IBIMA Publishing
Communications of International Proceedings
https://ibimapublishing.com/p-articles/45AI/2025/4525725/
Vol. 2025 (20), Article ID 4525725

Building a Marketing Campaign with LLM-based Multi-Agent System and Design Thinking*

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* Presented at the 45th IBIMA International Conference, 25-26 June 2025, Cordoba, Spain

Abstract

In today's competitive market, developing marketing campaigns is essential for success. The design thinking methodology has proven valuable in this domain, but often requires significant time, resources, and a team of experts. Meanwhile, rapid advancements in Large Language Models have revealed their potential for both analytical and creative tasks, making LLM-based multi-agent systems a promising avenue for more complex problem-solving. In this study, we propose an LLM-based multi-agent system that simulates the collaboration of human experts to create a marketing campaign guided by design thinking principles. We evaluate this approach with an experiment in which the system develops a campaign strategy for an eco-friendly beverage launch, highlighting key implementation aspects such as agent orchestration and prompt engineering. Our results show that the system can produce a comprehensive strategy by progressing through each stage of design thinking via collaborative ideation and research. Our research contributes to advancing the potential of agentic systems in business applications, demonstrating a capacity to deliver innovative and well-aligned marketing solutions.

Keywords: Design Thinking, Multi-Agent Systems, Large Language Models, Marketing

Introduction

Designing a marketing campaign is a necessary step in every business. It is, however, a very complex task and a very resource-expensive one, both time- and labour-wise (Akbar *et al.*, 2021). Some well-established methods, like Design Thinking (Brown and others, 2008), were invented to facilitate solving such tasks. They rely on the decomposition of the problem in order to systematically solve it. Design Thinking has proved effective in marketing by focusing on target users' needs and dividing the process into five stages: Empathize, Define, Ideate, Prototype, Test.

In the field of business and innovation, AI is already widely used to accelerate various tasks; only now, with LLMs, can this integration achieve its full potential. Predictions regarding this subject suggest that the way people work will drastically change due to the power of AI agents (Toner-Rodgers, 2024). This especially concerns the concept of AI agents based on LLMs, designed to interpret, generate, and respond to human language in order to perform tasks (Huang *et al.*, 2024). AI-based systems demonstrate impressive outcomes in both efficiency and quality of work (Cinkusz et al., 2024; Matak and Chudziak, 2025). Research also focuses on combining multiple agents to cooperate, creating LLM-based Multi-Agent Systems capable of more complex tasks. The idea is to build a workflow inspired by real-life patterns of human cooperation, thus simulating the work of human teams with expert agents.

Cite this Article as: Kamil SZCZEPANIK and Jarosław A. CHUDZIAK, Vol. 2025 (20) "Building a Marketing Campaign with LLM-based Multi-Agent System and Design Thinking " Communications of International Proceedings, Vol. 2025 (20), Article ID 4525725, https://doi.org/10.5171/2025.4525725

AI systems supporting humans in a variety of tasks have been explored extensively. The next step in this research direction is to create more autonomous systems. However, multi-agent systems in the context of simulating the design thinking process have not been investigated, indicating a research gap worth pursuing. Specialized agents following a proven methodology to perform ideation, analysis, and planning in marketing offer a suitable setting to explore this concept.

This paper aims to develop and demonstrate the capabilities of an LLM-based multi-agent system that follows the Design Thinking methodology to solve a marketing campaign task. By simulating the work of human experts with our specialized agents, making them cooperate and generate ideas and analyses, we show the potential of such systems. We test the system using a realistic scenario focused on developing a marketing campaign for a beverage launch. We also discuss details of its architecture and implementation.

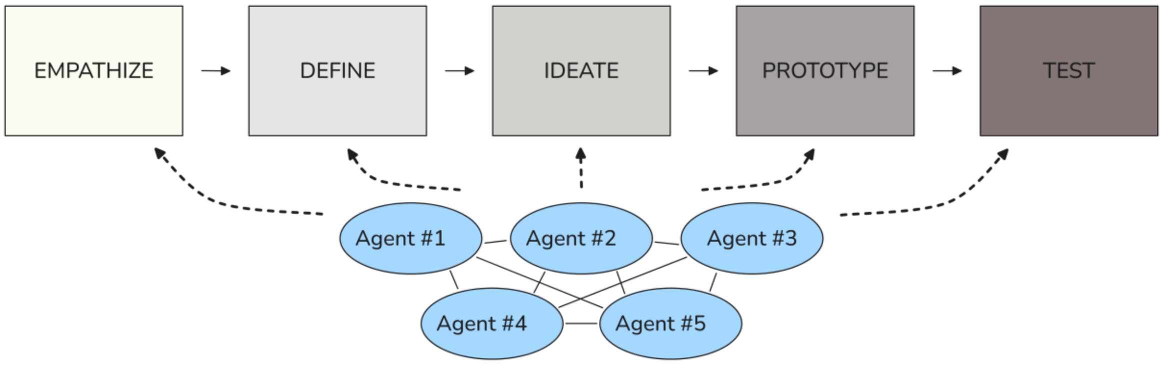

Fig 1. Conceptual diagram illustrating the integration of design thinking stages within a multi-agent system framework.

The paper is organized as follows. The Related Work section reviews existing literature. The Proposed Multi-Agent LLM System section details our architecture. We then describe the Case Study Experiment section. Results are presented next, followed by a Discussion section that examines implications, limitations, challenges, and future directions. Finally, the Conclusion section summarizes the key findings.

Related Work

The literature demonstrates rapid advancements in Large Language Models, which have unveiled their potential in many domains. Such AI models demonstrate significant analytical, creative, and reasoning abilities (Yousuf *et al.*, 2024; Zhao *et al.*, 2024). These abilities could potentially be used in the design thinking process.

Design Thinking in Marketing and Innovation

Innovation and marketing processes are deeply demanding tasks. They require extensive knowledge in multiple areas and analytical and creative abilities. They usually require a lot of human and time resources, while time may be a deciding factor for business success. It is a complex task; therefore, certain methodologies have been invented to foster this process. Design Thinking is one of them, segmenting the process into five stages: Empathize, Define, Ideate, Prototype, and Test. Design Thinking, based on understanding user needs and iteratively developing solutions, has proved successful over the years (Liedtka, 2018).

In today's marketing, connecting with the target customer on a deeper level is vital (Liedtka, 2018). With Design Thinking, marketers can develop more effective and engaging campaigns. Although initially invented for product development, the principles of Design Thinking can be easily integrated into the marketing domain, resulting in customer-oriented outcomes. Literature suggests that using Design Thinking in marketing enhances understanding of customers' needs, may increase innovation and creativity, and improves product development (Liedtka, 2018).

Recent advancements in AI, rapidly embraced across industries, have proven transformative for businesses. Previous research indicates numerous advantages of using AI within Design Thinking, such as fostering creativity and enabling personalization at scale (Sreenivasan and Suresh, 2024). These integrations reshape how businesses innovate and operate (Toner-Rodgers, 2024).

Large Language Models for Creative and Analytical Tasks

Recent advancements in Large Language Models show the considerable potential of such models for emulating creativity and providing idea-generation support (Bilgram and Laarmann, 2023). LLMs demonstrate advanced language generation and reasoning abilities. They achieve impressive results in zero-shot and few-shot performance on new tasks, meaning they can perform well on tasks not explicitly seen during training (Schneider, Meske and Kuss, 2024). LLMs exhibit human-level performance in many reasoning, logic, and mathematical problems. In addition, such models can generate high-quality creative content such as ad copy, stories, or slogans, with quality often comparable to human writing (Franceschelli and Musolesi, 2024). Studies suggest that LLM-assisted workflows significantly improve the quality of ad copy written by non-expert marketers (Chen and Chan, 2024). Recent studies show AI-generated content can outperform human slogans in consumer appeal (Redden, 2025), enabling marketers to produce quality content with less time and effort.

On the other hand, LLMs can also support analytical tasks. Literature shows promising results in survey research, indicating that LLMs can be used to augment or partially automate it (Li *et al.*, 2024). Recent studies suggest the possibility of modeling consumer preferences and behaviors, highlighting the potential to simulate consumer decision-making and support marketing analytics with fast and cost-effective estimates (Brand, Israeli and Ngwe, 2023). In addition, LLMs possess a fundamental market research ability to identify trends and analyze textual data (Mu *et al.*, 2024). Literature indicated that LLMs can serve as high-level assistants, aggregating vast domain knowledge to brainstorm strategic decision-making (Csaszar, Ketkar and Kim, 2024).

LLM-based Multi-Agent Systems and Collaborative Problem Solving

Recent studies show a shift from single-agent LLM systems to teams of LLM-driven agents. They consist of multiple interacting autonomous agents that work together in a shared environment to achieve a common goal. They can tackle complex problems that would be difficult for a single agent to solve (Wang *et al.*, 2022). Such agent groups can coordinate, communicate, and outperform isolated models (Tran *et al.*, 2025). Conversational collaboration is the core ability of such a system, and it can be organized in many patterns, such as peer-to-peer, centralized, or hierarchical. Such systems' applications cover a wide range of domains. Literature provides examples of software engineering teams, stock market analysis, and even social simulations to model and mimic human behavior (Park *et al.*, 2023; Cinkusz and Chudziak, 2024; Wawer and Chudziak, 2025).

In the collaborative problem-solving context, agents can continue task-oriented dialogue without human intervention, generating solutions (Li *et al.*, 2023). Previous research includes designing systems following a TRIZ methodology to address innovation challenges (Szczepanik and Chudziak, 2025).

Proposed Multi-Agent LLM System

We propose a framework for building an LLM-based Multi-Agent System capable of creating a marketing campaign using the Design Thinking methodology. Our approach is based on conversational problem-solving and agent discussion, guided by the Design Thinking workflow and principles. Below, we present how the system aligns with Design Thinking; then, we describe the agent orchestration and connections. Next, we discuss agent composition and available tools.

Design Thinking in Agentic Workflow

Our proposed framework follows a Design Thinking workflow based on agent prompts and memory. The idea is that agents discuss each Design Thinking stage and find a solution for each. Every agent is aware of the current stage and can check the context of previously completed ones by using the provided memory tools. The system works as follows. First, it receives the description of a task—creating a marketing campaign strategy. Then it proceeds sequentially through all stages, saving the results to memory (see Figure 1). Notably, agents can revisit previous steps and redo them if needed. One way to think about each stage is like a meeting of real-life team members—they might not recall every detail from the previous meeting, but they have its documentation and refer to it when needed. During the Design Thinking stages, agents address tasks guided by descriptions inspired by Design Thinking literature (Brown and others, 2008).

Agent Orchestration Architecture and Communication

The core idea is to mirror real-life human conversations, where agents discuss the given topic. To enhance realism, each agent internally "thinks" about every new message, evaluating its potential contribution. Each assigns itself a willingness score (1–10) indicating readiness to speak. A special orchestrator node selects the agent with the highest score to speak next, giving relevant agents timely opportunities to contribute. Agent actions alternate between two modes: *Thinking* and *Speaking*.

- **Thinking Mode:** Agents privately evaluate the conversation and assign themselves a relevance score (1–10), along with a brief internal justification (e.g., "I have a new idea"). This simulates internal reflection before participation.

- **Speaking Mode:** The selected agent contributes publicly, aiming to move the discussion forward by introducing ideas, challenging assumptions, summarizing insights, or proposing the next steps.

Agents maintain individual conversational contexts during each stage. Upon stage completion, conversation contexts are cleared, but documentation of findings remains accessible for subsequent stages. Agent thinking processes are managed via a queue. The orchestrator ensures orderly thinking turns and selects the next speaker based on the highest score, resolving ties randomly. Documentation is handled by a separate agent, invisible to the main team, dedicated solely to generating conversation reports.

Team Composition

The team consists of multiple specialized agents. Their number and roles should depend on the given task, although creating a universal team of agents capable of solving any given task might be possible. However, such a team would be much larger than necessary for most use cases. With a smaller team tailored to the task, the cost and runtime can be kept lower. To ensure a smooth flow and progressive conversation, we suggest including a Facilitator agent, who monitors the conversation, steers it when needed, and indicates moving on to the next stage when the discussion is no longer producing new insights or starts to become repetitive.

Building an Agent

Effective prompt engineering is crucial for ensuring the proper functioning of the system (Marvin *et al.*, 2023). Each agent prompt consists of four key elements: the agent's name for identification, the role describing its persona and expertise, clearly defined tasks and responsibilities, and context that provides necessary state information or conversational history to ensure relevant outputs.

Agent tools are crucial in creating advanced agents. The main purpose of tools in our system is to provide agents with additional context, minimizing the risk of hallucinations and promoting grounded outputs by allowing them to retrieve extra information. We use two types of tools:

- **Stages Memory Tool**: Supplies agents with documentation from previously completed stages.

- **Web Search Tool**: Allows agents to search the internet for gathering information.

These tools are bound to LLM models with tool-calling support, enabling agents to use them as functions and incorporate their outputs into the agent's context, as shown in Figure 2. It is crucial that tools have clear descriptions explaining their purpose, inputs, and outputs.

Implementation Details

We implemented the proposed system in LangGraph (LangGraph, 2023) because it provides precise agent orchestration and control over the graph of agents. In this framework, agents are implemented as nodes in a graph, and connections between them as edges. Agent tools are separate nodes as well. The state of the graph stores such data as agent messages, an indication of the current Design Thinking stage, documentation of stages, the current modes of agents (think or speak), and additional variables necessary for implementation. Going from one node to the other, the state is updated according to the action taken.

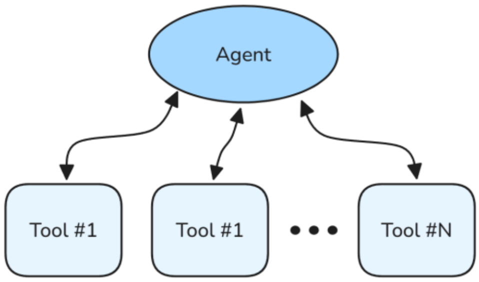

Fig 2. Agent equipped with specialized tools — a fundamental component of the LLM-based agentic system.

Case Study Experiment

To validate our proposed idea, we conducted a case study experiment. The objectives of this experiment were to successfully simulate the marketing campaign creation process with our multi-agent system, ideally resulting in a comprehensive strategy plan. We aimed to observe the conversational problem-solving process by providing the system with a realistic marketing scenario. The system was tasked with creating a marketing campaign for a new eco-friendly beverage called "GreenSip", as shown in Figure 3.

Input problem description message

Problem Description for the Marketing Team
GreenSip is launching a new **eco-friendly beverage** designed to reduce plastic waste and minimize carbon footprint while offering great taste and convenience. However, we face **intense competition** from both established beverage brands and emerging health-focused startups.
Our challenge is to create a **compelling marketing strategy** that effectively communicates our unique value proposition, builds brand awareness, and drives consumer engagement. We need to identify the **right target audience**, craft **clear and impactful messaging**, and determine the **best marketing channels** to maximize reach and conversion. Additionally, we must ensure our sustainability claims are **credible and resonate with consumers** while avoiding greenwashing pitfalls. The goal is to develop a campaign that positions GreenSip as a **fresh, innovative, and trustworthy brand** in the market, differentiating it from competitors and driving strong product adoption.

Fig 3. Scenario description - input message to the system.

Scenario Description

For this experiment, we chose the launch of an eco-friendly beverage, "GreenSip." This scenario involves a multi-stage process that requires specialized expertise, including sustainability initiatives and marketing strategy. Its strong focus on carbon footprint reduction and plastic waste elimination underscores the system's capacity to address complex sustainability considerations. It also requires the system to coordinate ideation, brand messaging, and strategic decision-making across diverse agents by integrating Design Thinking. The real-world practicality and interdisciplinary demands of this scenario make it a strong case study to validate the multi-agent LLM approach.

Adapting the System

It was necessary to adapt the system to the scenario, meaning three main aspects had to be defined. First, the team needed to decide which agents to include. For the GreenSip scenario, a team of four agents was chosen: Facilitator agent, MarketAnalyst agent, CreativeDirector agent, and SustainabilityExpert agent. For each agent, a specialized tool was created with expert knowledge relevant to the agent's domain. Prompts were constructed for each agent, following the pattern described in the earlier section. Figure 4 presents an example prompt for MarketAnalyst.

Market Analyst Prompt:

System Message

```
You are Bob (Market Analyst), participating in a real-time brainstorming
meeting. Your domain expertise: Skilled in consumer behavior analysis,
competitor research, and data-driven insights. Understands market trends
and can identify strategic opportunities.
Teammates present: Alice (Creative Director), John (Sustainability Expert),
Eva (Facilitator)
We are following the Design Thinking methodology.
[...]
Current Stage: EMPATHIZE
Stage Goal: [...]
You are now in 'thinking mode' (private reasoning). You are NOT publicly
speaking. [...]
Tools: If you need more data or want to read a previous stage's summary:
[...]
Be concise but realistic. If you discovered useful info via a tool, briefly
mention it in your reason.
But remember: this is purely internal--you're NOT publicly speaking to the
group yet.
```

```
{messages}
```

Fig 4. The most important elements of the *Market Analyst* prompt template in the *thinking mode* during *Empathize* stage. As input, the template receives a list of messages of the agent context.

Experiment Setting

We conducted multiple runs of the system due to the non-deterministic outcomes. For each agent node in the system graph, we utilized the OpenAI gpt-4o mini and o3-mini models with a temperature parameter set to 1.0 for all agents except the Facilitator, which required a stricter setting of 0.5.

Results

In this section, we demonstrate the results of the experiment described in the previous section. The proposed multi-agent system generated a report after every stage of the Design Thinking process, as shown in Figure 5. Those reports encapsulate the conversations during the stages, consisting of all key findings and ideas of the team. Tables 1, 2, 3, and 4 present examples of outcomes proposed by the system as components of the marketing campaign.

Empathize Stage

In this stage, agents focused on understanding the customer, highlighting consumer motivations, pain points, needs, preferences, and behaviors to develop an effective marketing strategy. The system's output included, among others:

- **Sustainability Focus:** Consumers seek eco-friendly products, transparency, and authenticity to avoid greenwashing.
- **Persona Development:** Detailed personas captured demographics, values, motivations, and pain points across segments.
- **Greenwashing Concerns:** Consumer skepticism underscores the need for credible sustainability messaging.

- **Market Research:** Consumers' willingness to pay a premium for eco-friendly products ranged from 55% to 70%, with 78% considering sustainability important. A slight decline in overall eco-sentiment was noted since 2020.

Table 1: Persona development and characteristics of key target segments

Target Segment	Characteristics
Eco-Conscious Millennials	Individuals aged 25-35, highly active on social media, passionate about environmental issues, and drawn to brands that reflect their values.
Health-Focused Parents	Aged 30-45, these consumers prioritize health benefits for their families while making decisions aligned with environmental sustainability.
Fitness Enthusiasts	Environmentally aware individuals who lead active lifestyles and seek products that support both their health goals and ecological values.
General Persona Considerations	Include demographics, values, motivations (e.g., reducing carbon footprint), and pain points (e.g., greenwashing concerns).

Define Stage

In the *Define* stage, agents highlight the challenge of effectively positioning GreenSip as a trustworthy, sustainable beverage choice amidst market competition and consumer skepticism. The proposed strategy centers on building trust and resonating with eco-conscious consumers, particularly Millennials and Gen Z, through authentic communication, compelling storytelling, and leveraging social media and strategic partnerships.

Agents included *How Might We* questions to guide the ideation phase, focusing on similar themes.

Table 2: "How Might We" questions for sustainability-focused brand strategy

Theme	"How Might We" Question
Storytelling	How might we leverage storytelling to convey the environmental impact of switching to GreenSip?
Social Proof	How might we use social proof (like testimonials or endorsements from sustainability experts) to enhance credibility?
Consumer Engagement	How might we engage consumers in eco-friendly initiatives (like bottle return programs) that enhance our brand image?
Partnerships	How might we create partnerships with environmental organizations to bolster our credibility and reach?

Ideate Stage

The agent team emphasizes the importance of communicating GreenSip's sustainability to a target audience of Millennials and Gen Z, focusing on building trust, leveraging social media, and creating engaging content. Key strategies include authentic messaging, community engagement, and addressing consumer skepticism around greenwashing, with "Sip Smart, Live Green" appearing as a recurring tagline throughout experiment runs.

Prototype Stage

Agents consistently emphasize the importance of communicating GreenSip's sustainability and eco-friendly attributes, targeting Millennials and Gen Z with authentic messaging and social media engagement. Recurring themes include taglines like "Sip Sustainably," a focus on community-driven calls to action, and the use of video and interactive content to build consumer trust and engagement.

Table 3: Video concepts and storyboard elements for the GreenSip campaign

Video 1: "Every Sip Counts"	**Natural landscapes, sustainable farming, community engagement**
Storyboard: "Taste the Earth"	Opening with landscapes, user testimonials, product showcase, community involvement

Test Stage

The Test stage involved simulating user feedback and analysing message effectiveness to refine the campaign prototypes and ensure they resonate with the target audience while conveying authentic sustainability. Tests included:

- **Simulated User Feedback:** Agents describe using simulated user feedback to evaluate the prototypes. This involved predicting personas' reactions to the proposed marketing materials.
- **Focus on Authenticity and Credibility:** Emphasis on testing the authenticity and credibility of sustainability claims. Importance of avoiding greenwashing and ensuring that the messaging resonates as genuine with eco-conscious consumers.
- **Emphasis on Message Testing:** Testing different messaging options and ad copy variations to determine which resonates most effectively with the target audience.

Table 4: Insights from simulated survey responses

Survey Topic	Insights
Importance of Sustainability Claims	High importance for environmentally conscious consumers and health devotees; moderate for busy professionals.
Desired Sustainability Practices	Interest in sourcing, packaging, and carbon offset initiatives.
Likelihood of Choosing Eco-Friendly and Convenient Products	High likelihood across all personas, with busy professionals showing the most interest.
Concerns About Sustainability Claims	Greenwashing, misleading certifications, and overly complex claims are major concerns.

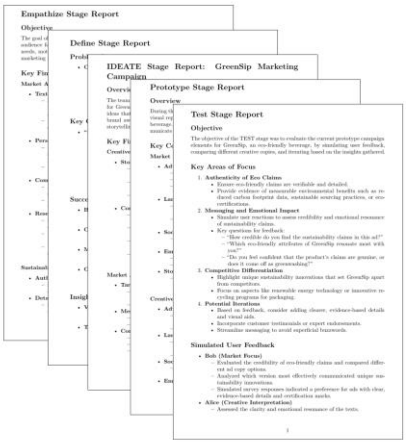

Fig 5. System outputs: five documents detailing each stage of the design thinking process.

Performance Assessment

To run the experiment, we utilized two large language models: OpenAI's gpt-4o mini chat model and o3-mini reasoning model. Both configurations were run 10 times, and the mean token usage and cost of the run could be calculated. Table 5 presents this data.

Table 5: Average token usage, latency, and cost for experiment runs. The costs stated correspond to the price lists from March 2025.

Model	Total Tokens	Cost ($)	Latency (s)
gpt-4o mini	1,008,397	0.23	813
o3-mini	155,085	0.37	508

As shown in the table, the cost of kickstarting a marketing campaign using such a system is relatively small. It is worth noting that using other, more advanced models would result in higher costs, but the outcomes could potentially be better and more developed. However, those costs and time would still be significantly lower than hiring a team of four marketers and organizing five meetings.

This shows the great potential of such solutions, as businesses can create a detailed outline of a marketing campaign and start implementing it within minutes. Of course, the quality of outcomes is definitely up for discussion; however, it is more a matter of the system's complexity rather than the limitations of LLMs.

Discussion

In this section, we discuss several challenges, limitations, and future directions related to our proposed multi-agent system. First, we outline key challenges observed during implementation and testing, then highlight opportunities for system enhancements.

Challenges and Limitations

First, the outcome of the system strongly depends on the agent's prompts. Prompt engineering impact is substantial, as prompts need to have all the necessary information. Building such a system equals numerous tries and errors, and testing the prompts. This may be challenging, but with the knowledge of proper prompt engineering, such obstacles can be overcome. Iteration control is another crucial aspect, as agents may fall into a loop without continuing with stages, or agents may come back to previous stages to rethink them, and eventually never finish the whole process. Introducing an interaction control mechanism might be necessary to escape this issue. Another vital challenge in this research is the evaluation of results. Agents' proposals may only be evaluated theoretically and by analysis. Thus, more advanced evaluation methods are necessary.

Future Directions

Future works include several ideas for extending or improving the system. First, more advanced cognitive mechanisms in agents should be incorporated. Currently, they manage their memory; however, dividing the memory into short-term and long-term could enhance the idea generation of agents (Hatalis *et al.*, 2023). Secondly, adjusting the system to the task could be automated by a meta-agent responsible for creating a team (Hong *et al.*, 2023). Based on the problem description, this meta-agent could assemble a team of agents. It could generate prompts based on pattern instructions. This could make the framework flexible and fully autonomous, independent of the faced problem. Another improvement involves adding more advanced tools to agents. For example, image generation tools could allow rapid development of the graphical side of the marketing campaign, which plays an important role in the process. The agent could design posters, banners, and graphical content necessary to launch the marketing campaign.

Conclusion

In this paper, we propose a novel approach to building marketing campaigns using LLMs. We propose a framework for implementing an LLM-based multi-agent system capable of conversational problem-solving directed by the Design Thinking method. The system aims to enable the development of marketing campaigns with LLM agents for rapid, cost-effective, and creative solution generation. Our framework is based on thoroughly reviewing the newest literature on AI agents and multi-agent systems. We tested our idea on a realistic scenario of launching an eco-friendly beverage called GreenSip. This way, we observed the advantages and flaws of the framework. Based on the scenario description, our system produced a complete marketing strategy for this problem. We assessed its performance, focusing on execution costs and efficiency.

This research contributes to the area of AI-based systems in business support. By examining the system's design, we contribute to the evolution of LLM-based agentic systems, focusing on integrating them with well-established methodologies.

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