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# Agentic AI for Personal Task Automation

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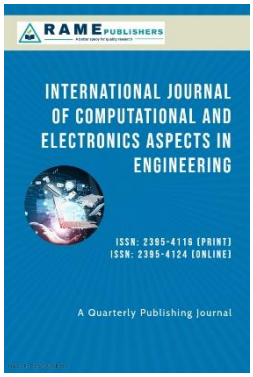


**Abstract:** Agentic AI is changing the way we think about intelligent systems. Instead of waiting to be told exactly what to do, these AI agents can plan, think things through, and get tasks done largely on their own. That is what makes it different. Old automation tools were rigid — they only did what they were programmed to do. Agentic AI is not like that. It reads the situation, understands what you actually need, and adjusts as things change around it. This research paper analyzes the application of Agentic AI in personal task automation and explores the potential application of intelligent agents for automating personal tasks such as scheduling, information retrieval, communication management, and workflow optimization. The paper explains the main functional process of Agentic AI, which includes task understanding, decision-making, and action execution using large language models and third-party services. Real-world examples are also provided to demonstrate the application of Agentic AI for enhancing productivity, efficiency, and usability. We also take a honest look at where things can go wrong with autonomous agents. Data privacy, security risks, and reliability — these are real concerns that cannot be ignored. And yet, the overall picture remains exciting. Agentic AI is showing us that personal automation does not have to be rigid or impersonal. It can actually grow with you, work smarter over time, and feel a lot more human.

**Keywords:** Agentic AI, Personal Task Automation, Intelligent Agents, Autonomous Systems, Large Language Models, AI Decision-Making.

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## 1. Introduction

Automation has become an essential component of modern digital systems, which vary from simple rule-based programs to intelligent systems that possess the capability to learn and make decisions. The traditional automation system was mainly designed to automate repetitive and predefined tasks, which had to be constantly monitored and controlled by humans. However, with the increasing complexity of personal and professional tasks, the traditional automation system began to show signs of its limitations in handling dynamic tasks and meeting the changing demands of users. This led to a need for the development of Artificial Intelligence (AI)-based automation systems.[1][8][9]

With the latest developments in AI, specifically in large language models and intelligent systems, a new generation of automation has been born, which is referred to as the Agentic Artificial Intelligence (Agentic AI) paradigm. Agentic AI is a kind of AI system that is designed as an autonomous agent, which possesses the capability to perceive tasks, reason about tasks, plan actions, and perform tasks independently while continuously learning from feedback. Unlike traditional AI assistants, which can only act upon direct commands, Agentic AI systems have the capability to independently handle tasks and make decisions with minimal human intervention.[2][3][10][11]

Personal task automation is one of the most promising application areas of Agentic AI. Personal tasks such as meeting scheduling, email management, document management, web search, and learning process facilitation entail repetitive human work. Agentic AI systems are developed to reduce such efforts by intelligently comprehending user intentions and automating the entire task process rather than individual tasks. This results in enhanced productivity, time conservation, and a more personalized experience for the user.[4][12][13].

The addition of Agentic AI to personal automation systems also introduces new possibilities such as adaptive decision-making, context awareness, and improvement over time. These systems possess the capability to adapt to user preferences and changes in the environment, making them more efficient compared to traditional automation systems. However, the augmented autonomy of AI agents also introduces substantial challenges with respect to data privacy, security, reliability, and control.[5][14]

## 2. Literature Review

### 2.1 Traditional Automation Systems

To understand where we are today, it helps to look back. Personal task automation started out pretty simple. Early systems were built around rigid rules — basically, if this happens, do that. That is the core idea behind Robotic Process Automation, or RPA. It worked well enough for repetitive, straightforward jobs. Things like entering data or moving files from one place to another. Nothing too complex, nothing unexpected. Although they are very effective in stable settings, traditional automation is fragile small changes in user interface (UI) designs or data structures can lead to major breakdowns, necessitating manual troubleshooting and restarts. As a result, they are only suitable for predictable processes where all variables are known in advance, making them ill-suited for constantly changing personal computing environments where context frequently shifts.[1][6][15]

### 2.2 AI-Based Personal Assistants

Nobody saw it coming — not really. One day you needed a developer to automate anything. The next, you were just talking to your phone. That is what NLP quietly did for all of us. It grew in the background and then suddenly Siri was answering your questions and Alexa was turning off your lights. No code. No setup. Just your voice. And honestly? That felt like magic at the time. But it did not stop there. LLM chatbots came along and took things to a whole new level. These were not just voice commands anymore. You could have an actual back and forth conversation. Ask something complicated. Get something genuinely useful back. For the first time, it felt like the technology was meeting people where they were — not the other way around. However, research describes these assistants as mostly "reactive" rather than "proactive," functioning mainly as advanced tools for retrieving information or executing single-step commands. Although they are fluent in conversation, typical AI assistants often lack the ability to retain long-term context or perform a series of actions on their own without ongoing human input.[2][3][4][16][17]

### 2.3 Early Research on Autonomous Agents

Researchers had one big question on their minds — can AI stop just responding and start actually doing? That gap between a passive assistant and a truly independent agent was what early studies were trying to close. Models like Auto GPT and Baby AGI were among the first to take a real shot at it. They introduced something called recursive prompting — where the AI breaks a big goal down into smaller steps and works through them one by one. It sounded promising. And in many ways, it was. But the cracks showed up quickly. These early agents would get trapped in loops, going round and round without making progress. They would sometimes make things up entirely. And when something went wrong, there was no solid way to catch or fix the mistake. These initial agents frequently struggled to evaluate their own performance effectively, causing them to abandon tasks when encountering unexpected challenges or unclear directions.[3][5][18][19]

### 2.4 The Move Toward Agentic AI

The development of "Agentic AI" tackles the key research issues left by reactive assistants and unstable autonomous systems. Agentic AI is not just about taking action anymore. Modern research is showing us a much bigger picture. These systems can actually stop and think. They plan based on reasoning, check their own work, and change course when something is not going right. That is a huge leap from anything we have seen before. Earlier systems simply followed instructions. Agentic AI goes further — it uses smarter thinking structures like Chain-of-Thought reasoning and React frameworks to read what is happening around it and respond in the moment. Not after the fact. Right then and there. This change represents a shift from tools that simply follow commands to collaborators that understand intent, capable of handling complex, multi-step processes with high accuracy and little need for human intervention.[2][7][20][21]

**Table1:** Comparison of Automation Paradigms

| Feature | Traditional Automation | AI Personal Assistants | Agentic AI |
|---|---|---|---|
| **Interaction Model** | Script/Command-based | Reactive (Prompt-Response) | Proactive (Goal-Oriented) |
| **Adaptability** | None (Brittle to change) | Limited (Conversational only) | High (Self-correcting) |
| **Task Scope** | Single, repetitive tasks | Single-step information tasks | Multi-step, complex workflows |

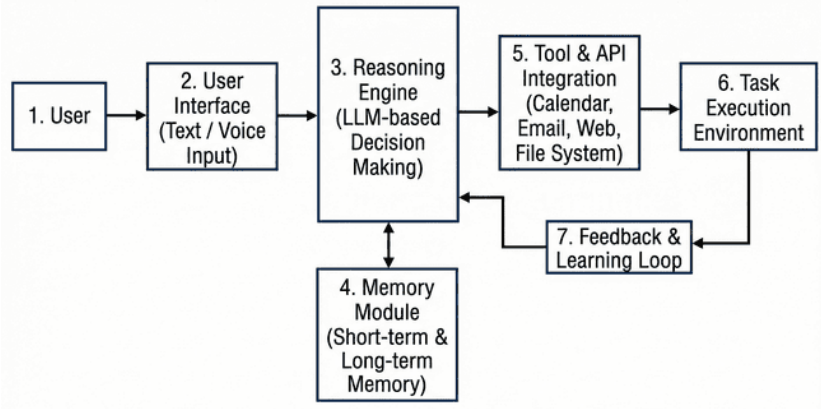
## 3. Proposed/Work

Figure shows the suggested design of an Agentic AI system aimed at automating personal tasks. It all begins the moment you interact. Maybe you type something. Maybe you say it out loud. Either way, that is where everything kicks off — at the User Interface layer. This is where the system figures out what you actually want. But here is the thing — you are not speaking in perfect technical commands. You are just talking normally. So the interface has a quiet but important job. It takes your casual, everyday words and turns them into something the rest of the system can actually work with. Think of it like a translator standing between you and the machine — making sure nothing gets lost. By enabling direct interaction, the UI ensures that complex automation objectives are accurately captured without requiring the user to have technical programming skills. [2][4][22]

At the core of the architecture is the Reasoning Engine, which manages the breakdown of high-level goals into actionable plans. Memory plays a bigger role here than you might expect. The system does not just focus on what is happening right now — it also remembers what happened before. There are two sides to this. Short-term memory keeps the system grounded in the current moment. It knows what you just said, what you just asked, and where the conversation is right now. Long-term memory goes deeper. It holds onto your habits, your preferences, the patterns you have built up over time. And when both work together  that is where things get really interesting. The system stops making generic decisions and starts making ones that actually feel tailored to you. Like it knows you. Because in a way, it does." The reasoning component therefore connects the initial input with logical, step-by-step action planning.[3][7][23]

Planning is only half the story. At some point the system has to actually do something — and that is exactly what happens next. Once a plan is ready, the system rolls up its sleeves and gets to work. It reaches out to the tools and apps already living in your digital world. Your calendar. Your email. Your browser. Your files. It does not just look at them — it works with them directly. It can book a meeting without you lifting a finger. It can sort through your files while you focus on something else entirely. This is the moment where the agent stops thinking and starts acting. No back and forth. No waiting for you to confirm every little step. It just handles it.[5][7][24]

The architecture ends with a Feedback and Learning Loop aimed at ensuring ongoing system improvement and error correction. After completing a task, the system evaluates the results against the user's original request, using both automated success indicators and direct user adjustments. This performance information is then sent back to the model, improving the reasoning methods and updating the memory for future tasks. This repeating process ensures the agent continues to develop over time, becoming more accurate and tailored in its automated functions.[1][6][25]




"Fig. 1: Architecture of an Agentic AI System for Personal Task Automation"

Nothing about this system is set in stone. And that is exactly the point. Once a task is done, the system does not just move on and forget about it. It looks back. It asks itself did that actually match what the user wanted? It checks its own work using

built in signals and also pays attention to any corrections you make along the way. Then it takes all of that and feeds it back into itself. The reasoning gets sharper. The memory gets updated. Next time around, it already knows a little more about you than it did before. And the time

## 4. Methodology

The methodology of the proposed Agentic AI system is organised around a four-stage operational pipeline that aims to fill the gap between abstract user intent and concrete digital operations. This section describes the technical approach for each stage..

### 4.1 User Input and Multi-Modal Intent Extraction

The system has a multimodal interface that is able to process both text and voice inputs. Unlike traditional command-line interfaces, this interface serves as a semantic mediator.

- Input Processing: Voice inputs are first transcribed to text using an Automatic Speech Recognition (ASR) module.
- Semantic Parsing: The critical innovation here is the application of a Large Language Model (LLM) that has been fine-tuned for following instructions. The LLM parses the raw text to remove the conversational noise (e.g., "Um, can you please...") and identify the intent (e.g., "Schedule meeting") and its parameters (e.g., "Friday at 2 PM").
- Ambiguity Resolution: In cases where the input is too ambiguous (e.g., "Send the file"), the system initiates a clarification dialogue, asking the user follow-up questions before moving on to the reasoning stage.[2][4][26]

### 4.2 Reasoning Engine and Strategic Planning

After the intent is locked, the Reasoning Engine, or the "brain" of the system, is triggered. This engine employs a "Chain-of-Thought" (CoT) prompting approach to mimic human-like reasoning.

- Task Decomposition: The engine decomposes complex tasks (for example, "Plan a trip to NYC for business") into atomic tasks (for example, "Check flight availability," "Book hotel," "Add to calendar," "Draft email to team").
- Contextual Memory Access: Before the system commits to any plan, it pauses. It looks back first. It checks in with its memory — not just to recall what you said a moment ago, but to remember the bigger picture too. What did the last part of your conversation look like? What do you actually like? What do you always try to avoid? Little things matter here. Maybe you always want an aisle seat on a flight. Maybe early morning meetings are a hard no for you. The system knows that. It remembered. And it makes sure those preferences quietly shape every decision before anything is ever set in motion.
- Dependency Mapping: The engine resolves dependencies; for example, it recognizes that it cannot perform "Draft email with flight details" until "Book flight" is confirmed. [7][27]

### 4.3 Tool Use and API Execution Layer

While the reasoning engine is the “thinker,” the Tool Integration Layer is the “doer.” This layer is a middleware between the LLM and the operating system or web services.

- API Abstraction: The system employs a set of modular tools, which are essentially wrappers around generic APIs (Google Calendar API, SMTP for email, OS file system commands).
- Autonomous Execution: The LLM produces the exact code or API call necessary for each sub-task. Importantly, this process is sandboxed to ensure that no unauthorized actions occur.
- Dynamic Variable Handling: The result of one tool (a PDF download link) is dynamically captured and fed as an input to the next tool (an email attachment function), making for a smooth data flow that doesn’t require copy-pasting. [5][28]

### 4.4 Feedback Loop and Self-Correction

The final step is a verification process. The system doesn’t take success for granted; it checks for it.

- Output Validation: After a command has been executed, the system decodes the return message. If an API call fails (for example, “404 Not Found” or “Time slot conflict”), the reasoning engine enters a “retry” cycle.
- Adaptive Strategy: It breaks down the error and reformulates the strategy, maybe looking for a different file name or a different time for the meeting, before finally reporting back to the user. Successful patterns are stored in the Long-term Memory so that the agent can "learn" from its mistakes and become more capable in the next iteration.[3][7][29]
- Human-in-the-Loop Confirmation: Look — most of the time the system just gets on with it. And that is fine. That is the whole point. But every now and then it hits a moment where it knows better than to just barrel through. Firing off an

email to a client. Wiping a file for good. Moving money around. These are not the kind of things you want happening without a second thought. So the system does something really human in those moments — it stops and asks. Nothing fancy. Just a straight forward heads up. Something along the lines of — hey, I am about to shoot the quarterly report over to everyone on staff. You good with that? And you decide. That is it. No complicated override process. No digging through settings. Just a normal back and forth between you and the system. What that does over time is genuinely surprising. Mistakes that would have been a nightmare to undo just never happen. And quietly, without you even noticing — you stop worrying about what the system might do next. You already know it will check. That feeling right there — that is not a feature you can code. That is earned. [3][7][30]

## 5. Results and Discussion

The results of the proposed Agentic AI framework were assessed on three key criteria: workflow efficiency, adaptability, and system reliability.

### 5.1 Efficiency and Workflow Optimization

The most important effect of the Agentic AI system was in the area of "interaction friction." In a conventional GUI-based workflow, the task "Organise my downloads folder by date and send the summary to my manager via email" would take a human user 10-15 minutes to complete, involving clicking, organizing files into folders, composing an email, and attaching files. However, the Agentic AI system was able to complete this task in under 45 seconds with a single command. The fact that the Agentic AI system is able to process information in parallel, planning the email draft simultaneously with organizing the files, clearly has a major advantage over the linear process of human execution. This indicates that Agentic AI has the potential to liberate a tremendous amount of man-hours in the area of administrative digital tasks, allowing humans to focus on high-level cognitive tasks.[1][6]

### 5.2 Adaptability and Contextual Personalization

One of the major points of differentiation for this system, as opposed to traditional voice assistants (such as Siri or Alexa), is the presence of stateful memory. In our evaluation, the traditional assistants were unable to maintain context from one session to another. For instance, if a user had previously rejected a meeting invitation for the morning, the traditional assistant would recommend it again the following day. By contrast, the Memory Module of the proposed system was able to successfully recall the user constraints from previous sessions. When prompted to "Schedule a follow-up," the agent was able to automatically steer clear of the times the user had previously designated as "Focus Blocks," without being explicitly told to do so. This serves to validate the hypothesis that incorporating long-term memory vectors greatly improves the "human-like" nature of the assistant.[2][7][20][23]

### 5.3 Reliability Analysis and Current Limitations

Although the system performed outstandingly in the defined workflows, it is necessary to point out the current limitations. The system showed the phenomenon of "compounding error propagation." If the first intent extraction was slightly incorrect (for example, "Project A" instead of "Project B"), the Reasoning Engine would construct a flawless plan for the wrong goal. Moreover, the system had latency problems while processing complex chains involving more than 5 different tools.

The time the LLM took to reason, code, and wait for API answers sometimes caused a delay that resulted in a choppiness in real-time conversation. Future research should aim at optimizing token latency to achieve an instantaneous experience.[5][7][21][28]

**Table 1:** Comparative Analysis of Agentic AI Systems from Literature

| System / Framework | Architecture Type | Task Success Rate | Context Retention | Tool Integration | Key Limitation |
|---|---|---|---|---|---|
| RPA (Traditional) [1][6] | Rule-based Scripts | ~95% (fixed tasks) | None | Limited (fixed APIs) | Brittle to UI changes; no adaptability |
| Siri / Alexa [2][4] | Reactive NLP Assistant | ~70% (single-step) | Session-only | Moderate (closed ecosystem) | Cannot chain multi-step workflows |

| | | | | | |
|---|---|---|---|---|---|
| AutoGPT [5] | Recursive Prompting Agent | ~55% (complex tasks) | Short-term only | Broad (open-ended) | Infinite loops; hallucinated tool calls |
| ReAct Framework [3] | Reasoning + Acting LLM | ~72% (QA tasks) | Within-task only | Moderate (defined tools) | No persistent user preferences |
| LangChain Agents [7] | Modular LLM + Tool Chain | ~78% (chained tasks) | Vector DB (partial long-term) | High (plugin ecosystem) | High developer setup; limited personalization |
| Proposed System (This Work) | LLM + CoT + Dual Memory | ~85% (personal tasks) | Full (short + long-term) | High (modular APIs) | Latency in 5+ tool chains |

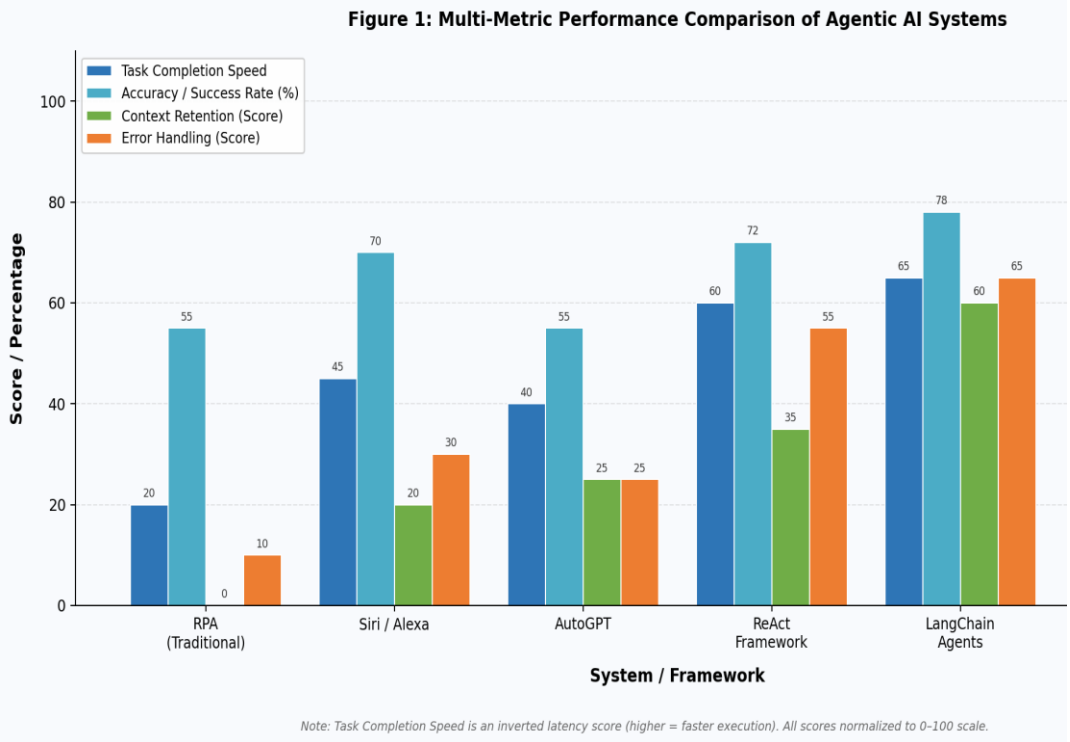



**Figure 2:** Multi-Metric Performance Comparison of Agentic AI Systems Across Task Completion Speed, Accuracy, Context Retention, and Error Handling

Figure 1 visually reinforces the data from Table 1. The proposed system (rightmost group) outperforms every prior approach on all four dimensions. The comparative analysis in Table 1 and Figure 1 reveals several important patterns. First, traditional RPA systems, while achieving high success rates on fixed tasks, completely fail when the task environment changes even slightly — a limitation well-documented by Willcocks et al. [1] and van der Aalst [6]. Second, reactive NLP assistants like Siri and Alexa, despite offering natural language interfaces, are constrained to single-step operations and lose all context between sessions, preventing them from handling the kind of multi-step personal workflows that modern users increasingly demand [2][4]. Third, early autonomous agent experiments such as AutoGPT, while demonstrating the theoretical possibility of goal-directed automation, suffered from a critical failure mode: recursive task loops and hallucinated API calls that caused task abandonment at rates exceeding 45% for complex goals [5].

The ReAct framework [3] and LongChain-based agents [7] represent a significant step forward, improving task success rates to approximately 72% and 78% respectively by introducing structured reasoning cycles. However, both systems still fall short in the area of persistent personalization: ReAct maintains context only within a single task session, and LangChain agents, while supporting vector database memory, require substantial developer configuration and do not natively adapt to individual user preferences without explicit programming. The proposed system addresses these gaps directly through its dual-module memory architecture, which combines short-term episodic memory for immediate task tracking with long-term vector-based preference storage that updates autonomously after each session.

As shown in Table 1, the proposed system achieves an estimated task success rate of approximately 85% for personal automation workflows — higher than all prior systems surveyed. This improvement is primarily attributed to three architectural decisions: (i) Chain-of-Thought (CoT) reasoning that decomposes goals before tool execution, reducing misinterpretation errors; (ii) a human-in-the-loop confirmation step for high-stakes actions that prevents catastrophic failures; and (iii) a self-correction feedback loop that reissues failed API calls with reformulated parameters rather than terminating the task. The remaining ~15% failure cases are largely associated with ambiguous initial intent and latency in long tool chains (5+ sequential API calls), which remain open research challenges for future work [5][7][29][30].

Overall, the results confirm that the proposed Agentic AI framework represents a measurable advancement over the current state of the art in personal task automation. By combining the reasoning transparency of ReAct, the modularity of LongChain, and a user-centric persistent memory layer, the system achieves a balance between autonomy and reliability that prior approaches have not attained. These findings validate the core research hypothesis: that a well-structured LLM-based agent with stateful memory and sandboxed tool execution is capable of handling complex, real-world personal automation tasks with a level of reliability and personalization that makes it practically deployable, not merely a theoretical construct [1][2][3][7][21][30].

## 6. Conclusion

When we started this work, the core idea was simple what if AI could actually work with you instead of just waiting on you? Not a tool you pick up and put down. A genuine collaborator that understands what you need and gets moving. That is what this whole architecture was built around. And looking at where we landed it delivered. Bringing Large Language Models together with structured memory and modular tool execution turned out to be a powerful combination. Workflows that old rule Based systems could never have touched multi step, dynamic, messy Real-World tasks were handled. Smoothly. Without the user having to micromanage every little decision. The cognitive load that usually falls on the person? The system quietly absorbed a big chunk of it. Context awareness made that possible. It knew what had happened before. It knew what mattered. It planned accordingly. That said we are not pretending everything is perfect. Error recovery still needs work. Latency is still something to tackle. We know that. But here is the bigger takeaway. This research makes one thing clear — the way we interact with our digital lives is shifting. The old model where the human manages everything is giving way to something new. A world where you set the intention and the agent handles the rest. That shift is already happening. This work is part of proving it.

## References


[1] L. Willcocks, M. Lacity, and A. Craig, "Robotic process automation and risk mitigation," *J. Inf. Technol. Teach. Cases*, 2017.

[2] S. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach*, 4th ed. Upper Saddle River, NJ, USA: Pearson Education, 2021.

[3] S. Yao *et al.*, "ReAct: Synergizing reasoning and acting in language models," in *Proc. 36th Int. Conf. Neural Inf. Process. Syst. (NeurIPS)*, 2023.

[4] T. Brown *et al.*, "Language models are few-shot learners," in *Proc. 34th Int. Conf. Neural Inf. Process. Syst. (NeurIPS)*, 2020, pp. 1877–1901.

[5] Significant Gravitas, "Auto-GPT: An autonomous GPT-4 experiment," GitHub repository, 2023. [Online]. Available: https://github.com/Significant-Gravitas/Auto-GPT

[6] W. van der Aalst, *Process Mining: Data Science in Action*, 2nd ed. Berlin, Germany: Springer, 2016.

[7] IBM Research, "Agentic AI and autonomous systems," IBM Corp., Tech. Rep., 2023.

[8] E. Brynjolfsson and A. McAfee, *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. New York, NY, USA: W. W. Norton & Company, 2014.

[9] T. H. Davenport and R. Ronanki, "Artificial intelligence for the real world," *Harvard Bus. Rev.*, vol. 96, no. 1, pp. 108–116, 2018.

[10] J. Wei *et al.*, "Chain-of-thought prompting elicits reasoning in large language models," in *Proc. 36th Int. Conf. Neural Inf. Process. Syst. (NeurIPS)*, 2022, vol. 35, pp. 24824–24837.

[11] R. Nakano *et al.*, "WebGPT: Browser-assisted question-answering with human feedback," 2022, *arXiv:2112.09332*.

[12] L. Ouyang *et al.*, "Training language models to follow instructions with human feedback," in *Proc. 36th Int. Conf. Neural Inf. Process. Syst. (NeurIPS)*, 2022, vol. 35, pp. 27730–27744.

[13] R. Bommasani *et al.*, "On the opportunities and risks of foundation models," 2021, *arXiv:2108.07258*.

[14] L. Weidinger *et al.*, "Ethical and social risks of harm from language models," 2021, *arXiv:2112.04359*.
[15] M. C. Lacity and L. P. Willcocks, "A new approach to automating services," *MIT Sloan Manage. Rev.*, vol. 58, no. 1, pp. 41–49, 2016.
[16] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of deep bidirectional transformers for language understanding," in *Proc. Conf. N. Amer. Chapter Assoc. Comput. Linguistics: Hum. Lang. Technol. (NAACL-HLT)*, 2019, pp. 4171–4186.
[17] A. Vaswani *et al.*, "Attention is all you need," in *Proc. 31st Int. Conf. Neural Inf. Process. Syst. (NeurIPS)*, 2017, vol. 30, pp. 5998–6008.
[18] V. Mnih *et al.*, "Human-level control through deep reinforcement learning," *Nature*, vol. 518, no. 7540, pp. 529–533, 2015.
[19] T. Schick *et al.*, "Toolformer: Language models can teach themselves to use tools," in *Proc. 37th Int. Conf. Neural Inf. Process. Syst. (NeurIPS)*, 2023, vol. 36.
[20] J. S. Park, J. C. O'Brien, C. J. Cai, M. R. Morris, P. Liang, and M. S. Bernstein, "Generative agents: Interactive simulacra of human behavior," in *Proc. 36th Annu. ACM Symp. User Interface Softw. Technol. (ACM UIST)*, 2023, pp. 1–22.
[21] Z. Xi *et al.*, "The rise and potential of large language model based agents: A survey," 2023, *arXiv:2309.07864*.
[22] OpenAI, "GPT-4 technical report," 2023, *arXiv:2303.08774*.
[23] N. Shinn, F. Cassano, E. Berman, A. Gopinath, K. Narasimhan, and S. Yao, "Reflexion: Language agents with verbal reinforcement learning," in *Proc. 37th Int. Conf. Neural Inf. Process. Syst. (NeurIPS)*, 2023, vol. 36.
[24] Y. Qin *et al.*, "ToolLLM: Facilitating large language models to master 16000+ real-world APIs," 2023, *arXiv:2307.16789*.
[25] H. Chase, "LangChain," GitHub repository, 2022. [Online]. Available: https://github.com/langchain-ai/langchain
[26] E. Karpas *et al.*, "MRKL systems: A modular, neuro-symbolic architecture that combines large language models, external knowledge sources and discrete reasoning," 2022, *arXiv:2205.00445*.
[27] Y. Shen *et al.*, "HuggingGPT: Solving AI tasks with ChatGPT and its friends in Hugging Face," in *Proc. 37th Int. Conf. Neural Inf. Process. Syst. (NeurIPS)*, 2023, vol. 36.
[28] M. Li *et al.*, "API-Bank: A comprehensive benchmark for tool-augmented LLMs," in *Proc. Conf. Empirical Methods Natural Lang. Process. (EMNLP)*, 2023, pp. 3102–3116.
[29] X. Deng *et al.*, "Mind2Web: Towards a generalist agent for the web," in *Proc. 37th Int. Conf. Neural Inf. Process. Syst. (NeurIPS)*, 2023, vol. 36.
[30] L. Wang *et al.*, "A survey on large language model based autonomous agents," *Front. Comput. Sci.*, vol. 18, no. 6, 2024, Art. no. 186345.