proactive agents that integrate extensive sensory perceptions with tool-augmented LLM reasoning to deliver proactive services, offering a new vision for proactive agents that more closely aligns with the mission of a personal assistant.
- We propose ContextAgent, the first framework for context-aware proactive LLM agents. ContextAgent employs a novel context extraction method that derives sensory and persona contexts from massive sensor perceptions. Additionally, we design a context-aware reasoner with think before action capabilities that can integrate both sensory and persona contexts for reasoning, predict the necessity of proactive services, and call external tools when necessary to assist the user.
- We introduce ContextAgentBench, the first benchmark for the comprehensive evaluation of context-aware proactive LLM agents. Extensive evaluation on ContextAgentBench shows that ContextAgent outperforms six baselines by achieving up to 8.5% higher accuracy for proactive predictions, 7.0% higher F1-score for tool calling, and 6.0% higher accuracy for tool arguments.

2 Related Works

Reactive LLM-based Agents. Recent studies have proposed various LLM agents to perform complex tasks, such as automated web navigation [12, 56], software engineering [46], personal assistant [44, 42], and household robotics [6]. Additionally, prior research has primarily focused on enhancing the core capabilities of LLM agents, including task planning [47], function calling [29, 21, 32], experience reflection [54, 33], generalization abilities [38, 27], and multi-agent collaboration [34, 22, 53]. Other studies have explored the LLM agents in mobile systems, such as autonomous UI operations on smartphones [37, 18, 49] and embedded programming [31, 13, 45]. However, although numerous frameworks and optimizations have been proposed, prior research has primarily focused on reactive LLM agents that require explicit textual instructions from users and cannot utilize the extensive contextual information from sensor perceptions on wearable devices to enable proactive assistance.

Proactive LLM Agents. Proactive agents aim to autonomously initiate services based on environmental observations, without requiring explicit user instructions, evolving from early rule-based or periodic triggers [3] to recently proposed LLM-based approaches [55, 24]. Ask-before-plan [52] employs re-asking strategies to proactively reduce ambiguity in a user's instructions and enhance subsequent planning, although it still requires an initial user query. ProAgent [50] is a proactive cooperation framework among multiple robot agents, while its proactive design primarily focuses on predicting teammates' actions in multi-agent systems rather than the user's intention. Recent studies, such as Proactive Agent [24] and CodingGenie [55], also propose proactive LLM agents that monitor the user interface environment on computer systems and proactively provide assistance with tasks such as coding and writing. However, existing work either leverages observations on computer interfaces or employs a re-asking strategy to gather more information, without utilizing the rich sensory contexts to proactively initiate services. Moreover, prior works primarily use LLMs for direct inference rather than integrating external tools, resulting in limited proactive service functionality.

LLM Agent Benchmark. A diverse and large-scale benchmark is essential for the comprehensive evaluation of LLM agents. However, existing benchmarks primarily focus on reactive LLM agents [46, 29, 26, 11, 21], where the agent needs to take user instructions as inputs and perform task planning and tool calling. Although a recent work [24] proposes ProactiveBench, it is limited to an enclosed environment, i.e., desktop UI, and does not leverage the rich contextual information from multimodal sensors on wearable devices. Additionally, ProactiveBench relies on direct LLM inference for responses, instead of calling diverse external tools. Therefore, a research gap remains in developing a comprehensive benchmark for evaluating proactive LLM agents that incorporate the rich contextual information from wearable devices for proactive reasoning with tool-calling capabilities.

3 Context-aware Proactive Agent Task

3.1 Task Definition

In contrast with existing reactive LLM agents and proactive agents that rely solely on observations from desktop interfaces or direct inference, we formalize context-aware proactive LLM agents as:

$(\mathcal{T}, \mathcal{P_S}, \mathcal{T_C}, \mathcal{R}) = \mathcal{A}(\mathcal{S}, \mathcal{P})$, where $\mathcal{A}$ is the context-aware proactive LLM agent, which integrates the sensory perceptions $\mathcal{S}$ and persona context $\mathcal{P}$ as input. Here $\mathcal{S}$ contains sensor perceptions from multi-modal wearables such as smart glasses and earphones, including egocentric video $\mathcal{S_V}$, audio $\mathcal{S_A}$, and smartphone notification $\mathcal{N}$. We denote the sensory context $\mathcal{C}$ as the implicit cues within the raw sensory perceptions $\mathcal{S}$ that help determine the need for proactive services. We also formalize that the agent should consider user personas $\mathcal{P}$ for proactive reasoning, including a person's identity, preferences, and historical behaviors. Using these contexts, the agent generates $(\mathcal{T}, \mathcal{P_S}, \mathcal{T_C}, \mathcal{R})$, where $\mathcal{T}$ denotes the explicit thought traces. $\mathcal{PS}$ denotes the proactive score, which triggers proactive services when $\mathcal{P_S} \geq \mathcal{TR}$. $\mathcal{T_C}$ represents the planned tool chains that LLM agents should call in sequence, where $\mathcal{T_C} = (t_i, a_i)_{i=1}^{N}, t_i \in T$, with t_i as each tool to be called and a_i as the corresponding arguments. T is the tool set that the agent can use. $\mathcal{R}$ is the agent's final response, summarizing the sensory context, persona context, reasoning traces, and tool results. Note that proactive assistance is only initiated when $\mathcal{P_S} \geq \mathcal{TR}$, otherwise the agent does not respond or disturb the user.

3.2 Task Construction

Recognizing the shortcomings of existing LLM agent benchmarks, we present ContextAgentBench, the first benchmark designed to evaluate context-aware proactive LLM agents.

Design Choices. Our dataset includes the following key features: 1) *Sensory Context.* Our dataset contains sensory context obtained from wearables (e.g., smart glasses and earphones), which capture shared perceptions of the user *ubiquitously*. This hands-free captured sensory context is more suitable for proactive agents as it can reduce the user's physical and cognitive workload, aligning with the mission of proactive agents. 2). *Persona Context*. We incorporate diverse personas to support more comprehensive and personalized scenarios for proactive services. 3) *Proactive Assistance with Tool Calling.* The dataset targets tool-using LLM agents that map the contexts to proactive assistance by utilizing multiple external tools to generate more informative responses, rather than direct inference.

Formulation and Exemplar Design. Each sample in our dataset contains seven parts: $(\mathcal{S}, \mathcal{C}, \mathcal{P}, \mathcal{T}, \mathcal{P_S}, \mathcal{T_C}, \mathcal{R})$. Next, we introduce the design of initial exemplars.

Multi-dimensional Context Information. Annotators first write textual descriptions of their egocentric perceptions, including what they see, hear, and any mobile device notifications, for both proactive and non-proactive scenarios that they encounter in daily life. This sensory perception can be captured from an egocentric perspective using various wearable devices. The context information contains the visual context $\mathcal{C_V}$, acoustic context $\mathcal{C_A}$, and the notifications on smartphone $\mathcal{N}$. Annotators also summarize them into contextual information $\mathcal{C}$, providing a comprehensive description of the user's current conditions. Annotators write the user personas $\mathcal{P}$ for the sample if necessary. The persona can include any information about a person's preferences or identity.

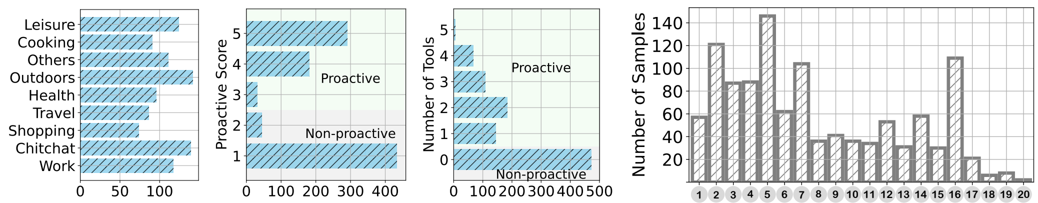
Proactive Score with Planned Tool Chains. Next, annotators are instructed to analyze the current context and assign a proactive score $\mathcal{P_S}$. We define $\mathcal{P_S}$ on a scale from 1 to 5, where 1 means no proactivity is required and 5 means a high level of proactivity. Annotators also receive a tool set T that includes the usable tools, tool names, tool descriptions, arguments, and formats predefined by the developers. Details are in the Appendix D. For samples identified as requiring proactivity, we request annotators to further label the planned tool chains $\mathcal{T_C}$, specifying the external tools that agents should use. If $\mathcal{P_S} = 1$ or 2, both $\mathcal{T_C}$ and $\mathcal{R}$ are `None`, as there is no need for proactivity.

We instruct the annotators to create samples spanning nine everyday scenarios, ranging from work to chitchat. We ask annotators to document their thought processes, including their analysis of the current context, their rationale for assigning the proactive score, and the planned tool chains. Each annotator also cross-reviewed the samples produced by others, evaluating both the format and plausibility to avoid overproactivity and ensure the correctness of annotations. Through this process, we acquire 200 human-created exemplars to serve as the seed dataset.

Automated Diversification Pipeline. Relying solely on manual efforts to scale the dataset presents challenges, as scenarios and contextual information created by humans may lack diversity and generalizability. Moreover, human fatigue during annotation can introduce bias, potentially compromising the dataset's quality. Therefore, we develop an automated diversification pipeline to use LLMs for data generation, producing a large-scale dataset with diverse samples.

Information Source. We first prepare several resources to help LLMs generate synthetic data, including the tool set (Appendix D), an extensive persona pool, and the initial exemplars. The personas in our pool are sourced from [14], which includes one billion individual identities and preferences.

Generation with Verification. Next, we prompt LLMs to generate diverse samples by utilizing the initial exemplars, tool set, and persona pool for reference. We employ two strategies during generation: scenario-aware and proactive score-aware. In the first strategy, we group the seed dataset by scenarios and instruct LLMs to generate samples based on specific scenarios within the nine categories. In the second strategy, LLMs are prompted to generate samples based on a specific proactive score. Details are in the Appendix B. After generation, annotators first evaluate the context and annotations for rationality. Next, we execute a script to verify the correctness of the data format and tool arguments. We perform several iterations of the above process to obtain ContextAgentBench.



(a) Scenarios. (b) Proactive score. (c) Tool number. (d) Tool distribution.

Figure 3: Statistics of ContextAgentBench, including the sample distribution across different scenarios, proactive scores, and the number and types of tools. In subfigures (a)–(c), the x-axis shows the number of samples, whereas in (d) it denotes the tool index.

Consideration of Sensor Data. We also collect raw sensor data from copyright-free internet platforms [1] to pair with the textual contextual information in ContextAgentBench. Specifically, we first randomly select samples from ContextAgentBench, and scrape the videos from Pexels [1] based on the textual descriptions of the visual context information. Note that we exclusively collect videos captured from an egocentric perspective. Additionally, for samples with audio conversations, we self-collect both video and audio to align with the textual context information. Finally, we obtain the ContextAgentBench-Lite, consisting of 300 human-verified samples with raw sensor data.

Dataset Statistics. Fig. 3 shows the statistics of our dataset. We collected 1,000 samples for ContextAgentBench and 300 samples for ContextAgentBench-Lite. Our dataset covers 9 daily life scenarios and includes 20 tool types, with each sample potentially involving the use of up to five tools. We provide more details on the dataset and tool definitions in the Appendix C.

4 ContextAgent Framework

This section presents the framework of ContextAgent, introducing how it utilizes the massive sensory contexts for tool-augmented proactive LLM agent services. Fig. 4 shows the overview of ContextAgent. First, ContextAgent extracts proactive-oriented contexts from multi-modal sensory perceptions. Next, ContextAgent integrates these contexts for tool-augmented proactive services.

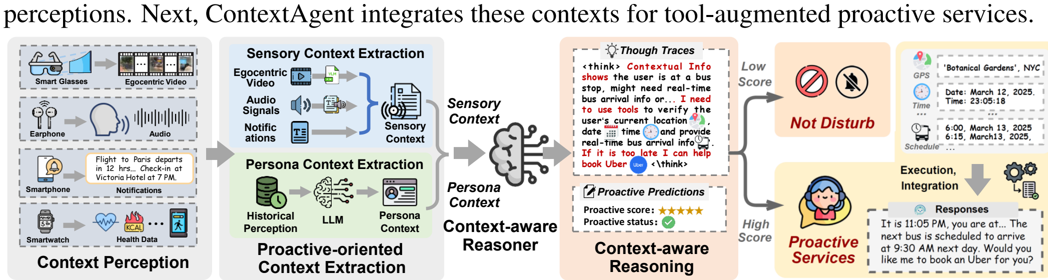


Figure 4: Overview of ContextAgent. ContextAgent extracts sensory context from massive sensor perceptions. Then it integrates both sensory and persona contexts into LLM reasoning, generating thought traces, proactive predictions, and calling external tools for proactive services when necessary.

4.1 Proactive-oriented Context Extraction

Previous studies focus on extracting sensory contexts and use LLMs to summarize insights [28]. However, relying solely on these sensory contexts can lead to inferior proactive predictions. Therefore, ContextAgent employs a proactive-oriented context extraction method. In ContextAgent, contexts comprise two types: *sensory context* and *persona context*. The sensory context includes insights for the user's surroundings and actions, which are crucial for inferring user intent. Persona context encompasses user personal information, including their past behaviors, preferences, and identity, which helps LLM agents to determine the need and urgency for proactive assistance. This subsection provides details on how ContextAgent extracts these contexts from extensive sensory perceptions.

Sensory Context. ContextAgent first employs Vision Language Models (VLMs) [19] to transform raw egocentric videos into visual contexts $\mathcal{C}_{\mathcal{V}}$. Although existing VLMs can generate video descriptions, they often produce overly simplistic descriptions that overlook crucial cues for understanding user intent or overly detailed, redundant insights, both of which can hinder the LLM agent's proactive predictions. Thus, instead of using the zero-shot VLMs, ContextAgent employs in-context learning (ICL) to generate proactive-oriented visual contexts $\mathcal{C}_{\mathcal{V}}$. ContextAgent also employs speech recognition model to generate acoustic contexts $\mathcal{C}_{\mathcal{A}}$. Details and the prompts for sensory context extraction are in the Appendix B. Finally, ContextAgent integrate these contexts into the final context information $\mathcal{C} = [\mathcal{C}_{\mathcal{V}}, \mathcal{C}_{\mathcal{A}}, \mathcal{N}]$, which includes visual contexts $\mathcal{C}_{\mathcal{V}}$, acoustic contexts $\mathcal{C}_{\mathcal{A}}$, and textual information from smartphone notifications $\mathcal{N}$, such as calendar events and hotel reservations.

Persona Context. Since the need for assistance highly depends on the user's personal preferences, ContextAgent also integrates persona context into its reasoning. In this work, we use persona contexts within ContextAgentBench for experiments. In practice, these contexts can be continuously updated by utilizing LLMs to extract insights from historical sensory data like daily conversations [44].

4.2 Context-aware Proactive Reasoning

While existing LLM agents can handle complex tasks based on explicit user instructions [20, 56, 9], they face challenges when processing sensory contexts and correctly mapping them to the appropriate tools for proactive services. Next, we will introduce the context-aware reasoner in ContextAgent.

Context-aware Reasoner. ContextAgent employs a context reasoner $\mathcal{A}_{\mathcal{S}}$ to reason over the generated contexts and provide proactive services, denoted as: $(\mathcal{T}, \mathcal{P}_{\mathcal{S}}, \mathcal{T}_{\mathcal{C}}) = \mathcal{A}_{\mathcal{S}}(\mathcal{C}, \mathcal{P})$. The context reasoner is an LLM that integrates both sensory context $\mathcal{C}$ and persona context $\mathcal{P}$ as input to generate thought traces $\mathcal{T}$, proactive scores $\mathcal{P}_{\mathcal{S}}$, and planned tool chains $\mathcal{T}_{\mathcal{C}}$. To enable ContextAgent with think before action capabilities, we distill the reasoning traces from advanced LLMs, e.g., Claude-3.7-Sonnet [2], and construct Chain-of-Thought (CoT) [35]-based training data for fine-tuning. During inference, once $\mathcal{P}_{\mathcal{S}} \geq \mathcal{TR}$, ContextAgent will initiate the proactive services. Here, $\mathcal{TR}$ is a threshold to determine the proactive trigger, where $\mathcal{TR}$ is set to 3 in this work. Additionally, ContextAgent generates tool chains $\mathcal{T}_{\mathcal{C}}$ for enhanced proactive services. ContextAgent will automatically execute the planned tools sequentially and integrate their results with the sensory context, persona context, and thought traces into the LLM to generate final responses.

Training Scheme. We use supervised fine-tuning (SFT) with CoT to train the context reasoner in ContextAgent. Specifically, we construct the SFT dataset $\mathcal{D}_{SFT} = \{(\mathcal{X}, \mathcal{T}, \mathcal{Y})\}$. Here, $\mathcal{X}$ contains the sensory context $\mathcal{C}$ and persona context $\mathcal{P}$. The thought traces $\mathcal{T}$ divided by <think> and </think>, are distilled from advanced LLMs [2], enabling ContextAgent to "think before acting", generating explicit thought traces before proactive predictions and tool calls. The output $\mathcal{Y}$ contains proactive scores $\mathcal{P}_{\mathcal{S}}$ and planned tool chains $\mathcal{T}_{\mathcal{C}}$. Details of the training are in the Appendix A.

5 Experiments

5.1 Metrics and Baselines

Metrics. We employ two categories of metrics to evaluate the performance of context-aware proactive LLM agents, including proactive prediction and tool calling. Details of each metric are as follows.

- **Proactive Prediction.** We first evaluate the agent's ability to accurately determine the need for initiating proactive services. Specifically, we use four metrics to assess proactive prediction performance, including the accuracy of proactive predictions (**Acc-P**), missed detections (**MD**), false detections (**FD**), and the root mean square error (**RMSE**) between predicted proactive scores and ground-truth. Acc-P, MD, and FD are commonly used in the existing work [24], while RMSE provides a finer-grained evaluation of the performance of predicted proactive scores.
- **Tool Calling.** To evaluate the agent's tool calling performance, we follow existing works [5, 8] and use standard metrics such as **Precision**, **Recall**, and **F1-score** to compare the tool names in

Table 1: Main results on ContextAgentBench.

Model	Method	Proactive Predictions				Tool Calling			
		Acc-P↑	MD.↓	FD.↓	RMSE↓	Precision↑	Recall↑	F1-score↑	Acc-Args↑
Llama-3.1-8B-Ins	Proactive Agent	0.676	0.017	0.306	1.915	0.397	0.290	0.318	0.081
	Vanilla ICL	0.742	0.224	0.033	1.853	0.608	0.533	0.552	0.269
	CoT	0.699	0.278	0.023	1.960	0.590	0.539	0.551	0.209
	ICL-P	0.742	0.242	0.015	1.922	0.608	0.553	0.567	0.262
	ICL-All	0.757	0.229	0.012	1.872	0.631	0.565	0.582	0.270
	Vanilla SFT	0.813	0.068	0.117	1.572	0.609	0.581	0.580	0.405
	ContextAgent	0.874	0.030	0.095	1.408	0.660	0.627	0.626	0.448
DeepSeek-R1-7B	Proactive Agent	0.544	0.411	0.044	3.093	0.467	0.454	0.457	0.019
	Vanilla ICL	0.646	0.248	0.105	2.568	0.457	0.433	0.437	0.078
	CoT	0.653	0.319	0.027	2.760	0.528	0.501	0.507	0.109
	ICL-P	0.690	0.227	0.081	2.466	0.518	0.479	0.486	0.126
	ICL-All	0.704	0.268	0.0272	2.540	0.545	0.510	0.518	0.103
	Vanilla SFT	0.823	0.068	0.108	1.630	0.621	0.570	0.579	0.386
	ContextAgent	0.888	0.027	0.085	1.319	0.676	0.648	0.647	0.468
Qwen2.5-7B-Ins	Proactive Agent	0.799	0.136	0.064	2.038	0.578	0.536	0.546	0.038
	Vanilla ICL	0.816	0.088	0.095	1.752	0.590	0.545	0.553	0.326
	CoT	0.833	0.085	0.081	1.790	0.585	0.527	0.541	0.272
	ICL-P	0.833	0.091	0.074	1.819	0.610	0.556	0.568	0.303
	ICL-All	0.867	0.088	0.044	1.721	0.635	0.577	0.591	0.301
	Vanilla SFT	0.775	0.088	0.136	1.774	0.589	0.551	0.558	0.398
	ContextAgent	0.894	0.013	0.091	1.264	0.672	0.644	0.645	0.459

the predicted tool set with those in the ground-truth tool set. We also use **Acc-Args** to evaluate whether the proactive agent can correctly generate the structured data for tool calls, including the tool names and arguments. If an argument of any tool is incorrect, the entire sample is considered incorrect. For Acc-Args, we calculate the accuracy only for the correctly predicted tools to ensure a fair comparison of different approaches.

Baselines. We compare ContextAgent with several baselines, including Proactive Agent [24], vanilla ICL, CoT, ICL-P, ICL-All, and vanilla SFT. For the Proactive Agent, we follow [24] and modify the task instructions in the system prompt to adapt to our proactive agent task. For the vanilla ICL, we use few-shot demonstrations with only context information. For the CoT baseline, we include both context information and thought traces. For the ICL-P baseline, we include context information and personas, and for the ICL-All baseline, we incorporate context information, thought traces, and personas into the prompt. For the vanilla SFT, we use the SFT dataset with contextual information for fine-tuning. We conduct experiments on 10 LLMs, comprising **(1) proprietary LLMs** including GPT-4o [17] and GPT-3.5 [48], **(2) open-source LLMs** including Llama-3.1-70B-Instruct [15] and Qwen2.5-72B-Instruct [40], and **(3) small LLMs** including Llama-3.1-8B-Instruct, Qwen2.5-7B-Instruct, Qwen2.5-3B-Instruct, Qwen2.5-1.5B-Instruct, DeepSeek-R1-Distill-Qwen-7B [10], and DeepSeek-R1-Distill-Qwen-1.5B. Details of the baselines and implementation are in the Appendix B.

5.2 Results on Benchmarks

Quantitative Results on ContextAgentBench. Tab. 1 shows the overall performance of ContextAgent on ContextAgentBench. Results show that when using Llama3.1-8B-Instruct as the base LLM, ContextAgent consistently achieves the highest performance across all metrics, with increases of 8.5% in Acc-P, 7.0% in F1-score, and 6.0% in Acc-Args. Fig. 5 shows that ContextAgent can achieve performance comparable to or even exceeding baselines that employ 70B-scale LLMs and proprietary LLMs, with metrics such as Acc-P (-1.5%), F1-score (-3.0%), and Acc-Args (+6.6%). Due to space constraints, Fig. 5 shows only three key metrics. See Tab. 4 in Appendix E for full comparison.

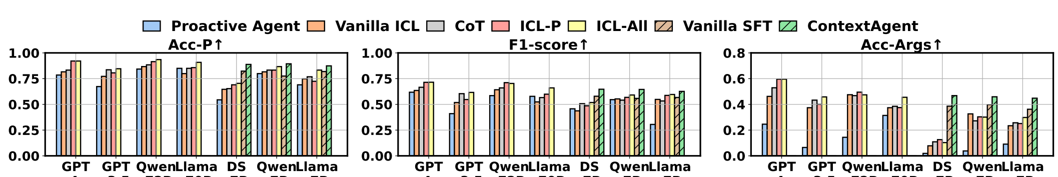


Figure 5: Main results on ContextAgentBench. 'DS' refers to 'DeepSeek'.

Quantitative Results on ContextAgentBench-Lite. Fig. 6 shows the performance of ContextAgent on ContextAgentBench-Lite. The results indicate that both ContextAgent and the baselines experience slight performance degradation. However, ContextAgent still achieves the highest performance across all metrics compared to the baselines. When using Qwen2.5-7B-Instruct as the base LLM, ContextAgent achieves improvements of 6.2% Acc-P, 3.0% F1-score, and 7.6% Acc-Args, over the best baseline. It can even achieve comparable and even higher performance than baselines using 70B-scale and proprietary LLMs. Complete results are provided in Tab. 5 within Appendix E.

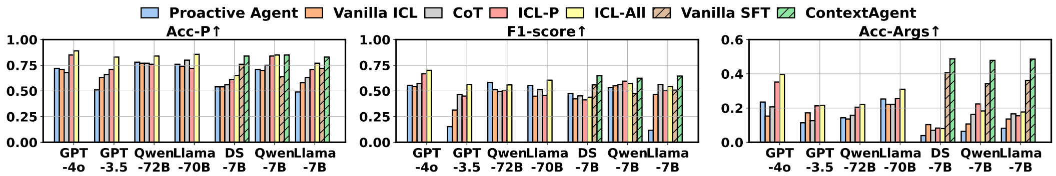


Figure 6: Main results on ContextAgentBench-Lite.

Qualitative Results. Fig. 7 and Fig. 8 show the qualitative results of ContextAgent, including examples of both proactive and non-proactive cases. **First**, ContextAgent integrates both sensory and persona contexts for reasoning and offers appropriate proactive services. **Second**, it can further map these contexts to planned tool chains such as the weather and agenda checker, and integrate external knowledge for enhanced proactive service. Fig. 7 shows that ContextAgent can employ GPS, datetime tools, bus schedule checkers, and ride-booking apps like Uber when the user is approaching a bus station. Furthermore, during casual conversations involving proposed outdoor activities, ContextAgent uses tools such as a weather checker, datetime tool, and agenda checker to proactively assist the user in evaluating feasibility and making informed decisions. **Third**, ContextAgent can leverage persona context to generate more personalized proactive predictions. For instance, Fig. 7 shows that for health-conscious individuals deciding what to order at a restaurant, ContextAgent proactively offers food-related health information and suggestions. Fig. 8 shows that the persona contexts also help ContextAgent to determine not to disrupt the users. See Appendix E for more qualitative results.

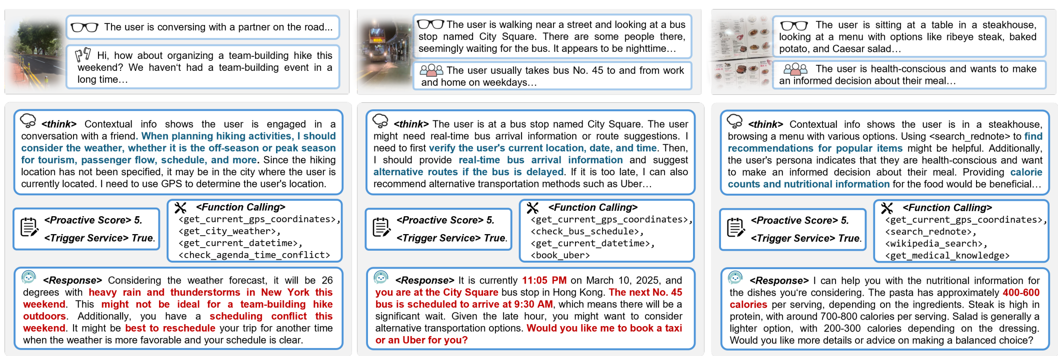


Figure 7: Qualitative results of ContextAgent in proactive cases, showing sensory and persona contexts, and ContextAgent's thought traces, proactive predictions, tool calls, and final responses.

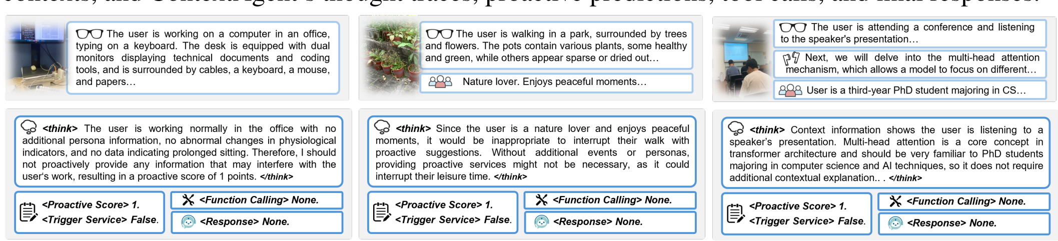


Figure 8: Qualitative results of ContextAgent in non-proactive cases.

5.3 Ablation Study and Discussion

Sensory Context Perception. We conduct experiments using the zero-shot Qwen-2.5-VL as the VLM for sensory context extraction in ContextAgent. Tab. 2 shows that this causes ContextAgent to decrease in Acc-P, F1-score, and Acc-Args by 3.0%, 3.3%, and 1.9%, respectively. We observe that the context generated by zero-shot VLM lacks key proactive-oriented cues, such as simply describing the user tying their shoe while sitting on the floor. In contrast, our sensory context extraction module

Table 2: Ablation study. "w/o persona" means the agent does not use persona context during both the training and testing stages. "w/o think" means that the SFT training data does not include the thought process. "w/o poce" means the agent does not use proactive-oriented context extraction.

Dataset	Method	Proactive Predictions				Tool Calling			
		Acc-P↑	MD.↓	FD.↓	RMSE↓	Precision↑	Recall↑	F1-score↑	Acc-Args↑
ContextAgentBench	wo/ persona	0.806	0.081	0.112	1.639	0.611	0.574	0.579	0.405
	wo/ think	0.857	0.030	0.112	1.397	0.645	0.607	0.612	0.419
	ContextAgent	0.874	0.030	0.095	1.408	0.660	0.627	0.626	0.448
ContextAgentBench-Lite	wo/ persona	0.720	0.150	0.130	1.972	0.554	0.516	0.522	0.360
	wo/ think	0.820	0.100	0.080	1.546	0.648	0.623	0.625	0.409
	wo/ poce	0.800	0.080	0.120	1.661	0.648	0.604	0.612	0.467
	ContextAgent	0.830	0.070	0.100	1.510	0.687	0.637	0.645	0.486

captures detailed scenario information about the gym and specific fitness equipment, providing deeper insight into the user's conditions and intents and resulting in higher performance.

Persona Context. We also conduct experiments to study the impact of user personas by removing them during both the training and testing phases. Tab. 2 shows that removing personas consistently leads to significant performance drops, with Llama-3.1-8B-Ins experiencing decreases of up to 9.0% in Acc-P, 12.3% in F1-score, and 12.6% in Acc-Args. Results show that personas are crucial for the proactive agent task, impacting both proactive predictions and tool-calling capabilities.

Thought Traces. We also investigate the impact of thought traces for the context-aware proactive agent task. Specifically, we first remove the thought traces from the SFT dataset, enabling ContextAgent to generate only proactive predictions and tool calling. Tab. 2 shows that incorporating thought traces distilled from the advanced LLMs results in positive benefits, with improvements of 1.7%, 1.4%, and 2.9% in Acc-P, F1-score, and Acc-Args, respectively. Additionally, we observe that integrating those thought traces can significantly improve ICL performance. Tab. 4 and Tab. 6 show that ICL-All achieves up to 20.1% improvement in Acc-P compared to ICL-P, which does not utilize thought traces. Results validate the effectiveness of thought traces for this task.

Different Base LLMs. We conduct experiments using different base LLMs in ContextAgent. Tab. 7 shows that Llama-3.1-8B and Qwen2.5-7B achieve comparable performance and outperform DeepSeek-R1-7B. We also test LLMs in 1.5B to 3B sizes. More details are in the Appendix E.

5.4 Out-of-Domain Evaluation

We also evaluate ContextAgent under an out-of-distribution (OOD) setting. We randomly split ContextAgentBench based on scenarios. Samples from six scenarios are used for training, while those from the remaining three scenarios are used for evaluation. Fig. 9 shows that ContextAgent achieves up to 90.9% Acc-P, 68.9% F1-score, and 51.6% Acc-Args under OOD settings. Furthermore, ContextAgent outperforms the best baseline by 1.9% in Acc-Args, 10.7% in F1-score, and 8.3% in Acc-P, validating its generalization capabilities. Tab. 6 in Appendix E presents the complete results.

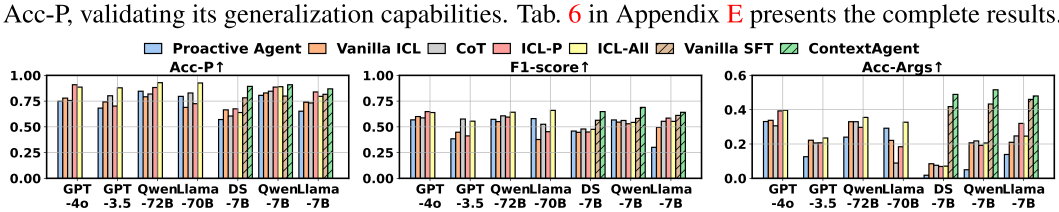


Figure 9: Results on out-of-domain experiments.

6 Conclusion

This paper introduces ContextAgent, the first framework for context-aware proactive LLM agents. ContextAgent can harness the context information from extensive sensory perceptions and tool-augmented LLM reasoning for enhanced proactive services. To evaluate this new task, we further introduce ContextAgentBench, the first benchmark for evaluating context-aware proactive LLM agents. Our research takes a step towards further aligning with the vision of proactive AI assistants by leveraging rich context from hands-free wearable sensors to enhance proactive LLM reasoning.

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Appendix

A Implementation Details

Our experiments are conducted using 8 A6000 GPUs. For SFT, we use the AdamW optimizer with a learning rate of 0.0001 and apply LoRA techniques during model training. We set the LoRA rank to 8 and train the model using a cosine scheduler with a 10% warmup ratio. For ContextAgentBench (including both in-domain and OOD settings), we train for one epoch, whereas for ContextAgentBench-Lite, we train for five epochs. The batch size is set to 64. For ICL-based baselines, we randomly select 10 samples from the dataset as demonstrations included in the prompt.

B Prompts

This section introduces the details of the prompts used in this work, including the system prompt used in ContextAgent and baselines, the prompt used in the data generation pipeline, and the prompt used in proactive-oriented context extraction.

System Prompt in ContextAgent. Fig. 10 shows the prompt used in ContextAgent. It contains both static prompt and runtime prompt. The static prompt includes task instructions and toolset definitions that remain constant throughout. The task instructions guide the LLM in understanding its role as a context-aware proactive agent and highlight the key considerations for this task. The toolset definitions allow LLM agents to identify the available external tools and understand how to use them, including their names, arguments, and formats (See Appendix D). The runtime prompt includes user personas and contextual information, which vary across different samples in the dataset.

Prompt Template for ContextAgent

Task Instructions

You are a proactive LLM agent. You will receive both sensory and persona contexts. The sensory contexts are captured by the multi-modal sensors on the user's wearable devices, such as smart glasses and earphone. Persona context is the personal information like identity and preference. Based on these contexts, you need to generate a thought and determine whether to initiate a proactive service for the user or not. Only propose assistance when you fully understand the user's actions. When generating the response, consider whether you need to call external tools to complete the task. The following are the tool names and their arguments. Please only select tools from the specified tool sets and make sure to use the correct format for their arguments.

Tool set

- GetCityWeather: {*Description*: …, *Arguments*: …}
- CheckAgendaTimeConflict: {*Description*: …, *Arguments*: …}
- ……
- GoogleSearch: {*Description*: …, *Arguments*: …}

Now you will receive the sensory and persona contexts.
Persona Context: { Personas Context }
Sensory Context: { Sensory Context }

Figure 10: System prompt for ContextAgent.

System Prompt for Baselines. Fig. 11 shows the prompt template used in baseline approaches. To ensure a fair comparison, we keep the task instructions and toolset definitions in the prompt the same as those used in ContextAgent. For the baseline of Proactive Agent, we do not include any samples in the example part of the prompt template. For Vanilla ICL, CoT, ICL-P, and ICL-All, we randomly select ten samples from the training set and incorporate them into the prompt. In Vanilla ICL, the few-shot examples contain only sensory context. In CoT, we additionally include thought traces in the few-shot examples. For ICL-P, we incorporate persona context into the few-shot demonstrations, and for ICL-All, we integrate sensory context, persona context, and thought traces into the few-shot demonstrations. Additionally, for the Vanilla SFT baseline, we use the prompt template shown in Fig. 10, but without including the persona context.

Prompt Template for ICL-based Baselines

Task Instructions

You are a proactive LLM agent. You will receive both sensory and persona contexts. The sensory contexts are captured by the multi-modal sensors on the user's wearable devices, such as smart glasses and earphone. Persona context is the personal information like identity and preference. Based on these contexts, you need to generate a thought and determine whether to initiate a proactive service for the user or not. Only propose assistance when you fully understand the user's actions. When generating the response, consider whether you need to call external tools to complete the task. The following are the tool names and their arguments. Please only select tools from the specified tool sets and make sure to use the correct format for their arguments.

***## Tool set*:**

- GetCityWeather: {*Description*: …, *Arguments*: …}
- CheckAgendaTimeConflict: {*Description*: …, *Arguments*: …}
- ……
- GoogleSearch: {*Description*: …, *Arguments*: …}

***## Examples*:** {Examples}

Strictly follow the following format for your outputs:

- For proactive samples, the output format should be…
- For not require proactive samples, the output format should be…

Now you will receive the sensory and persona contexts.

***## Persona Context*:** { Personas Context }

***## Sensory Context*:** { Sensory Context }

Figure 11: Prompt template for baselines.

Prompt for Data Generation Pipeline. Fig. 12 shows the prompt template used for data generation. We include the required format of data, examples of persona[1] and completed data samples, and detailed descriptions of the accessible tools. Besides, it specifies the structure and formulation of each component within a data sample to guide LLMs to generate high-quality samples. During data generation, we use two strategies, including scenario-aware and proactive score-aware. LLMs are guided to generate samples for different scenarios and target proactive scores separately, which enables LLMs to more effectively learn scenario-specific and score-specific patterns from the provided examples. And when generating samples requiring proactive services, LLMs are instructed to consider using tools from our tool set. To further enhance the diversity of the generated samples, we employ various LLMs, including GPT-4o[2], Claude-3.7-Sonnet[3], and Gemini-2.0-Flash[4], for generation.

Prompt for Proactive-oriented Context Extraction. Fig. 13 shows the prompt template used for proactive-oriented context extraction. With the prompt, the VLM is guided to focus on objective, detailed scene understanding and key cues capturing (e.g., location, objects, and user actions), which are important parts for determining whether the user needs proactive assistance. To ensure consistency and output quality, we include five example descriptions within the prompt. These examples illustrate the expected level of detail, structure, and tone, enabling the model to align its output with the expected format. Based on the clear content and formatting guidelines, generated descriptions can provide high-quality context information for the following tasks, including predicting the necessity of proactive services and tool planning. In this study, we employ Qwen-2.5-VL [7] and Whisper [30] to extract the visual and acoustic contexts, respectively.

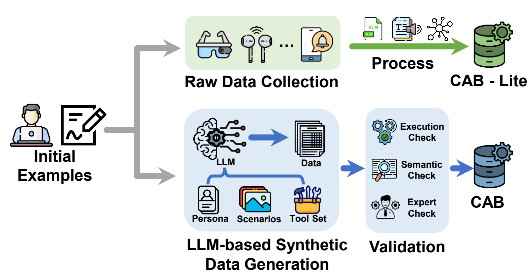

Figure 14: Flowchart illustrating the pipeline for constructing our benchmark. 'CAB' refers to 'ContextAgentBech'.

[1] https://github.com/tencent-ailab/persona-hub

[2] https://openai.com/index/gpt-4o-system-card/

[3] https://www.anthropic.com/claude/sonnet

[4] https://deepmind.google/technologies/gemini/flash/

Prompt for Data Generation

Task Instructions
You are a professional data generation specialist responsible for creating high-quality training examples for the development of a proactive AI assistant system integrated with smart glasses. Your mission is to generate realistic data samples that accurately represent situations in which the AI assistant should proactively trigger functions or tools to assist users based on contextual perceptions. Contextual perceptions include text descriptions of the physical environment or natural conversations with other people. This information can be captured by sensor data, such as RGB data, audio data, and more.

***## Task Objective*:**
Generate comprehensive, realistic training examples to determine when an AI assistant should proactively offer assistance and when it should wait for explicit user queries. Consider two important factors when initiating proactive service: contextual information from the physical environment and the user's persona.

***## Data Format Requirements*:**
Each example must follow this exact structure and include all fields:
"example-[number]": {
"Category": [domain area such as Work, Travel, Health, …, and Others.],
……
"Response": [natural-sounding, helpful response the assistant should provide],
}

***## Persona*:** When creating personas for examples, use the following samples as a guide. Generated personas should follow this style, concise descriptions that capture key user characteristics, habits or preferences that would influence their interaction with proactive assistance: {Personas Examples}

***## Tool Set*:** When generating data examples, you should limit the tools used to the following toolset, which includes commonly used tools, AI models, or apps on the user's mobile devices. The following dictionary provides the names of the tools and their functions. {Tool Set}

***## Guidelines for Professional Data Generation*:**
- First-Person Perspective: All "Vision" descriptions must be from the user's point of view as captured by smart glasses (what the user is looking at, not the user themselves).
  ……
- Logical Consistency: Ensure all fields align logically (e.g., a high proactive score should correspond with actions and responses that provide significant value).

***## Example Reference*:** {Examples}

When generating examples, remember these key considerations:
- Would users genuinely appreciate proactive assistance in this scenario?
  ……
- Do not give strong assumption on "Mobile API data", only limited to information that can be obtained from smartphone api/app notification

Please generate {Generated Number} diverse, high-quality examples with proactive score of {Proactive Score} for the {Category} category. Format your response as a valid JSON object with each example following the exact structure specified above.

Figure 12: Prompt template for the data generation pipeline.

C Dataset Details

As described in Sec. 3.2, the annotators first brainstorm and design initial exemplars to construct the seed dataset. We then utilize an automated diversification pipeline to scale the dataset. Fig. 14 shows the flowchart of our pipeline to generate the ContextAgentBench (CAB) and ContextAgentBench-Lite (CAB-Lite). Additionally, we also collect raw video and audio data based on the textual descriptions of context information in the dataset. This raw data is sourced from both copyright-free internet platforms[5] and our own collections. The self-collected samples are primarily used to gather chitchat scenarios. This study has received IRB approval. All participants offered informed consent before any data were collected. Additionally, we have blurred sensitive parts of the video, such as faces, to ensure participants' privacy.

[5] https://www.pexels.com/license/

Prompt for Proactive-oriented Context Extraction

Task Instructions
You are an advanced first-person vision description specialist. Your task is to analyze video frames and generate detailed, objective descriptions specifically for the "Vision" field in proactive AI assistant training examples. These descriptions represent what the user's smart glasses or other ego camera would capture from their perspective.

Description Requirements
Your vision descriptions must:
1. Be factual and detailed ……
2. Maintain first-person perspective ……
3. Balance detail with conciseness ……
4. Use clear, straightforward language ……
5. Follow the pattern of the provided examples ……

Example Style Guide
Your descriptions should follow the style of these examples:
Example-1: "The user is in a room filled with multiple individuals, all seated around a circular table, appearing to be gathered for a meeting."
……
Example-5: "The user is walking near a busy street and looking at a bus stop named 'University.'"

Key Elements to Include
When describing the frame, focus on:
1. Location and setting - Where the user is (office, store, outdoors, restaurant, etc.)
2. Key objects in view - What items are visible and relevant to understanding the scene
3. People present - If others are visible, their general arrangement and actions
4. Observable user activity - What the user appears to be doing based on what's in view
5. Text or signage - Any readable text that is prominent in the view
6. Spatial arrangement - The general layout of important elements in the scene

Important Guidelines
- Write in third person, referring to "the user" as shown in the examples
- Keep descriptions to 1-2 concise sentences
- Focus on what is directly observable, not what might be happening
- Include specific named elements when visible (like "bus stop named 'University'")
- It's acceptable to mention what the camera/smart glasses "detects" as in Example-2
- Provide enough context for the proactive system to understand the situation
- Avoid interpretations about the user's intentions or thoughts

Please analyze the provided frame and generate a "Vision" field description following these guidelines and matching the style of the examples.

Figure 13: Prompt template for the proactive-oriented context extraction.

D Tool Definition

ContextAgentBench contains 20 tools. Given that the main focus of this study is to bridge the sensory context with tool-based LLM agents, we adopt the definitions of tools from existing work[6]. Tab. 3 provides detailed information about the tools, including their names, tool descriptions, and input and output arguments.

E More Results

Full Results on Benchmark. We compare the performance of ContextAgent to baselines using different base LLMs. Since our approach requires model fine-tuning, we implement it only on LLMs smaller than 7B parameters. However, we also provide the performance of baselines using 70B parameter LLMs and other advanced commercial LLMs as a reference. Tab. 4 shows the full experiment results on ContextAgentBench. Results show that ContextAgent consistently outperforms the baselines when using the same LLMs. We also observe that the baseline approach ICL-All using GPT-4o can achieve highest performance with 92.1% Acc-P, 71.5% F1-score, and 59.6% Acc-Args.

[6] https://github.com/AlibabaResearch/DAMO-ConvAI/tree/main/api-bank/

Table 3: The definition of the 20 tools used in ContextAgentBench.

Index	**Name**	**Description**	**Input**	**Output**
1	GetCityWeather	Get the weather for a specified city at a given time.	[text] The city to fetch weather for. [text] The time to fetch weather for.	[text] Weather condition for a specified city at a given time.
2	DateTime	Get the current date and time.	None.	[text] Current date and time.
3	CheckAgendaTimeConflict	Check if there is a time conflict in the user's agenda for a given datetime and return all events as a summarized string.	[text] The time to check for conflicts.	[text] A summary of all events and whether there is a conflict.
4	WikipediaSearch	Search on Wikipedia.	[text] Search query.	[text] Wikipedia search result.
5	GetCurrentGPS.	Get the current GPS coordinates of the user.	None.	[text] GPS coordinates of the user.
6	GetOnlineProductPrice	Get the price of a product from an online store.	[text] The name of the product to search for.	[text] The price of the product as a string.
7	SearchRednote	A platform where people share tips on travel, fitness, cooking, and more, allowing users to search for relevant strategies.	[text] The search query.	[text] The search results from rednote.
8	VisualLanguageModel	Visual Language Model that can answer the user's questions based on the given image.	[image] Any image. [text] The prompt containing the user's question.	[text] The response from the VLLM.
9	GoogleMap	Get the route and distance from the current location to the destination using Google Maps API.	[text] The starting location. [text] The destination location.	[text] The route and distance information.
10	BookUber	Book an Uber ride from the current location to the destination.	[text] The starting location. [text] The destination location.	[text] The Uber ride booking confirmation.
11	GetHealthData	Get health data from the user's smart device.	None.	[text] The health data as a string.
12	GetMedicalKnowledge	Get medical expert knowledge from the up-to-date medical knowledge database.	[text] The query string containing the medical topic or symptoms.	[text] The medical expert knowledge as a string.
13	PlayMusic	Play a song from the user's music library.	None.	[text] The song playing confirmation.
14	AddtoAgenda	Add an event to the user's agenda.	[text] The name of the event to add. [text] The time of the event.	[text] The confirmation message.
15	CheckBusSchedule	Check the bus schedule for a specific bus stop.	[text] The name of the bus stop.	[text] The bus schedule information.
16	GoogleSearch	Search on Google.	[text] Search query.	[text] Description of the search result.
17	SetTimer	Set a timer for a specific duration.	[text] The duration of the timer.	[text] The timer set confirmation.
18	QueryStock	This API queries the stock price of a given stock code and date.	[text] The stock code of the given stock. [text] The date of the stock price.	[text] The stock price of the given stock.
19	AddMeeting	This API allows users to make a reservation for a meeting and store the meeting information (e.g., topic, time, location, attendees) in the database.	[text] The topic of the meeting. [text] The start time of the meeting. [text] The location where the meeting to be held.	[text] Success or failed.
20	SendEmail	This API for sending email, given the receiver, subject and content.	[text] The receiver address of the email. [text] The subject address of the email. [text] The content of the email.	[text] The status of the email.

Table 4: Main results on ContextAgentBench.

Model	Method	Proactive Predictions				Tool Calling			
		Acc-P↑	MD.↓	FD.↓	RMSE↓	Precision↑	Recall↑	F1-score↑	Acc-Args↑
GPT-4o	Proactive Agent	0.785	0.197	0.017	2.239	0.696	0.591	0.618	0.246
	Vanilla ICL	0.816	0.166	0.017	2.079	0.703	0.614	0.635	0.462
	CoT	0.833	0.142	0.023	2.016	0.732	0.645	0.666	0.529
	ICL-P	0.921	0.061	0.017	1.507	0.797	0.685	0.714	0.596
	ICL-All	0.921	0.057	0.020	1.472	0.788	0.690	0.715	0.596
GPT-3.5-Turbo	Proactive Agent	0.673	0.010	0.316	1.815	0.493	0.380	0.410	0.065
	Vanilla ICL	0.772	0.064	0.163	1.710	0.602	0.490	0.518	0.374
	CoT	0.836	0.088	0.074	1.534	0.662	0.584	0.604	0.433
	ICL-P	0.806	0.040	0.153	1.713	0.634	0.517	0.547	0.400
	ICL-All	0.846	0.054	0.098	1.439	0.681	0.595	0.616	0.458
Qwen2.5-72B-Ins	Proactive Agent	0.843	0.064	0.091	1.717	0.670	0.555	0.585	0.144
	Vanilla ICL	0.867	0.078	0.054	1.324	0.695	0.625	0.642	0.475
	CoT	0.884	0.071	0.044	1.254	0.708	0.643	0.660	0.468
	ICL-P	0.915	0.040	0.044	1.078	0.774	0.687	0.711	0.495
	ICL-All	0.935	0.037	0.027	1.059	0.750	0.688	0.703	0.474
Llama3.1-70B-Ins	Proactive Agent	0.850	0.061	0.088	1.643	0.642	0.554	0.578	0.314
	Vanilla ICL	0.799	0.013	0.187	1.442	0.582	0.501	0.524	0.374
	CoT	0.850	0.020	0.129	1.237	0.637	0.543	0.566	0.385
	ICL-P	0.857	0.000	0.143	1.322	0.660	0.578	0.599	0.375
	ICL-All	0.908	0.003	0.088	1.061	0.712	0.644	0.660	0.455
DeepSeek-R1-7B	Proactive Agent	0.544	0.411	0.044	3.093	0.467	0.454	0.457	0.019
	Vanilla ICL	0.646	0.248	0.105	2.568	0.457	0.433	0.437	0.078
	CoT	0.653	0.319	0.027	2.760	0.528	0.501	0.507	0.109
	ICL-P	0.690	0.227	0.081	2.466	0.518	0.479	0.486	0.126
	ICL-All	0.704	0.268	0.027	2.540	0.545	0.510	0.518	0.103
	Vanilla SFT	0.823	0.068	0.108	1.630	0.621	0.570	0.579	0.386
	ContextAgent	0.888	0.027	0.085	1.319	0.676	0.648	0.647	0.468
Qwen2.5-7B-Ins	Proactive Agent	0.799	0.136	0.064	2.038	0.578	0.536	0.546	0.038
	Vanilla ICL	0.816	0.088	0.095	1.752	0.590	0.545	0.553	0.326
	CoT	0.833	0.085	0.081	1.790	0.585	0.527	0.541	0.272
	ICL-P	0.833	0.091	0.074	1.819	0.610	0.556	0.568	0.303
	ICL-All	0.867	0.088	0.044	1.721	0.635	0.577	0.591	0.301
	Vanilla SFT	0.775	0.088	0.136	1.774	0.589	0.551	0.558	0.398
	ContextAgent	0.894	0.013	0.091	1.264	0.672	0.644	0.645	0.459
Llama3.1-8B-Ins	Proactive Agent	0.690	0.006	0.302	1.831	0.376	0.280	0.305	0.091
	Vanilla ICL	0.748	0.193	0.057	1.898	0.612	0.526	0.548	0.234
	CoT	0.768	0.159	0.071	1.770	0.596	0.512	0.533	0.257
	ICL-P	0.724	0.268	0.006	2.207	0.658	0.563	0.587	0.251
	ICL-All	0.833	0.139	0.027	1.624	0.662	0.573	0.596	0.298
	Vanilla SFT	0.819	0.071	0.108	1.650	0.597	0.567	0.567	0.362
	ContextAgent	0.874	0.030	0.095	1.408	0.660	0.627	0.626	0.448

Additionally, ContextAgent with a 7B parameter LLM achieves performance comparable to the best baseline using a 70B LLM, with only 0.4% lower Acc-P, 1.5% lower F1-score, and 0.4% higher Acc-Args, respectively, demonstrating the strong performance of ContextAgent.

Tab. 5 shows the full results on ContextAgentBench-Lite. Tab. 6 shows the full results on ContextAgentBench under OOD settings. Similarly, we observe that ContextAgent consistently achieves the highest performance when using the same base LLMs as the baselines. In addition, ContextAgent can still achieve performance comparable to the baselines that use 70B scale LLMs. For example, ContextAgent using Qwen2.5-7B-Ins can achieve 0.7% lower Acc-P, 1.9% higher F1-score, and 16.9% higher Acc-Args compared to the best baseline with Llama3.1-70B-Ins. Results validate the effectiveness of ContextAgent.

Impact of Thought Traces on ICL. We also analyze the effectiveness of thought traces on ICL. First, we observe that CoT generally outperforms Vanilla ICL on ContextAgentBench, both in-domain and OOD settings. This indicates that incorporating thought traces into few-shot demonstrations can enhance the performance of ICL. Additionally, we observe that ICL-All also outperforms ICL-P most of the time. This suggests that even after integrating persona context, further incorporating thought traces can offer benefits to ICL approaches for this task. Furthermore, we observe that thought traces provide greater benefits for 70B-sized LLMs compared to 7B LLMs. For instance, using Llama3.1-70B-Ins, ICL-All achieves a 20.1% higher Acc-P, a 20.7% higher F1-score, and a 14.3% higher Acc-Args than ICL-P on ContextAgentBench under OOD settings. This may be

Table 5: Main results on ContextAgentBench-Lite.

Model	Method	Proactive Predictions				Tool Calling			
		Acc-P↑	MD.↓	FD.↓	RMSE↓	Precision↑	Recall↑	F1-score↑	Acc-Args↑
GPT-4o	Proactive Agent	0.720	0.260	0.020	2.481	0.630	0.531	0.555	0.235
	Vanilla ICL	0.710	0.270	0.020	2.517	0.600	0.525	0.544	0.153
	CoT	0.680	0.310	0.010	2.630	0.607	0.557	0.571	0.207
	ICL-P	0.850	0.130	0.020	1.770	0.755	0.635	0.667	0.352
	ICL-All	0.890	0.110	0.000	1.627	0.782	0.675	0.701	0.397
GPT-3.5-Turbo	Proactive Agent	0.510	0.010	0.480	2.174	0.220	0.128	0.152	0.114
	Vanilla ICL	0.630	0.050	0.320	2.253	0.410	0.282	0.314	0.172
	CoT	0.660	0.190	0.150	2.186	0.531	0.439	0.464	0.126
	ICL-P	0.710	0.020	0.270	1.854	0.545	0.415	0.450	0.213
	ICL-All	0.830	0.060	0.110	1.578	0.635	0.537	0.561	0.216
Qwen2.5-72B-Ins	Proactive Agent	0.780	0.180	0.040	2.258	0.670	0.550	0.582	0.143
	Vanilla ICL	0.770	0.120	0.110	2.000	0.595	0.481	0.512	0.136
	CoT	0.770	0.120	0.110	1.786	0.575	0.467	0.494	0.158
	ICL-P	0.760	0.030	0.210	1.612	0.605	0.471	0.506	0.205
	ICL-All	0.840	0.020	0.140	1.349	0.646	0.530	0.559	0.221
Llama3.1-70B-Ins	Proactive Agent	0.760	0.150	0.090	2.076	0.620	0.529	0.554	0.253
	Vanilla ICL	0.740	0.050	0.210	1.889	0.530	0.421	0.449	0.222
	CoT	0.800	0.060	0.140	1.649	0.585	0.491	0.515	0.222
	ICL-P	0.720	0.010	0.270	1.841	0.546	0.426	0.457	0.255
	ICL-All	0.857	0.035	0.107	1.300	0.684	0.581	0.605	0.310
DeepSeek-R1-7B	Proactive Agent	0.540	0.420	0.040	3.119	0.490	0.470	0.475	0.039
	Vanilla ICL	0.540	0.310	0.150	2.849	0.455	0.411	0.423	0.103
	CoT	0.560	0.320	0.120	2.796	0.465	0.447	0.452	0.070
	ICL-P	0.610	0.240	0.150	2.624	0.445	0.400	0.413	0.083
	ICL-All	0.650	0.260	0.090	2.541	0.455	0.434	0.439	0.080
	Vanilla SFT	0.760	0.120	0.120	1.786	0.581	0.561	0.559	0.406
	ContextAgent	0.840	0.050	0.110	1.510	0.678	0.641	0.648	0.487
Qwen2.5-7B-Ins	Proactive Agent	0.710	0.210	0.080	2.328	0.575	0.515	0.532	0.064
	Vanilla ICL	0.700	0.280	0.020	2.596	0.595	0.533	0.550	0.107
	CoT	0.750	0.230	0.020	2.306	0.630	0.541	0.564	0.163
	ICL-P	0.840	0.080	0.080	1.783	0.656	0.570	0.595	0.224
	ICL-All	0.850	0.100	0.050	1.780	0.615	0.565	0.573	0.183
	Vanilla SFT	0.640	0.190	0.170	2.206	0.520	0.457	0.476	0.342
	ContextAgent	0.850	0.050	0.100	1.403	0.667	0.615	0.624	0.479
Llama3.1-8B-Ins	Proactive Agent	0.490	0.000	0.510	2.469	0.200	0.088	0.117	0.082
	Vanilla ICL	0.580	0.320	0.100	2.623	0.500	0.450	0.466	0.136
	CoT	0.630	0.360	0.010	2.306	0.595	0.553	0.564	0.166
	ICL-P	0.710	0.210	0.080	2.315	0.535	0.495	0.506	0.155
	ICL-All	0.770	0.170	0.060	1.757	0.598	0.526	0.543	0.177
	Vanilla SFT	0.720	0.120	0.160	1.959	0.536	0.497	0.508	0.362
	ContextAgent	0.830	0.070	0.100	1.510	0.687	0.637	0.645	0.486

because the limited parameters in smaller LLMs result in inherently limited knowledge, making it challenging for them to fully learn the distilled thought traces from more advanced LLMs.

Impact of Different Base Models. We test using different LLMs as the base model in ContextAgent. Table 7 shows that 1.5B to 3B LLMs (e.g., Qwen2.5-1.5B-Instruct) perform only 2.9%, 3.9%, and 5.5% lower on Acc-P, F1-score, and Acc-Args, respectively, compared to 7B LLMs. This reveals the opportunities to deploy ContextAgent on mobile devices without accessing the cloud, further reducing privacy concerns and system overhead [41].

Tab. 8 and Tab. 9 show the ablation study using different base LLMs. The results show that persona context is crucial for the task. Removing it from ContextAgent can lead to significant decreases across all metrics, with Acc-P and Acc-Args reductions of up to 12.0% and 14.3%, respectively. Additionally, sensory context perception and thought traces can also bring positive benefits.

Performance Across Different Tool Chain Lengths. Although Tab. 4 shows that ContextAgent outperforms the baselines on ContextAgentBench, we provide a detailed analysis in this section. Specifically, we examine the performance of ContextAgent across samples with varying tool chain lengths, categorizing them into three groups: 0–1 tools (level 1), 2 tools (level 2), and 3–5 tools (level 3), as shown in Tab. 10, Tab. 11, and Tab. 12, respectively. Results show that ContextAgent achieves significantly higher F1-score, and Acc-Args than the baselines on the level 2 and level 3 samples. For level 3 samples, ContextAgent can achieve 30.3% and 16.0% higher Acc-P and Acc-Args,

Table 6: Results on out-of-domain experiments.

Model	Method	Proactive Predictions				Tool Calling			
		Acc-P↑	MD.↓	FD.↓	RMSE↓	Precision↑	Recall↑	F1-score↑	Acc-Args↑
GPT-4o	Proactive Agent	0.749	0.234	0.016	2.446	0.652	0.542	0.568	0.331
	Vanilla ICL	0.779	0.207	0.013	2.253	0.681	0.573	0.600	0.338
	CoT	0.756	0.234	0.010	2.407	0.659	0.565	0.587	0.306
	ICL-P	0.909	0.076	0.013	1.514	0.735	0.619	0.648	0.393
	ICL-All	0.886	0.100	0.013	1.701	0.719	0.611	0.639	0.397
GPT-3.5-Turbo	Proactive Agent	0.682	0.010	0.307	1.757	0.478	0.352	0.384	0.126
	Vanilla ICL	0.742	0.050	0.207	1.797	0.555	0.412	0.448	0.222
	CoT	0.802	0.183	0.013	2.152	0.658	0.549	0.576	0.206
	ICL-P	0.702	0.000	0.297	1.589	0.521	0.376	0.412	0.207
	ICL-All	0.879	0.020	0.100	1.452	0.657	0.521	0.555	0.235
Qwen2.5-72B-Ins	Proactive Agent	0.846	0.070	0.083	1.806	0.657	0.545	0.573	0.240
	Vanilla ICL	0.792	0.090	0.117	1.600	0.627	0.522	0.551	0.330
	CoT	0.819	0.140	0.040	1.564	0.678	0.583	0.607	0.330
	ICL-P	0.882	0.013	0.103	1.199	0.675	0.569	0.595	0.297
	ICL-All	0.929	0.020	0.050	1.036	0.717	0.618	0.642	0.355
Llama3.1-70B-Ins	Proactive Agent	0.796	0.107	0.097	1.950	0.659	0.551	0.580	0.292
	Vanilla ICL	0.689	0.020	0.291	1.840	0.445	0.350	0.377	0.221
	CoT	0.829	0.026	0.143	1.386	0.629	0.489	0.525	0.089
	ICL-P	0.725	0.003	0.271	1.734	0.533	0.423	0.453	0.184
	ICL-All	0.926	0.003	0.070	1.127	0.756	0.626	0.660	0.327
DeepSeek-R1-7B	Proactive Agent	0.571	0.391	0.036	3.040	0.475	0.453	0.459	0.018
	Vanilla ICL	0.665	0.254	0.080	2.621	0.483	0.435	0.447	0.085
	CoT	0.605	0.347	0.046	2.777	0.516	0.467	0.479	0.076
	ICL-P	0.675	0.237	0.087	2.527	0.489	0.438	0.450	0.069
	ICL-All	0.639	0.321	0.040	2.637	0.505	0.466	0.476	0.071
	Vanilla SFT	0.782	0.087	0.130	1.743	0.585	0.565	0.564	0.418
	ContextAgent	0.893	0.026	0.080	1.249	0.681	0.645	0.648	0.489
Qwen2.5-7B-Ins	Proactive Agent	0.806	0.147	0.046	2.139	0.605	0.556	0.567	0.050
	Vanilla ICL	0.829	0.120	0.050	1.898	0.597	0.532	0.546	0.207
	CoT	0.846	0.123	0.030	1.836	0.612	0.545	0.562	0.218
	ICL-P	0.886	0.050	0.063	1.584	0.569	0.517	0.530	0.192
	ICL-All	0.890	0.040	0.070	1.502	0.593	0.527	0.543	0.206
	Vanilla SFT	0.799	0.077	0.123	1.685	0.607	0.585	0.582	0.433
	ContextAgent	0.909	0.020	0.070	1.172	0.711	0.699	0.689	0.516
Llama3.1-8B-Ins	Proactive Agent	0.652	0.013	0.334	1.918	0.403	0.266	0.301	0.139
	Vanilla ICL	0.739	0.163	0.097	2.052	0.565	0.470	0.496	0.210
	CoT	0.732	0.220	0.046	1.934	0.623	0.529	0.554	0.247
	ICL-P	0.839	0.137	0.023	1.907	0.659	0.558	0.585	0.320
	ICL-All	0.796	0.173	0.030	1.822	0.623	0.527	0.553	0.246
	Vanilla SFT	0.816	0.090	0.093	1.161	0.628	0.619	0.611	0.460
	ContextAgent	0.869	0.036	0.093	1.369	0.661	0.645	0.641	0.480

Table 7: Overall performance of ContextAgent using different LLMs as base models.

Category	Model	Size	Proactive Predictions				Tool Calling			
			Acc-P↑	MD.↓	FD.↓	RMSE↓	Precision↑	Recall↑	F1-score↑	Acc-Args↑
7B ∼ 8B	LLaMA3	8B	0.898	0.028	0.074	1.254	0.685	0.653	0.652	0.465
	Qwen2.5	7B	0.883	0.040	0.076	1.215	0.682	0.653	0.653	0.481
	DeepSeek-R1	7B	0.888	0.038	0.074	1.275	0.659	0.648	0.639	0.434
1.5B ∼ 3B	Qwen2.5	3B	0.869	0.043	0.086	1.336	0.652	0.610	0.615	0.421
	DeepSeek-R1	1.5B	0.882	0.041	0.076	1.245	0.686	0.652	0.652	0.447
	Qwen2.5	1.5B	0.869	0.038	0.091	1.312	0.642	0.612	0.613	0.410

respectively, when using Qwen2.5-7B-Ins as the base LLM, validating its strong performance in scenarios that require multiple external tools for proactive services.

More Qualitative Results. We also provide more qualitative results of ContextAgent in Fig. 15 and Fig. 16. Results indicate that ContextAgent initiates the proactive support when it perceives contexts such as the user showing interest in a product or putting clothes into a washing machine. Additionally, integrating knowledge from external tools, such as online product prices and app-based recommendations, can further enhance the usefulness of these proactive services. Moreover, when ContextAgent detects contexts like leisure time enjoying the sunset or beach waves, or normal daily

Table 8: Ablation study on ContextAgentBench. “w/o persona” means the agent does not use persona information during both the training and testing stages. “w/o think” means that the SFT training data does not include the thought process.

Model	Method	Proactive Predictions				Tool Calling			
		Acc-P↑	MD.↓	FD.↓	RMSE↓	Precision↑	Recall↑	F1-score↑	Acc-Args↑
Qwen2.5-7B	wo/ persona	0.775	0.078	0.146	1.799	0.571	0.531	0.532	0.364
	wo/ think	0.857	0.030	0.112	1.415	0.634	0.592	0.599	0.411
	ContextAgent	0.894	0.013	0.091	1.264	0.672	0.644	0.645	0.459
Llama3.1-8B	wo/ persona	0.806	0.081	0.112	1.639	0.611	0.574	0.579	0.405
	wo/ think	0.857	0.030	0.112	1.397	0.645	0.607	0.612	0.419
	ContextAgent	0.874	0.030	0.095	1.408	0.660	0.627	0.626	0.448
DeepSeek-R1-7B	wo/ persona	0.799	0.092	0.109	1.742	0.609	0.575	0.580	0.409
	wo/ think	0.884	0.017	0.099	1.355	0.652	0.625	0.625	0.439
	ContextAgent	0.888	0.027	0.085	1.319	0.676	0.648	0.647	0.468

Table 9: Ablation study on ContextAgentBench-Lite. “w/o poce” means the agent does not use proactive-oriented context extraction.

Model	Method	Proactive Predictions				Tool Calling			
		Acc-P↑	MD.↓	FD.↓	RMSE↓	Precision↑	Recall↑	F1-score↑	Acc-Args↑
Qwen2.5-7B-Ins	wo/ persona	0.740	0.150	0.110	1.951	0.568	0.536	0.543	0.336
	wo/ think	0.820	0.060	0.120	1.490	0.630	0.605	0.608	0.412
	wo/ poce	0.830	0.090	0.080	1.568	0.663	0.610	0.622	0.460
	ContextAgent	0.850	0.050	0.100	1.403	0.667	0.615	0.624	0.479
Llama3.1-8B-Ins	wo/ persona	0.720	0.150	0.130	1.972	0.554	0.516	0.522	0.360
	wo/ think	0.820	0.100	0.080	1.546	0.648	0.623	0.625	0.409
	wo/ poce	0.800	0.080	0.120	1.661	0.648	0.604	0.612	0.467
	ContextAgent	0.830	0.070	0.100	1.510	0.687	0.637	0.645	0.486
DeepSeek-R1-7B	wo/ persona	0.720	0.150	0.130	2.000	0.575	0.517	0.535	0.394
	wo/ think	0.810	0.060	0.130	1.578	0.657	0.608	0.612	0.438
	wo/ poce	0.790	0.100	0.110	1.562	0.663	0.585	0.606	0.433
	ContextAgent	0.840	0.050	0.110	1.510	0.678	0.641	0.648	0.487

activities such as walking upstairs, it correctly identifies that no proactive support is needed, thus reducing unnecessary interruptions.

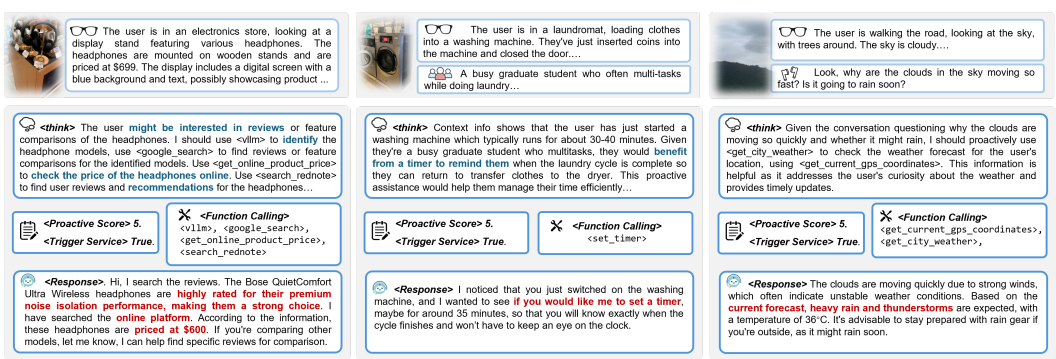

Figure 15: Qualitative results of ContextAgent in proactive cases, showing sensory and persona contexts, and ContextAgent's thought traces, proactive predictions, tool calls, and final responses.

F Limitations

Although ContextAgent demonstrates strong performance in the context-aware proactive agent task, we summarize the limitations and future directions for this work as follows. First, the current tool set in ContextAgent includes twenty tools with APIs. The recent emergence of the Model Context Protocol (MCP) aims to standardize these external tools, which can be integrated into ContextAgent to further enhance the standardization of tool calls and the diversity of tool types. Second, although

Table 10: Results for the Level-1 samples in ContextAgentBench.

Model	Method	Proactive Predictions				Tool Calling			
		Acc-P↑	MD.↓	FD.↓	RMSE↓	Precision↑	Recall↑	F1-score↑	Acc-Args↑
GPT-4o	Proactive Agent	0.835	0.138	0.025	1.983	0.789	0.789	0.789	0.246
	Vanilla ICL	0.835	0.138	0.025	1.997	0.776	0.784	0.778	0.462
	CoT	0.835	0.128	0.035	1.970	0.775	0.784	0.777	0.529
	ICL-P	0.928	0.046	0.025	1.432	0.860	0.866	0.862	0.596
	ICL-All	0.923	0.046	0.030	1.421	0.839	0.851	0.842	0.596
GPT-3.5-Turbo	Proactive Agent	0.517	0.005	0.476	2.104	0.467	0.467	0.467	0.065
	Vanilla ICL	0.702	0.051	0.246	1.820	0.617	0.620	0.617	0.374
	CoT	0.815	0.071	0.112	1.525	0.706	0.717	0.710	0.433
	ICL-P	0.733	0.035	0.230	1.872	0.625	0.630	0.627	0.400
	ICL-All	0.800	0.051	0.148	1.542	0.709	0.717	0.712	0.458
Qwen2.5-72B-Ins	Proactive Agent	0.800	0.061	0.069	1.684	0.700	0.702	0.700	0.144
	Vanilla ICL	0.835	0.082	0.082	1.353	0.729	0.743	0.734	0.475
	CoT	0.856	0.076	0.066	1.254	0.747	0.759	0.751	0.468
	ICL-P	0.887	0.046	0.066	1.081	0.805	0.810	0.806	0.495
	ICL-All	0.923	0.035	0.041	0.981	0.806	0.815	0.808	0.474
Llama3.1-70B-Ins	Proactive Agent	0.825	0.041	0.133	1.676	0.687	0.692	0.688	0.314
	Vanilla ICL	0.697	0.020	0.282	1.688	0.548	0.553	0.550	0.374
	CoT	0.774	0.030	0.194	1.394	0.612	0.625	0.616	0.385
	ICL-P	0.784	0.000	0.215	1.529	0.654	0.666	0.658	0.374
	ICL-All	0.861	0.005	0.133	1.176	0.736	0.748	0.740	0.455
DeepSeek-R1-7B	Proactive Agent	0.707	0.225	0.066	2.444	0.671	0.671	0.671	0.019
	Vanilla ICL	0.697	0.143	0.159	2.215	0.588	0.594	0.590	0.078
	CoT	0.759	0.200	0.041	2.328	0.705	0.707	0.706	0.109
	ICL-P	0.759	0.117	0.123	2.065	0.658	0.666	0.660	0.126
	ICL-All	0.825	0.133	0.041	1.978	0.714	0.717	0.715	0.103
	Vanilla SFT	0.779	0.056	0.164	1.783	0.628	0.651	0.635	0.386
	ContextAgent	0.856	0.015	0.128	1.423	0.712	0.748	0.723	0.468
Qwen2.5-7B-Ins	Proactive Agent	0.820	0.082	0.097	1.843	0.692	0.702	0.695	0.038
	Vanilla ICL	0.769	0.087	0.143	1.868	0.642	0.661	0.648	0.326
	CoT	0.794	0.082	0.123	1.874	0.668	0.676	0.670	0.272
	ICL-P	0.805	0.082	0.112	1.845	0.683	0.697	0.688	0.303
	ICL-All	0.851	0.082	0.066	1.724	0.735	0.748	0.739	0.301
	Vanilla SFT	0.733	0.061	0.205	1.905	0.588	0.605	0.593	0.398
	ContextAgent	0.856	0.005	0.138	1.396	0.701	0.728	0.709	0.459
Llama3.1-8B-Ins	Proactive Agent	0.533	0.010	0.456	2.169	0.328	0.328	0.328	0.091
	Vanilla ICL	0.794	0.117	0.087	1.593	0.707	0.707	0.707	0.234
	CoT	0.774	0.117	0.107	1.637	0.659	0.661	0.659	0.257
	ICL-P	0.794	0.194	0.010	1.900	0.753	0.753	0.753	0.251
	ICL-All	0.861	0.097	0.041	1.379	0.748	0.748	0.748	0.298
	Vanilla SFT	0.774	0.061	0.164	1.778	0.635	0.671	0.647	0.362
	ContextAgent	0.841	0.015	0.143	1.485	0.695	0.733	0.707	0.448

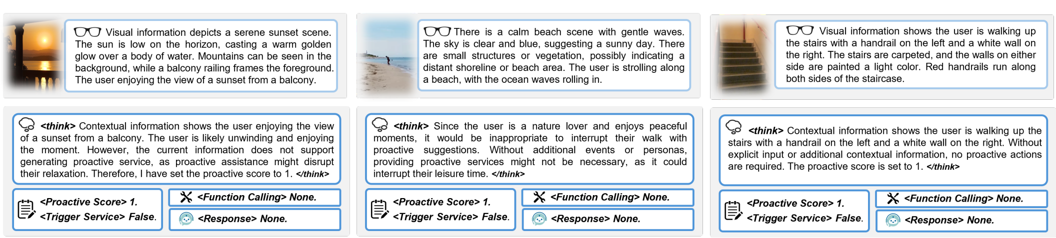

Figure 16: Qualitative results of ContextAgent in non-proactive cases.

ContextAgentBench currently includes nine life scenarios, it can be further diversified to enhance the ContextAgent's capabilities and practicality for daily use.

G Broader Impacts

In this paper, we explore the context-aware proactive LLM agents for the first time, and propose a framework called ContextAgent. By utilizing the rich contextual information from sensory perceptions alongside tool-based LLM reasoning, ContextAgent significantly enhances both perception and functionality compared to existing approaches, resulting in improved proactive service. ContextAgent utilizes sensor data from wearable devices such as smart glasses and earphones. This

Table 11: Results for the Level-2 samples in ContextAgentBench.

Model	Method	Proactive Predictions				Tool Calling			
		Acc-P↑	**MD.**↓	**FD.**↓	**RMSE**↓	**Precision**↑	**Recall**↑	**F1-score**↑	**Acc-Args**↑
GPT-4o	Proactive Agent	0.651	0.348	0.000	2.761	0.500	0.255	0.337	0.256
	Vanilla ICL	0.674	0.325	0.000	2.676	0.333	0.209	0.249	0.467
	CoT	0.720	0.279	0.000	2.645	0.472	0.325	0.370	0.534
	ICL-P	0.883	0.116	0.000	1.855	0.511	0.290	0.364	0.606
	ICL-All	0.883	0.116	0.000	1.848	0.546	0.314	0.391	0.590
GPT-3.5-Turbo	Proactive Agent	0.953	0.046	0.000	1.229	0.581	0.290	0.387	0.070
	Vanilla ICL	0.814	0.186	0.000	1.867	0.407	0.220	0.282	0.366
	CoT	0.790	0.209	0.000	1.994	0.480	0.302	0.359	0.449
	ICL-P	0.883	0.116	0.000	1.830	0.534	0.279	0.364	0.408
	ICL-All	0.883	0.116	0.000	1.532	0.492	0.325	0.379	0.472
Qwen2.5-72B-Ins	Proactive Agent	0.930	0.069	0.000	1.758	0.534	0.302	0.379	0.150
	Vanilla ICL	0.883	0.116	0.000	1.509	0.484	0.372	0.405	0.484
	CoT	0.907	0.093	0.000	1.430	0.511	0.372	0.418	0.478
	ICL-P	0.930	0.069	0.000	1.355	0.639	0.476	0.527	0.506
	ICL-All	0.907	0.093	0.000	1.486	0.542	0.453	0.479	0.493
Llama3.1-70B-Ins	Proactive Agent	0.837	0.162	0.000	1.935	0.503	0.302	0.367	0.333
	Vanilla ICL	1.000	0.000	0.000	0.849	0.531	0.395	0.439	0.381
	CoT	1.000	0.000	0.000	0.902	0.589	0.348	0.427	0.392
	ICL-P	1.000	0.000	0.000	0.821	0.624	0.418	0.486	0.385
	ICL-All	1.000	0.000	0.000	0.876	0.662	0.476	0.532	0.465
DeepSeek-R1-7B	Proactive Agent	0.279	0.720	0.000	3.882	0.058	0.034	0.042	0.021
	Vanilla ICL	0.465	0.534	0.000	3.348	0.129	0.104	0.110	0.082
	CoT	0.348	0.651	0.000	3.592	0.104	0.081	0.089	0.115
	ICL-P	0.465	0.534	0.000	3.306	0.089	0.058	0.067	0.129
	ICL-All	0.418	0.581	0.000	3.474	0.127	0.081	0.096	0.096
	Vanilla SFT	0.860	0.139	0.000	1.486	0.472	0.337	0.377	0.404
	ContextAgent	0.930	0.069	0.000	1.181	0.536	0.441	0.464	0.471
Qwen2.5-7B-Ins	Proactive Agent	0.674	0.325	0.000	2.663	0.302	0.220	0.248	0.040
	Vanilla ICL	0.907	0.093	0.000	1.372	0.461	0.383	0.408	0.324
	CoT	0.930	0.069	0.000	1.422	0.418	0.279	0.325	0.270
	ICL-P	0.860	0.139	0.000	1.861	0.434	0.314	0.351	0.302
	ICL-All	0.883	0.116	0.000	1.758	0.476	0.314	0.368	0.316
	Vanilla SFT	0.744	0.255	0.000	1.823	0.412	0.372	0.377	0.419
	ContextAgent	0.977	0.023	0.000	0.927	0.542	0.465	0.479	0.479
Llama3.1-8B-Ins	Proactive Agent	1.000	0.000	0.000	0.940	0.383	0.197	0.259	0.088
	Vanilla ICL	0.558	0.441	0.000	2.583	0.290	0.162	0.205	0.231
	CoT	0.674	0.325	0.000	2.151	0.352	0.209	0.255	0.252
	ICL-P	0.534	0.465	0.000	2.672	0.418	0.232	0.294	0.241
	ICL-All	0.651	0.348	0.000	2.327	0.383	0.232	0.282	0.291
	Vanilla SFT	0.860	0.139	0.000	1.599	0.395	0.325	0.348	0.371
	ContextAgent	0.907	0.093	0.000	1.462	0.503	0.430	0.445	0.468

hands-free, egocentric perception not only offers a better understanding of the user's conditions and intentions but also reduces both cognitive and physical workload, perfectly aligning with the vision of a proactive assistant. In addition, to bridge the gap in evaluating this new task, we introduce ContextAgentBench, the first benchmark to evaluate context-aware proactive LLM agents. Furthermore, ContextAgent serves as a bridge between research on sensory context perception in ubiquitous mobile systems and the emerging LLM agents, thereby opening up new research perspectives and directions. We hope our research will help advance the development of proactive, human-centric AI assistants.

Table 12: Results for the Level-3 samples in ContextAgentBench.

Model	Method	Proactive Predictions				Tool Calling			
		Acc-P↑	**MD.**↓	**FD.**↓	**RMSE**↓	**Precision**↑	**Recall**↑	**F1-score**↑	**Acc-Args**↑
GPT-4o	Proactive Agent	0.714	0.285	0.000	2.604	0.523	0.158	0.239	0.253
	Vanilla ICL	0.857	0.142	0.000	1.817	0.732	0.332	0.434	0.466
	CoT	0.910	0.089	0.000	1.564	0.784	0.406	0.504	0.534
	ICL-P	0.928	0.071	0.000	1.463	0.794	0.357	0.467	0.598
	ICL-All	0.946	0.053	0.000	1.309	0.794	0.415	0.516	0.598
GPT-3.5-Turbo	Proactive Agent	1.000	0.000	0.000	0.845	0.517	0.149	0.231	0.068
	Vanilla ICL	0.982	0.017	0.000	1.069	0.702	0.244	0.351	0.377
	CoT	0.946	0.053	0.000	1.093	0.647	0.337	0.422	0.440
	ICL-P	1.000	0.000	0.000	0.790	0.741	0.305	0.408	0.408
	ICL-All	0.981	0.017	0.000	0.886	0.727	0.374	0.462	0.468
Qwen2.5-72B-Ins	Proactive Agent	0.928	0.071	0.000	1.797	0.669	0.237	0.343	0.144
	Vanilla ICL	0.964	0.035	0.000	1.043	0.738	0.407	0.503	0.482
	CoT	0.964	0.035	0.000	1.101	0.720	0.451	0.528	0.477
	ICL-P	1.000	0.000	0.000	0.790	0.770	0.422	0.518	0.504
	ICL-All	1.000	0.000	0.000	0.916	0.717	0.428	0.511	0.487
Llama3.1-70B-Ins	Proactive Agent	0.946	0.053	0.000	1.232	0.595	0.268	0.356	0.318
	Vanilla ICL	1.000	0.000	0.000	0.668	0.738	0.398	0.497	0.381
	CoT	1.000	0.000	0.000	0.801	0.758	0.407	0.497	0.392
	ICL-P	1.000	0.000	0.000	0.719	0.708	0.394	0.480	0.386
	ICL-All	1.000	0.000	0.000	0.707	0.668	0.410	0.482	0.460
DeepSeek-R1-7B	Proactive Agent	0.285	0.714	0.000	3.964	0.142	0.048	0.070	0.040
	Vanilla ICL	0.607	0.392	0.000	2.991	0.251	0.125	0.158	0.081
	CoT	0.517	0.482	0.000	3.348	0.238	0.105	0.137	0.111
	ICL-P	0.625	0.375	0.000	2.945	0.363	0.148	0.203	0.130
	ICL-All	0.500	0.500	0.000	3.313	0.279	0.117	0.158	0.098
	Vanilla SFT	0.946	0.053	0.000	1.093	0.714	0.467	0.542	0.400
	ContextAgent	1.000	0.000	0.000	0.755	0.721	0.444	0.529	0.455
Qwen2.5-7B-Ins	Proactive Agent	0.821	0.178	0.000	2.129	0.392	0.199	0.255	0.039
	Vanilla ICL	0.910	0.089	0.000	1.586	0.506	0.263	0.334	0.332
	CoT	0.892	0.107	0.000	1.742	0.425	0.196	0.258	0.271
	ICL-P	0.910	0.089	0.000	1.690	0.488	0.251	0.316	0.306
	ICL-All	0.910	0.089	0.000	1.679	0.410	0.184	0.246	0.305
	Vanilla SFT	0.946	0.053	0.000	1.157	0.731	0.504	0.576	0.417
	ContextAgent	0.964	0.035	0.000	0.972	0.672	0.489	0.549	0.465
Llama3.1-8B-Ins	Proactive Agent	1.000	0.000	0.000	0.731	0.538	0.177	0.260	0.090
	Vanilla ICL	0.732	0.267	0.000	2.228	0.526	0.174	0.257	0.235
	CoT	0.821	0.178	0.000	1.889	0.567	0.225	0.308	0.264
	ICL-P	0.625	0.375	0.000	2.741	0.508	0.153	0.233	0.245
	ICL-All	0.875	0.125	0.000	1.752	0.574	0.222	0.306	0.299
	Vanilla SFT	0.946	0.053	0.000	1.149	0.620	0.389	0.459	0.369
	ContextAgent	0.964	0.035	0.000	1.043	0.657	0.406	0.477	0.466