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Digital Personal Assistants Using Agentic LLM's

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Abstract: *The LLM-powered agents are designed to be proactive and adaptable, capable of complex reasoning and task execution. A central concept is Agency, defined as the model's capacity to proactively manage collaboration and interaction. Researchers measure agency using a framework based on social-cognitive theory, which identifies key features like intentionality, motivation, selfefficacy, and self-regulation.*
LLM agents are being explored for various applications, including digital personal assistance, customer service, and e-commerce. In one study, LLM agents acted as "digital twins" to simulate customer behavior and evaluate the performance of agentic AI systems. The study found that while the agents made more diverse choices, their actions and feedback were aligned with human participants, making them a valuable tool for evaluation.
Efforts are also underway to standardize the design of these blocks and proposing a Cognitive Skills Module with domain-specific capabilities. This standardization would allow for the development of multi-agent systems where specialized agents collaborate to complete complex tasks specified in natural language, improving efficiency and reliability. This new era of LLM-powered agents promises to reinvent workflow automation and drive industry specific applications. systems by identifying core building.

Keywords: Agentic Systems, Large Language Models, LLM powered Agents, Social Cognitive Theory, Self Efficacy, Self Regulation, Workflow Automation, Human-AI Collaboration, Efficiency and Reliability, Industry -specific Applications.

I. INTRODUCTION

The Topic describe a new era of AI driven by Large Language Models (LLMs) that are evolving from simple conversational tools into autonomous agentic systems. Unlike traditional assistants, these agents are proactive, adaptable, and can perform complex tasks. This shift is defined by the concept of Agency— the ability of an
LLM to proactively direct collaboration and shape events. Researchers measure agency based on four key features: intentionality, motivation, self-efficacy, and selfregulation.
To address the challenge of evaluating these rapidly evolving systems, a new method uses LLM agents as "digital twins" to simulate human users and provide feedback. A study found that these digital twins can provide reliable behavioral insights and feedback that align with human responses, making them a scalable evaluation tool.
For consistency and scalability, there is a push to standardize agent design, including a Cognitive Skills Module for domain-specific capabilities. This will enable multiagent systems where specialized agents collaborate on complex tasks, improving efficiency and reliability.
These advancements promise to reinvent workflow automation and drive industry-specific applications.

II. LITERATURE SURVEY

Digital personal assistants powered by agentic large language models (LLMs) are revolutionizing workflow automation by enabling autonomous decision-making, contextual understanding, and multistep task execution. These systems differ from traditional rulebased automation by leveraging LLMs to interpret natural language, reason through complex problems, and interact with external tools and APIs to perform tasks dynamically. Research highlights that agentic LLMs are not just passive information processors but active agents capable of planning, adapting, and learning from interactions [1].

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Efficiency is another critical area of focus. The paper highlights the importance of optimizing both LLM inference and memory management to ensure that personal agents operate effectively on mobile and edge devices. Techniques such as vector databases and retrieval-augmented generation (RAG) are discussed as ways to enhance memory retrieval and reduce computational overhead. Additionally, the use of lightweight models and on-device inference is emphasized to improve performance while maintaining low power consumption and fast response times
[2].

The study by Sharma et al. (2024) explores the agency of large language models (LLMs) in human-AI collaboration, emphasizing how LLMs can exhibit traits like intentionality, motivation, selfefficacy, and self-regulation to enhance collaborative tasks. The research introduces a framework grounded in social-cognitive theory to measure and manage LLM agency in dialogue, using a dataset of 83 humanhuman collaborative interior design conversations annotated for agency features. The findings indicate that LLMs demonstrating strong intentionality, motivation, selfefficacy, and self-regulation are more likely to be perceived as highly agentive, facilitating more effective and satisfying human-AI interactions [3].

Recent research by L. Sun et al. (2025) investigates whether LLM agents can simulate customer behaviors to evaluate agentic-AIbased shopping assistants, highlighting the potential of agentic AI to enhance digital personal assistants by enabling autonomous decision-making and task execution. The literature suggests that integrating LLMs with planning and external tools allows personal assistants to handle complex queries and improve user experience in domains like digital banking and ecommerce [4]

EXISTING WORK

Key concepts from the existing work include:

ReAct: A seminal framework that combines Reasoning and Acting in language models, allowing them to interleave thinking with tool-specific actions.

Tree of Thoughts: A reasoning framework that expands on the popular Chain-of-Thought method, enabling a more deliberate, tree-like search for solutions to complex problems.

AutoGen: A multi-agent conversation framework that allows specialized agents to collaborate and communicate to solve tasks, forming the basis for "conversational programming."

This body of work highlights the shift from single-turn, reactive language models to multi-turn, proactive agents that can plan, reason, and selfcorrect.

III. METHODOLOGY

The "Methodology" section details an innovative method for evaluating LLM agents. The core of this method is the use of "digital twins", which are LLM agents programmed to mimic human customers in a simulated environment. This approach allows for scalable and efficient testing of agentic AI systems.

Objective: The primary goal was to see if LLM agents could reliably simulate human customer behavior to evaluate a new agentic AI-based shopping assistant.

Agent Personas: The LLM agents were assigned distinct personas with specific attributes, such as their shopping habits, preferences, and goals. This ensured a diverse and realistic set of simulated customers.

Experimental Setup: The agents were placed in a controlled, simulated ecommerce environment. They were given specific tasks, such as finding a particular product or comparing prices, and were instructed to interact with the AI-based shopping assistant.

Data Collection: The study collected a variety of data from the agents' interactions, including their clickstream data (what they clicked on), their natural language queries, and their feedback on the shopping experience.

Validation: To confirm the validity of the digital twin approach, the researchers conducted a parallel study with a group of human participants. The data from the LLM agents was then compared to the human data. The results showed a strong correlation between the two, demonstrating that the agent-based simulation was a reliable proxy for human behavior. This methodology provides a proof of concept that LLM agents can be used as a valuable tool for evaluating and improving the performance of other AI systems, offering a more efficient alternative to traditional humansubject research.

PROPOSED WORK

A Standardized Architecture: The document proposes a modular framework that includes a Cognitive Skills Module. This module is designed to provide domain-specific capabilities, making the agents more versatile and adaptable.

Multi-Agent Collaboration: The framework supports the creation of multi-agent systems where specialized agents can collaborate to solve complex, multi-step tasks. This improves efficiency and reliability by allowing different agents to handle specific parts of a problem.

Application: The proposed work aims to reinvent workflow automation and drive industryspecific applications by using this new standardized, collaborative agent architecture.

IV. CONCLUSION

The core theoretical conclusion from the existing literature is that LLMpowered agentic systems represent a fundamental paradigm shift from static, reactive tools to autonomous, selfregulating, cognitive software architectures. This shift is supported by two major theoretical advancements that validate the LLM's role as a true cognitive agent.

First, the research confirms the Validation of Quantifiable Agency by successfully translating human psychological concepts into engineering principles. The development and empirical testing of the Four-Feature Agency Framework (Intentionality, Motivation, SelfEfficacy, and Self-Regulation) establishes the theoretical foundation for measuring and programming human-like collaborative qualities into AI. This work moves the field beyond mere accuracy to focus on qualitative collaboration, asserting that for LLMs to succeed as reliable partners, they must exhibit the quantifiable capacity to proactively manage interaction and maintain selfbelief in their actions.

Second, the work establishes a new theoretical basis for Autonomous Reliability through Internal Regulation. Methodologies such as the Multi-Turn Agent structurally challenge the traditional sequential control flow by demonstrating that system reliability and efficiency are best achieved through the LLM's inherent capacity for self-correction.

By embedding periodic internal planning and status checks, the LLM functions as its own autonomous control loop, thus validating its theoretical role as an emergent, internal orchestrator of action. This principle is mirrored in the design of Personal LLM Agents (PLAs), where the integration of DualSystem Memory and a sophisticated Sensing Module confirms the need for an architecture capable of continuous self-evolution, deep contextual awareness, and managing sequential state coherence.

In essence, the collective conclusion is that the LLM agent is no longer a sophisticated component, but the defining architectural element of nextgeneration cognitive software, possessing both the measurable agency to collaborate with humans and the structural integrity to govern its own reliability in complex, realworld operations.

REFERENCES

[1]. F. Bacchin, "The Rise of LLM-powered Agents: Reinventing Workflow Automation with Agentic AI," Master Thesis, Dept. Math. "Tullio Levi-Civita", Univ. of Padova, Apr. 2025.

[2]. Y. Li et al., "Personal LLM Agents : Insights And Survey About The Capability, Efficiency And Security," arXiv preprint arXiv:2401.05459v2, May 2024.

[3]. Sharma et al., "Investigating Agency of LLMs in Human-AI Collaboration Tasks," arXivpreprint arXiv:2305.12815v2, Feb. 2024.

[4]. L. Sun et al., "LLM Agent Meets Agentic AI: Can LLM Agents Simulate Customers to Evaluate Agentic-AI-based Shopping Assistants?," arXiv preprint arXiv:2509.21501v1, Sep. 2025.