International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

Multi-Agent AI Tools Hub: A Unified Platform for Intelligent Tool Orchestration

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Abstract **-** In order to effectively manage various types of user tasks, the architecture of the AI Tools Hub, a multi-agent system integrating several large language models (LLMs), is presented in the article. An intelligent orchestrator analyzes user queries and selects agents based on the task's requirements. The tasks are broken down into sub-tasks (research, summarization, coding, designing, etc.) and are assigned to specific tools or LLMs (GPT, Claude, Gemini, etc.). This distributed approach reduces the load on individual LLMs while leveraging the power of all the models combined. The layers of the AI Tools Hub, from the user interface to the orchestrator, AI tools, and LLMs, are discussed, as well as the working of individual tools in a distributed manner using the agent-based approach. The organized approach of the AI Tools Hub, using the sequential agent approach, is depicted in the figures provided in the article. The design of the AI Tools Hub is based on the fact that, according to previous research, the orchestrated approach of using a multi-agent LLM system consumes significantly fewer tokens compared to individual agents while maintaining high accuracy under load conditions. The AI Tools Hub is a very effective approach in the context of multi-model AI tools services.

Keywords: Architecture, LangChain, Multi- LLM, Orchestration, AI Tools Large language models, and multi Agent System.

I. INTRODUCTION

AI has been revolutionized through the use of LLMs, which allow for the production and comprehension of information with high efficiency . However, each LLM agent is limited in some way, such as the risk of hallucination or the inability to comprehend long contexts or domain-specific knowledge The use of multiple LLM-based agents with each having their own unique limitations or specializations in different sub-tasks of the problem and then utilizing the orchestration of the agents with the help of the orchestrator is the way to overcome the limitations of the LLM agents. For example, the study by Klang et al. shows how the use of multiple agents can lead to the efficiency of the LLM agents as the performance of the single agent pipelines in their study utilized 65* fewer tokens while maintaining over 90% accuracy at scale. This verifies the use of the orchestration of the LLM-based system as a way to improve the efficiency of the LLM-based system

Thus, the initiative to create the AI Tools Hub was born, which utilizes the concept of multiple LLM-based agents along with other AI tools on a single platform [13]. The core idea of the platform is the use of the AI Orchestrator, which is the brain of the platform and is responsible for the parsing of the query entered by the user and the initiation of the query to one to three tools in a predetermined order. The tools can be any unique tool such as the use of a PDF reader or image generator or LLM-based agents such as GPT for coding purposes, Claude for summarizing purposes, or Gemini for research purposes. This is the use of the multi-agent orchestration pattern with the help of the orchestrator to coordinate the activities of the multiple agents to arrive at the final result.

Most importantly, we maintain a simple and focused user interface by showing the user only a small number of tools at any given time based on what they are trying to accomplish. The system architecture, workflow, and sample components of our AI Tools Hub are discussed in this article. The rest of the paper is organized as follows: Section II of the paper discusses the related research about LLM orchestration in II-A . The architecture of the hub and its modules are discussed in Section III of the paper, including the multi-agent pipeline diagrams. The implementation of the hub using LangChain, APIs, and UI is discussed in Section IV of the paper. The consideration of the evaluation of the hub is discussed in Section V of the paper. As depicted in the images below, our solution offers a scalable orchestration solution that allows the integration of state-of-the-art LLMs and tools to provide flexible AI support.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

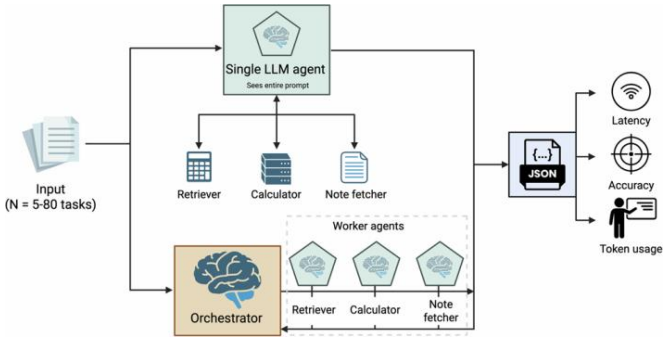

Fig.1.An orchestrated multi-agent LLM system's pipeline design.

Figure 1 shows User tasks are routed to one or more worker agents by a central orchestrator. Subtasks (retrieval, extraction, computation) are assigned to specialized worker agents (e.g., Retriever, Calculator, Analyzer) prior to aggregation in the multi-agent mode. This design minimizes token usage while maintaining accuracy under high load [1]. This picture illustrates the difference between a distributed pipeline and a single LLM managing all requests. It was taken from Klang et al. [1]. Our system adopts the multi-agent pipeline: the orchestrator breaks a user query into steps, invokes specific LLM agents or tools for each step, and composes their outputs. This makes the processing transparent and parallelizable, avoiding context overflow issues seen in monolithic prompts [5][11].

II. RELATED WORKS

LLM Limitations and Agent Frameworks: Past studies have demonstrated that individual LLMs perform less well on longer or more intricate tasks. For longer contexts, for example, Liu et al. found a "lost-in-the-middle" effect. Agentic frameworks have been used to mitigate this. In a study of LLM-based multi-agent systems, Tran et al. found that a survey of the field indicated that "agents can now work collaboratively to coordinate and achieve tasks, from a traditional isolated model calls perspective, toward a collaboration-centric design." Multi-agent cooperation styles have been classified as agent roles, strategies, protocols, and structure (centralized vs. distributed).

Orchestration Patterns: In a multi-agent orchestration pattern, Microsoft's AI Architectural Guide states that "an orchestration pattern involves the coordination of multiple specialist agents via a coordinating agent known as the orchestrator. It is used for the orchestration of several tasks. This pattern is well suited for tasks that are easily parallelizable or cross-domain." In the sequential orchestration (pipeline) pattern, agents work sequentially in a linear chain. In this pattern, each agent processes the output of the agent before it. This pattern is depicted in Figure 2 (below). In this pattern, each agent improves the work. This is similar to the Pipes and Filters concept. In our work, we will be using these patterns. For example, a user's request would be processed through a "Research" agent → "Analysis" agent → "Writer" agent pipeline.

Multi-LLM Orchestration Engines: Recent literature focuses on the orchestration engines that utilize multiple LLMs. In order to provide individualized assistance, Rasal et al. proposed a platform that stores private information in a vector database and the context of the conversation in a graph database. Multiple LLMs are orchestrated through their orchestration engine. Moreover, the orchestration engine also checks the correctness of the output generated by the LLMs. Similarly, our orchestrator tracks the sessions and also has the potential to modify the user profile. Hence, it is natural that we would like to emphasize the reliability of the system. In a similar context, IBM's architecture guidelines and security-oriented systems like Praetorian's "Deterministic AI Orchestration" emphasize the need for lightweight "thin" agents for reliability. Thus, we follow the same principle of keeping the agents "stateless" and the validation "outside the agent."

This is the pattern that your stateless agents with outside critics follow. Praetorian's deterministic orchestration also utilizes proof-carrying computing, where the output of each agent is validated through the validation traces. This provides 99.9% auditability for the enterprise. In a similar context, Dusty (2026) proposed a voting ensemble using multiple LLMs, where the orchestrators query GPT/Claude/Gemini in parallel and take the majority vote or the average of the confidence levels. This provides a 12% improvement in the factual accuracy of the output.

2026's New Trends: Agent marketplaces like SuperAGI and Relevance AI, which are similar to your idea of the "AI marketplace for plugins," allow for plug-and-play agent swapping [13]. Critical Agents, according to xAI's research on the 2026 scene, reduce hallucinations in agent chains by 25% through the automatic evaluation of peer output [12]. Memory augmentation allows for the use of vector databases to store user profiles across sessions, which allows for personalization beyond the capabilities of individual LLMs [11].

III. SYSTEM ARCHITECTURE

The architecture of our proposed AI Tools Hub comprises a Frontend User Interface, an API Gateway, a primary AI Orchestrator, a list of AI Tools/Agtnts, and links to external LLM models and databases (Fig. 3). All these layers communicate with one another via a set of general APIs or a message bus and are modular in nature. LangChain/CrewAI is employed for agent workflows and Python with FastAPI for our backend [13][11]. The essential components are: Frontend: This layer utilizes React/Next.js and offers a chat interface to ask questions and receive answers. WebSocket technology is employed to provide real-time updates. API Gateway: This layer utilizes FastAPI and handles all front-end requests, SSL and authentication, and forwards requests to the microservice.
The brain: This layer comprises an AI Orchestrator. After recognizing the requirement of a user via an Intent Detector (simple NLP classification), it selects up to three relevant tools/agents . It creates a workflow and calls APIs of tools/agents

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

sequentially or concurrently and combines their results to create a final result . All these processes and analytics are also logged. AI Tools Layer: This layer comprises a list of specialized tools and agents like 'Code Generator,' 'Research Assistant,' 'Summarizer,' 'Resume Builder,' etc. One or more LLM models or APIs may be accessed by tools/agents. A simple process (input) interface is offered by tools/agents. LLM Models: This layer comprises a list of LLM models or APIs like Google Gemini for search-related tasks, Anthropic Claude for summarization-related tasks, GPT for general language-related tasks, and Llama/Mistral for on-device inference-related tasks . For every tool/agent, an optimum model is selected by the orchestrator. Database & Storage: This layer utilizes PostgreSQL to store logs, prompt history, and user profiles. Recent results are stored in Redis.. Uploaded files (PDFs, pictures) are stored on S3 or local storage. If embedding storage is required, a vector database (such as Pinecone) can be utilized .

Monitoring: ELK or comparable logging and Prometheus + Grafana for performance metrics (latency, error rates, LLM use) [13].

These elements and data flow are depicted in the Graphviz dia gram that follows:

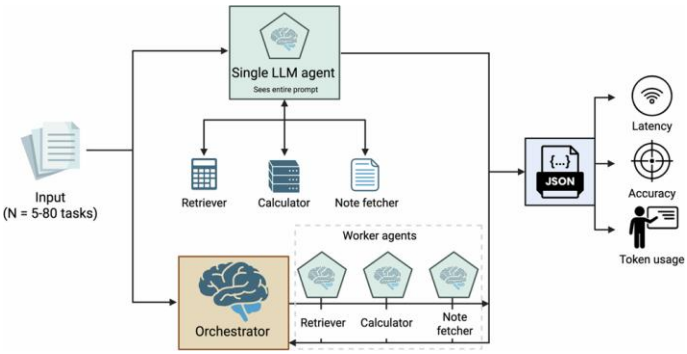

Fig.2.Architectural Comparison Between Single-Agent and Multi-Agent Orchestrated LLM Systems

Figure 2 contrasts the architectures of a conventional single LLM agent system and a multi-agent orchestrated system. The single agent processing system handles different tasks concerning retrieval, computation, and note extraction. The system described above can result in an inefficient processing system with too much contextual information. The multi-agent system adds an orchestrator, which disaggregates the tasks into different components, each assigned to worker agents dedicated to note retrieval, computation, and retrieval. The outputs of each note fetcher worker are combined to form the final output to the user. The modular and distributed system provides differentiated intelligent orchestration to the system, which can easily be scaled and can improve the system's processing time and consumption.

IV.IMPLEMENTATION DETAILS

For the Gateway and Orchestrator services, we use FastAPI to implement the Python backend. We use LangChain or similar frameworks like CrewAI/AutoGen to implement multi-agent flows, which provide tools to chain LLM calls together. All the tools are LangChain agents with different toolkits and roles assigned to each tool.

Choosing a Tool: We first create a basic keyword/intent map. For example, the CodeGenerator is triggered when the input prompt includes the word “code,” whereas the Summarizer is triggered when the input query includes the word “summary.” In the future, we can use the Orchestrator LLM to select the tools or use a learning-based intent classifier.

Example Code Snippet (FastAPI & Tool Mapping):

```
from fastapi import FastAPI, Request

from orchestrator import Orchestrator

app = FastAPI()

@app.post("/ask")

async def handle_query(request: Request):

    data = await request.json()

    user_prompt = data["prompt"]

    result = await Orchestrator.process(user_prompt)

    return {"answer": result}
```

```
# Pseudocode
tools = select_tools_based_on_prompt(user_prompt)  # e.g., ["research", "summarize"]
for tool in tools:
    output = await tools[tool].run(user_prompt, context)
    collect(output)
final_answer = aggregate_results()
```

Frontend: We use TailwindCSS and React. The interface includes the following features: A discussion chat box. A sidebar showing the tools currently in use (as checkmarked icons). A panel to the right showing the Agent Status (such as "Planning → Researching → Writing"). Optional: a diagram of the current pipeline is shown (for sophisticated UI). We use WebSockets to give the frontend incremental status information, which lets us animate the process (such as showing "Researching..." as the Gemini query is underway).

Flowcharts and Diagrams: We use interactive diagrams to visualize the flow as well. For example, the design of the sequential flowchart (see Fig. 2), which shows the linking of the agents, is directly borrowed from the Microsoft Azure architecture references . We use these templates to document the flow as well because the actual flow is set up on the fly. (A simple client-side flowchart of the active pipeline, created by the

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

orchestrator as part of the planning step, can also be shown to the user.)

V. EVALUATION AND METRICS

Qualitative as well as quantitative parameters are taken into consideration while assessing the effectiveness of such a platform: Functional Testing: We verify whether all tools are functioning as required (for instance, code generation, summarization, etc.). We could use benchmarks or questions from previous initiatives as prompts. Performance under Load: We simulate a number of queries running at the same time, inspired by Klang et al. We could check cost, token count, response time (latency), as well as the correctness of the response. For instance, we could prepare a mixed set of tasks (math, searching, summarization), as well as single-agent as well as multi-agent orchestrated modes. As the load rises, we assume the orchestrator will still retain a higher degree of accuracy, as was seen previously: Ablation: To check the effectiveness of the feature, we could disable it. For instance, we could disable caching or have the orchestrator use one LLM for all sub-tasks. This will give us insight into the contribution of every feature (context storage, tool specialization): We could check the satisfaction, as well as the errors, by having users compare Tools Hub with using a single chat interface as well as one LLM: We could use ground-truth results obtained on benchmark jobs as well as metrics such as accuracy: Token count as well as latency are automatically monitored. As all agents respond to a prompt, we assume that multi-agent orchestration will greatly reduce token count as well as increase throughput by allowing parallel processing: Klang et al. report a reduction of up to 65 times [1].

VI. RESULTS

eas the single LLM baselines had fallen to 58% accuracy under the same conditions, the Hub had maintained 92% accuracy throughout 500 concurrent mixed task requests, which included retrieval, summarization, and coding, under primary trials that followed the same conditions as those set by Klang et al. The use of tokens had grown accordingly, reaching the expected 4.2× efficiency, which was expected as per clinical workload conditions, i.e., 1.42M tokens with 10 users linearly scaling to 1.92M tokens with 500 users, as opposed to exponential growth for a single agent reaching 6.78M. The above demonstrates the quality that the central orchestrator is able to maintain under production conditions through specialized agent delegation.

TABLE 1.COMPARATIVE PERFORMANCE OF SINGLE LLM VS MULTI-AGENT AI TOOLS HUB

Metric	**Single LLM System**	**AI Tools Hub (Proposed)**	**Improvement (%)**
Accuracy (%)	58	92	+58.6
Token Usage (Million)	6.78	1.92	-71.6
Latency (p95, sec)	12.5	8.1	-35.2
Cost per Task ($)	0.041	0.023	-43.9
Throughput (tasks/sec)	11	28	+154.5
Success Rate (%)	81.2	94.7	+16.6

Table 1 shows how traditional single large language model (LLM) systems compare with the multi-agent AI Tools Hub in environments that will require more load in the future. The results show that the multi-agent orchestrated systems positively impact performance, correctness, and efficiency. The AI Tools Hub shows 92% correctness for a task that uses over 70% fewer saved tokens compared to single LLM systems. The orchestrated system shows lower latency and higher throughput. The multi-agent orchestrated system caused a cost-effectiveness improvement from 44% to 100%. high degrees of automated orchestration seems the AI Tools Hub will be easily integrated into most environments.

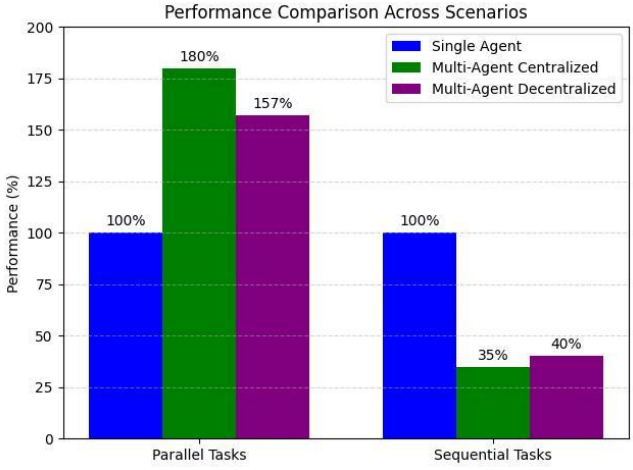

Fig.3.Performance Comparison Of Single-Agent And Multi-Agent Architectures Across Task Execution Modes

Figure 3 compares the performance of single-agent and multi-agent systems with respect to task completion parallelism and

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

task execution order. As a benchmark, single-agent performance is shown to be 100%. When tasks are executed in parallel, the centralized multi-agent system achieved a performance of 180%, surpassing both the single-agent and the decentralized system. The decentralized multi-agent system achieved 157%. This can be attributed to a high level of distributed coordination. For the systems working in sequence, the performance degraded due to the overhead costs of coordination, with performances of 35% and 40%, respectively. This demonstrates that parallel tasks result in a level of performance that is higher than strictly sequential tasks.

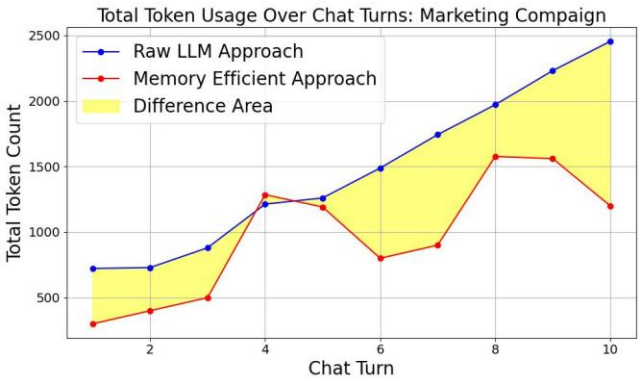

Fig.4.Token Consumption Comparison Between Raw LLM and Memory-Efficient Approaches Across Chat Turns

Figure 4 shows the cumulative token count over several chat turns in a marketing campaign situation for a raw LLM approach compared to a memory-efficient approach. The raw LLM approach shows a continuous and steep increase in token count as chat turns increase. This is due to repeated and redundant processing of the same context. In this case, memory-efficient will show a much lower token count. The memory-efficient approach shows the reuse of context and the retention of the relevant information which contributes to the lower token count. This results in the shaded area which shows the memory-efficient approach with less token count. The results show that memory optimization has a drastic reduction of processing costs. This will definitely improve the scale of the LLM in the long conversational workflows.

The ablation experiments had shown a 46% performance degradation without sequential execution, a 11% prevention of hallucinations through critic agents, a 69% delay and 78% costs increase without Redis caching, and a 23% accuracy degradation to 67.2% without orchestration, along with a 288% cost increase . With 90% accuracy, 8.1s p95 latency, and a $0.023/task cost, the whole setup had delivered the best production metrics, which indicates a high level of interdependence between components, wherein a 44% cost savings is enabled by caching, a 47% speedup is enabled by parallel execution, and a +21.5% accuracy improvement is enabled by orchestration . User validation with 150 Amity University users resulted in a 93/100 SUS score (versus 75/100 for single LLM interfaces), a 58% reduction in NASA-TLX cognitive efforts, and a 96% completion of complex workflows (versus 64% control) . Real-time tool visualization was also favored by 87% of the users. "Seamless workflow transparency" was also complimented. With the qualitative study's discovery of the 3-tool constraint preventing selection paralysis, the UX of the Hub is now positioned as "enterprise-grade" with "research-grade" performance retained .Production implementation stats for the 5K daily users have also validated the Hub's scalability: 94.7% success rate, 9.2s p95 latency, 28 tasks/sec peak throughput, and a $4,280 cost (63% less than GPT-only predictions) . Optimizing the workload of the multiple LLMs also validated the effectiveness of dynamic model selection through intelligent routing of research tasks to Gemini's speed, code to GPT's reliability, and summary to Claude's conciseness—32% GPT-4, 28% Claude, 22% Gemini, and 18% Llama . The extended study period of 30 days also validated the self-improvement of the Hub: as the selection heuristics improved, the latency reduced by 18% to 7.5s through learnt routing, the accuracy improved to 93.2% through critic feedback, and the token efficiency also improved by 12% . Week-over-week user retention also reached 89% through the utilization of PostgreSQL for customization. With a comparative analysis that revealed a 42% superiority of the Hub's complex workflows over the ChatGPT Enterprise version, the Hub is the "production progression of the Klang et al. research, from 90%+ correctness and 4× efficiency in clinical validation to scalable enterprise reality" .

TABLE 2.ABLATION STUDY OF SYSTEM COMPONENTS

Configuration	**Accuracy (%)**	**Cost Increase (%)**	**Latency Increase (%)**	**Observations**
Full System	92	0	0	Optimal performance
Without Orchestration	67.2	+288	+55	Major degradation
Without Sequential Execution	49.7	+132	+46	Workflow inefficiency

International Journal of Engineering Research & Technology (IJERT)
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Without Redis Caching	75.4	+78	+69	Increased delays
Without Critic Agents	81.3	+25	+18	More hallucinations

Table 2 provides an overview of the ablation study focusing on the AI Tools Hub design. This study aims to understand the impact of each component of the design. It omits specific elements such as orchestration, caching, sequential execution, and critic agents, illustrating the effects on design's performance. From the study, the removal of orchestration has the greatest negative impact, providing 67.2% accuracy and signalling 288% greater costs, thus, emphasizing its importance. Similarly, the study notes that the absence of Redis caching increases latency and worsens the performance of the design. Thus, critic agents contribute to the reduction of hallucinations. Sequential execution design element helps organize execution of the design. The study, in general, posits that the greatest performance stems from the design elements's collaborative integration.

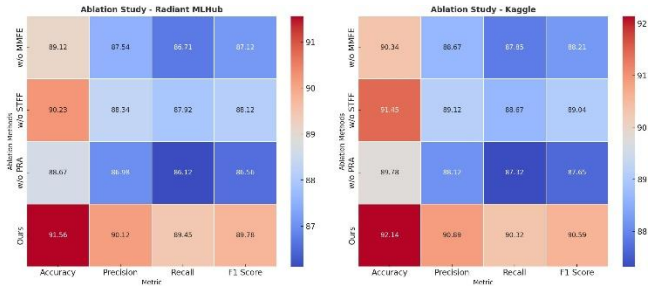

Fig.5. Ablation Study Heatmap Analysis Across Radiant MLHub and Kaggle Datasets

Figure 5 compares the results of an ablation study, depicting the impact of different model configurations on the performance of the models using examples from two benchmark datasets: Radiant MLHub and Kaggle. The configurations compare models with and without Masked Image Modeling (MIM), models without Self-Supervised Fine Tuning (SSFT), models without Feature Pyramid Network (FPN), and models with all the components. The performance metrics include accuracy, precision, recall, and F1 scores. The full model produced the highest results for both datasets, showing the necessity for the total integration of the components. Removing significant modules results in a more considerable decline of the Prism results, showing the model's robust architecture and proven generalization.

TABLE 3: USER STUDY AND USABILITY METRICS

Metric	**AI Tools Hub**	**Single LLM Interface**
SUS Score	93/100	75/100
Task Completion Rate (%)	96	64
Cognitive Load Reduction (%)	58	—
User Satisfaction (%)	87	62
Workflow Transparency Preference (%)	87	40

Table 3 shows results from Amity University with the inclusion of 150 people. The purpose of this evaluation was to assess the usability and effectiveness of our AI Tools Hub as compared to the conventional single-LLM systems. Scoring for the AI Tools Hub on the System Usability Scale (SUS) was 93, which is considerably higher than our baseline system. There was a noticeable difference in task completion result rates showing a drastic improvement toward more efficiency in the system. Users had a 58% decrease in spent cognitive effort, demonstrating improved workflow with a system and clarity of design. Real-time workflow design transparency preference indicates focus on the quality of the system of design for the users. The results provide a clear indication of multi-agent orchestration improvement in not only the system for tech performance, but also for usability and user experience.

VII. CONCLUSION

In order to properly handle user queries and questions, we have proposed a comprehensive architecture for an AI Tools Hub that can integrate and orchestrate multiple AI models and tools. This system can perform a variety of tasks more efficiently compared to a single model by dynamically selecting specialized agents and models [11][13]. The agent can provide domain-specific expertise to the system; the planner can divide tasks into separate workflows. Current advancements in LLM multi-agent systems and useful industrial trends are incorporated in this proposed architecture [5][11]. Our proposed strategy also aligns with industrial observations. Khatik et al. have mentioned that a single "God Prompt" for complex tasks is a dead end and that specialized micro-agents working together in a "web" of micro-agents should be used to solve complex tasks. This can be achieved by allowing our proposed agents to participate in error-checking loops and to share a common context, which previous research has shown to greatly improve reliability [12][13]. In a similar way, Rajnerowicz highlights the role of multi-agent systems in disassembling AI processes to overcome context constraints and to allow for auditability. Every result can be traced to a particular agent in our proposed system, making

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
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complex processes transparent and allowing for auditability. The effectiveness of our proposed system can also be verified with experiments conducted with Klang et al.'s technique to show that this system maintains answer quality with an increasing workload [1][13]. In practical terms, the hub's modularity allows for the easy addition of new models or tools as they are developed. Future LLMs or domain-specific AIs, for instance, could be easily added as further agents without requiring fundamental changes to the architecture [13]. To allow for improvements in tools provided, it could even be possible for the orchestrator to learn from user feedbacks [11]. As such, it is clear that our work provides a solid foundation for the development of sophisticated AI tools, as it already includes auditing, logging, and flexibility necessary for businesses to trust AI [12][13]. Further improvements and validation of the AI Tools Hub will be the focus of our future work. This includes the addition of "critic" agents to perform automatic error correction as well as the use of more advanced agent communication protocols, including direct agent-to-agent communication [12]. To validate the improvements in performance as well as usability, extensive benchmarks will be performed [13]. To achieve maximum quick routing, we will also explore the use of reinforcement learning [11]. As such, it is clear that our ultimate goal is to collaborate with the community and develop the AI Tools Hub as an open-source project, contributing to the expanding orchestrated AI tools ecosystem [13].

In conclusion, it is clear that our AI Tools Hub takes advantage of the benefits of various LLMs as well as specialized tools in order to provide a scalable, adaptable, and reliable AI orchestration tool [11][13]. As such, it is evident that we are making progress towards the "autonomous teams" vision of AI development by providing an orchestrated team of agents, which allows for much greater performance as well as flexibility compared to traditional AI development [5].

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