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# LLM-Based Multi-Agent Systems for Real-Time Marketing Adaptation to Weather and Seasonal Variability*

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## Abstract

In dynamic marketing environments, the ability to adapt campaigns in real time to changing external conditions and consumer interests is increasingly critical. This paper presents an LLM-based multiagent system designed to support real-time marketing adaptation by integrating weather data and online search trends. The system consists of specialized agents responsible for data collection, integration, data analysis and campaign analysis. By combining external real-time data with company-specific information, the architecture enables automatic identification of relevant correlations and generation of marketing recommendations tailored to current conditions. Use cases illustrate how the system enhances decision-making speed and personalization by providing useful information and content tailored to local trends and weather. This thesis contributes to the field by introducing a multi-agent system architecture that operationalizes large language models for adaptive data-driven marketing.

**Keywords**: LLM-Powered Multi-Agent Systems · Data-Driven Marketing · Multi-Agent Architecture · Artificial Intelligence.

## Introduction

Today's marketing strategies are confronted with dynamic environments characterized by rapid changes in consumer behavior and external influences leading marketers to increasingly face the challenges of quickly adapting to these changes in real time to ensure optimal campaign effectiveness. Among the most influential factors complicating marketing efforts are seasonal fluctuations and dynamic changes in demand, which significantly affect consumer interest and buying behavior (Martech Hub, no date; noble desktop, 2024).

Seasonality manifests itself as predictable, cyclical changes driven by factors such as calendar events, holidays, daily routines or industry cycles, and requires meticulous preparation and timely adjustment of marketing strategy (Zhou, 2023). On the other hand, dynamic changes in demand such as sudden shifts caused by unexpected events, weather fluctuations or social trends pose serious challenges due to their inherent unpredictability (Zurek and Rudy., no date). The complexity of these factors often exceeds the capabilities of traditional, hand-operated marketing approaches, which tend to be slow to process massive amounts of data in real time, and are consequently ineffective at delivering fast and accurate marketing responses (Fatouros et al., 2025; Cai et al., 2025).

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Meeting these challenges requires sophisticated, automated analytical tools capable of instantly processing diverse data sources in real time to identify meaningful correlations and useful insights. Recently, multi-agent systems based on large language models (LLMs) have emerged as promising solutions due to their ability to interpret complex data sets, dynamically adapt to changing inputs and autonomously generate context-aware results. However, their potential in marketing domains, particularly for real-time adaptation, remains under-explored.

To fill this gap, our paper presents a LLM-based multi-agent platform specifically designed for real-time marketing adaptation. Utilizing a number of specialized agents responsible for real-time collection of weather data and consumer trends, data integration, in-depth analysis and automated content creation the system provides marketers with immediate and precise campaign recommendations tailored to real-time conditions. The proposed platform demonstrates how the integration of automated analytical processing, predictive capabilities and real-time response can significantly enhance marketers' ability to effectively and quickly engage with changing consumer behavior and external market conditions.

## Related Works

In recent years the interest in integrating large language models (LLMs) with multi-agent system architectures to develop adaptive, interactive, and personalized environments was increased. Research in education has demonstrated how LLM-based agents can effectively simulate dynamic classroom settings and deliver tailored pedagogical support (Zhang et al., 2024; Wang, Zhou and Chen 2025). These studies have contributed to intelligent learning systems designed to adaptively respond to student interactions, thereby bridging traditional teaching methods and the modern demands of education(Wang, et al., 2025; Cao, et al., 2023; Ward, et al., 2024; Kostka and Chudziak, 2024).

Beyond education, multi-agent systems using LLM have shown great promise in software development (Cinkusz and Chudziak., 2024; Cinkusz, Chudziak and Niewiadomska-Szynkiewicz., 2024), finance (Szydłowski and Chudziak, 2024; Chudziak and Wawer, 2024), and marketing. Research indicates that agent-based platforms in software engineering can streamline collaborative workflows and efficiently manage extensive data processing tasks (Du et al., 2024; Li et al., 2024). In finance, automated decision-making and real-time market analysis have been greatly improved by integrating multi-agent systems powered by LLM (Luo et al., 2025; Yang et al., 2025; Cai et al., 2025). In marketing, research contributions highlight the benefits of real-time data integration and adaptive learning, showing that multi-agent architectures can be used to simulate complex customer behavior and optimize campaign performance (Fatouros et al., 2025; Kasuga and Yonetani, 2024), and evidence suggests that LLM-based agents can transform customer engagement and service delivery in small and medium-sized businesses.

Moreover, comprehensive research and evaluations provide a critical overview of current methodologies, challenges and emerging trends (Chen et al., 2024; Xu et al., 2024). Research focusing on personalized and adaptive learning environments highlights the potential of multi-agent systems to revolutionize education by offering personalized learning experiences, based on real-time input (Yu et al., 2024; integrail, 2024; Salazar, Ovalle and Duque, 2015; Li et al., 2024).

In summary, the literature clearly supports the effectiveness and potential of integrating LLM with multi-agent architectures from adaptive marketing and financial analytics to personalized education and collaborative software development. Building on these fundamental insights, this research specifically addresses the integration of real-time data streams with a multi-agent adaptive system for effective marketing adaptation.

## Problem Statement

In a rapidly changing market environment, today's marketers face challenges in effectively adapting their strategies to changes in consumer behavior and external conditions in real time. One such challenge is seasonality, which is defined as predictable, cyclical fluctuations in consumer interest (Martech Hub, no date). Seasonality can be associated with calendar cycles or cultural events and require tailored marketing efforts (Zhou, 2023), and examples of this are increased demand for ice cream in the summer, winter clothing in the colder months, or holiday products before the holiday season (Fig. 1).

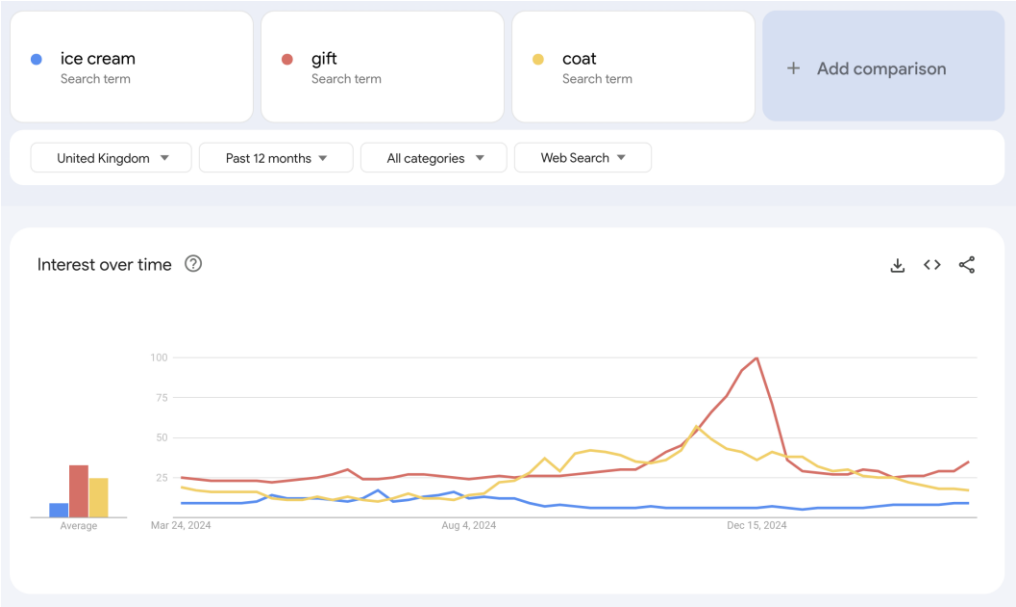



**Fig. 1. Search trends for specific things for last 12 month**

Another challenge is dynamic changes in demand (noble desktop, 2024), which are more unpredictable and often triggered by sudden external factors such as unexpected weather changes, viral social trends or crisis events such as the COVID-19 pandemic (Zurek and Rudy., no date). Such unpredictable changes complicate marketers' ability to respond quickly and effectively and lead to missed opportunities and suboptimal campaign results.

The designed platform is designed to support the process of predicting changes in consumer behavior by proposing a multi-agent LLM-based system specifically tailored for real-time marketing adaptation. It uses specialized agents responsible for collecting real-time weather data and consumer trends, seamless integration and advanced analytics, and generating personalized marketing content. As a result, it significantly increases marketers' responsiveness and flexibility, enabling more precise and effective targeting of marketing strategies in rapidly changing market conditions.

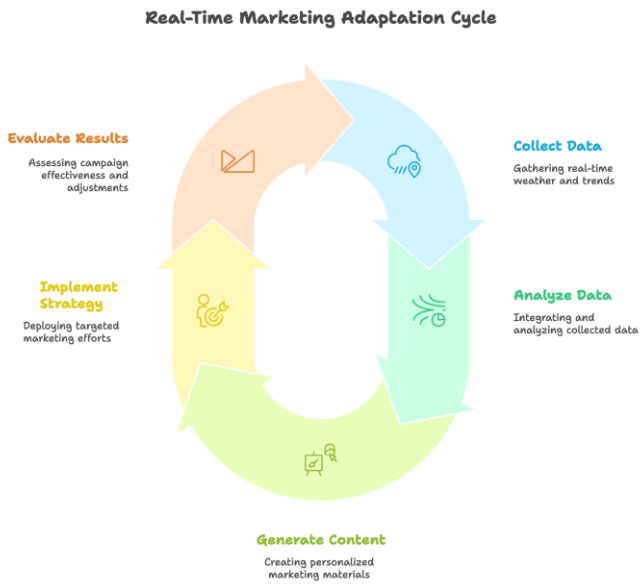



**Fig. 2. Real-time marketing adaptation cycle illustrating the platform's end-to-end decision loop**

Fig. 2 shows a typical real-time marketing adoption cycle that includes steps such as collecting fresh data, analyzing it, creating content, launching campaigns and reviewing results, which highlights the need for intelligent automated support systems that can help marketers act faster and make data-driven decisions in real time.

## Platform Overview and Implementation

This section provides an overview of the platform with illustration of the key elements of the system and their interrelationships, allowing a better understanding of the flow of data and the role of individual components and platform implementation, which introduces key technologies and tools and describes the design of the agent prompts.

### *Platform Overview*

The platform's operation is based on the cooperation of several key agents. The weather agent (Weather Collector) retrieves real-time weather data from OpenWeatherMap (OpenWeather, no date), providing information on current conditions. At the same time, the trends agent (Trends Collector) collects the latest data on popular Google Trends (Google Trends, no date) search topics, identifying what consumers are interested in at any given time. The data from the two sources is then combined by the Integrator, which creates a consistent data set organized by dimensions such as time, location and key search terms to determine the relationship between weather conditions and trends.

A key component of the platform is the database, which stores within itself data of companies along with their locations and products or services. Before using the platform, the platform user should add data to this database and keep it up to date. This is important in order for the system to be able to generate marketing recommendations based on fresh data and the Business Data Collector agent pulls this data in order to pass it on to the analyst.

In the next step, the Analytics Agent receives the integrated data and business data. After receiving the necessary data, it begins the analysis process and identifies correlations between local weather conditions and current trends, indicating which businesses and their products or services can benefit from targeted promotions. The agent also forecasts possible changes in demand and recommends specific promotional activities for identified products or services. The result of this agent is a prepared marketing analysis and created guidelines for promoting specific products.

The next stage is carried out by Content Creator, which transforms the analyst's recommendations into personalized marketing messages. The generated content highlights products or services, tailored to current weather conditions and consumer interests, and is designed to engage and encourage action.

Based on the marketing analysis received and the personalized marketing content, the marketer is able to create a marketing campaign. Once the marketer has created a marketing campaign, the campaign analyst reviews the campaign and provides targeted feedback, pointing out strengths, highlighting weaknesses and suggesting improvements. Through this cycle of analysis and feedback, the adaptive learning process enables the marketer to continuously adjust his strategies through data-driven marketing.

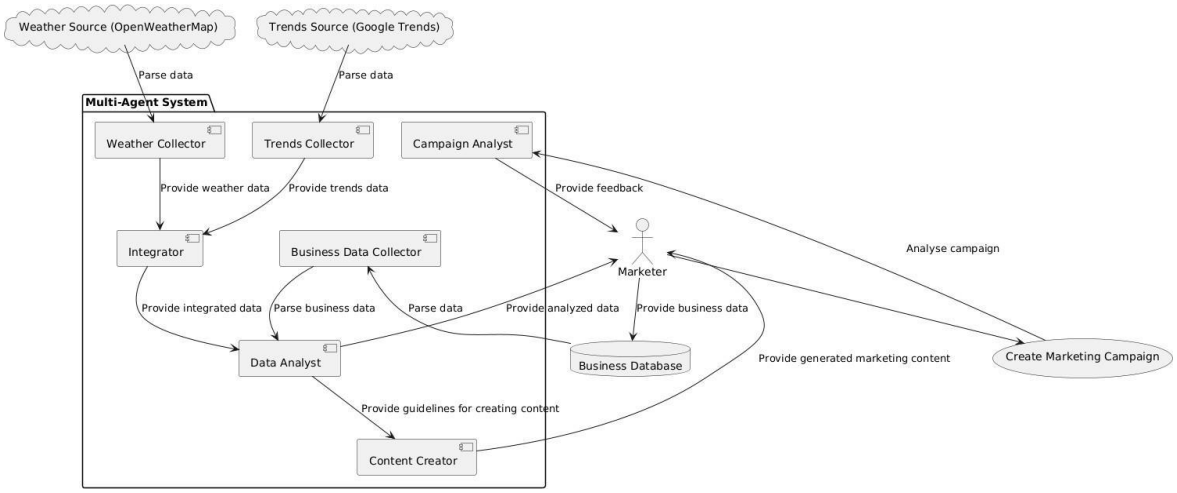



**Fig. 3. Platform overview**

Fig. 3 visually illustrates the key elements of the system and their interrelationships, allowing a better understanding of the flow of data and the role of individual components. The diagram serves a complementary function to the description in the text, offering a clear and intuitive view of the structure and operation of the system.

## *Technologies and Tools*

The implementation of the platform was based on a set of modern technologies that support multi-agent coordination and web development.

CrewAI (CrewAI, no date) was used as the main framework for building and managing the interactions between agents which allowed us to define specific roles, goals, and behaviors for each agent while handling task delegation and communication in a flexible way.

GPT-4o from OpenAI was selected as the core language model used by all agents. It provided advanced capabilities in understanding prompts, analyzing data, and generating natural language responses. Although we initially considered alternative models such as DeepSeek, GPT-4o was chosen due to its reliability and stable API access.

Streamlit (Streamlit, no date) was used to build the web-based interface. Its simplicity and tight integration with Python allowed us to quickly create an interactive environment where marketers can upload data, review reports, and receive content suggestions in real time.

This technology stack allowed us to develop the platform and smooth communication between components, enabling us to focus on designing agents.

## *Agent's Prompts*

The operation of the system is based on a set of agents, each of which is responsible for a specific stage of collecting, processing, analyzing data, generating a marketing report and analyzing the created campaign. The agents work together to customize learning experiences based on real-time data. These agents interact seamlessly to support marketers in adapting strategies to current conditions and consumer behaviors.

1. **Meteorological Intelligence Agent.**
- **Goal:** Retrieve live weather metrics—temperature, humidity, wind, and precipitation—from trusted sources.
- **Backstory:** A vigilant observer of the skies, constantly feeding the system with precise, real-time weather data for marketing analysis.
- **Task description:** Retrieve real-time weather data for location, including temperature, precipitation, and humidity. Ensure that the data is accurate and processed into a standardized format for further analysis.
2. **Real-Time Trends Data Collection Agent.**
- **Goal:** Detect trending search topics using Google Trends data.
- **Backstory:** A digital listener that captures real-time shifts in public interest and consumer curiosity across regions.
- **Task description:** Collect real-time "Trending Now" data using the Google Trends API for {country}. Focus on identifying the most popular topics in the country at the current moment.
3. **Synthesis Agent.**
- **Goal:** Merge weather and trends data into a structured, time-aligned and location-aware dataset.
- **Backstory:** A master of harmonizing inputs into usable, clean formats that power downstream analysis.
- **Task description:** Collect and merge weather data and trending topics data from into a unified dataset. Standardize the data format, aligning it by location and time for seamless integration and analysis.
4. **Data Analytics Agent.**
- **Goal:** Analyze combined datasets to identify marketing opportunities based on environmental and behavioral data.
- **Backstory:** The system's data strategist—identifying patterns and offering data-informed recommendations.
- **Task description:** Analyze integrated datasets (weather + trends) and cross-reference them with business/product data. Identify which businesses and products are most likely to benefit from current conditions. Generate prioritized recommendations and content guidelines.
5. **Content Creation Agent.**
- **Goal:** Generate tailored marketing messages that reflect current conditions and user interests.
- **Backstory:** A creative engine that turns data insights into compelling, timely marketing content.
- **Task description:** Generate personalized marketing content using insights and recommendations. Create social media posts, ads, or promotional emails optimized for location, trends, and seasonal relevance.
6. **Campaign Evaluation Agent.**
- **Goal:** Review submitted marketing campaigns and suggest improvements.
- **Backstory**: A virtual advisor combining marketing knowledge and analytical precision to guide users toward better content.
- **Task Description:** Analyze the provided marketing campaign text to evaluate its clarity, messaging, target audience alignment, and overall potential for success. Identify any critical issues that may undermine the campaign's effectiveness, and provide actionable recommendations for improvement. Offer mentoring feedback that clarifies what aspects can be improved, what the campaign's strengths are, and assign an overall effectiveness rating.

There are summarizations of the key agents in the system, describing their tasks and functionalities to support marketing data-driven adaptation. Using specialized agents, the platform can seamlessly combine real-time external data with company-specific insights, which is crucial for generating detailed marketing reports.

## Case Study

This section presents a case study that shows how the platform works in a realistic but controlled environment. It is divided into two parts: the first part explains how synthetic business data was created to simulate real companies, including their locations and the products or services they offer. That data was used to test how the system handles different types of information. And the second part shows two practical examples of how marketers can use the platform - first, to generate a personalized marketing report based on real-time weather and trends, and second, to receive helpful feedback on a campaign they have written. These examples demonstrate how the system can support better, faster marketing decisions by using live data.

### *Preparation of Simulated Business Environment*

The experiment was planned and conducted to evaluate the effectiveness of the multi-agent system in integrating different data sources and using them to generate personalized marketing report. The preparation was inspired by the approaches presented in the article "How to use ChatGPT to simulate Martech tools and marketing strategy" (Sirkin, 2024), which showed the possibilities of simulating marketing tools using AI models such as ChatGPT. Based on this, cutting-edge techniques were used to create a test database of companies that contained realistic information about companies, their locations, products and services offered.

This database was created to enable the analyst agent to identify products and services that could gain popularity in the context of changing weather conditions and search trends.

| A | B | C | D | E |
|---|---|---|---|---|
| **Business Name** | **Category** | **Location** | **Type** | **Item** |
| Outdoor Adventure Co. | Retail | Warsaw, Poland | Product | waterproof hiking boots |
| Outdoor Adventure Co. | Retail | Warsaw, Poland | Product | insulated winter jackets |
| Outdoor Adventure Co. | Retail | Warsaw, Poland | Product | camping tents (4-season) |
| Outdoor Adventure Co. | Retail | Warsaw, Poland | Product | collapsible umbrellas |
| Outdoor Adventure Co. | Retail | Warsaw, Poland | Product | thermal gloves |
| Outdoor Adventure Co. | Retail | Warsaw, Poland | Product | portable solar chargers |
| Outdoor Adventure Co. | Retail | Warsaw, Poland | Product | hydration backpacks |
| Outdoor Adventure Co. | Retail | Warsaw, Poland | Product | windproof travel pants |
| Outdoor Adventure Co. | Retail | Warsaw, Poland | Product | all-weather sleeping bags |
| Outdoor Adventure Co. | Retail | Warsaw, Poland | Product | trekking poles |
| Outdoor Adventure Co. | Retail | Warsaw, Poland | Service | gear rental |
| Outdoor Adventure Co. | Retail | Warsaw, Poland | Service | guided hiking tours |
| Urban Brew Cafe | Food & Beverage | Krakow, Poland | Product | artisan espresso beans |
| Urban Brew Cafe | Food & Beverage | Krakow, Poland | Product | iced matcha latte kits |
| Urban Brew Cafe | Food & Beverage | Krakow, Poland | Product | vegan pastries (croissants, muffins) |
| Urban Brew Cafe | Food & Beverage | Krakow, Poland | Product | seasonal pumpkin spice syrup |
| Urban Brew Cafe | Food & Beverage | Krakow, Poland | Product | cold-pressed juices |
| Urban Brew Cafe | Food & Beverage | Krakow, Poland | Product | gourmet hot chocolate mix |
| Urban Brew Cafe | Food & Beverage | Krakow, Poland | Product | reusable coffee tumblers |
| Urban Brew Cafe | Food & Beverage | Krakow, Poland | Product | organic herbal teas |
| Urban Brew Cafe | Food & Beverage | Krakow, Poland | Product | gluten-free granola bars |
| Urban Brew Cafe | Food & Beverage | Krakow, Poland | Product | locally sourced honey |
| Urban Brew Cafe | Food & Beverage | Krakow, Poland | Service | barista workshops |
| Urban Brew Cafe | Food & Beverage | Krakow, Poland | Service | subscription coffee boxes |
| Vivid Streetwear | Fashion | Gdansk, Poland | Product | graphic hoodies |
| Vivid Streetwear | Fashion | Gdansk, Poland | Product | water-repellent sneakers |

**Fig. 4. Example of generated data**

Fig. 4 represents the result of the simulation business data. This allowed the experiment to faithfully simulate real-world business scenarios, while also allowing the multi-agent system’s capabilities to be tested in a dynamic data environment.

## *Use Cases*

Three practical examples illustrate how the proposed platform effectively supports adaptive marketing activities in real time. In one scenario, a marketer uploads business data and locations, and the system generates a personalized marketing report based on real-time analysis. In the second one, the system creates personalized marketing messages based on data analysis agent response which promote business products. In the third, the advertiser sends a campaign proposal and receives constructive feedback on the created campaign. Feedback on the created campaign. These use cases highlight the platform's potential to transform data into useful information while promoting personalized data-driven marketing.

Generating adaptive marketing campaigns: The marketer uploads business data to the system and specifies the desired location. Once the data is provided, the platform automatically begins downloading current weather and trend data, integrating and analyzing the data in real time. Based on this analysis, the platform generates a detailed report that provides targeted recommendations for products and services to promote ensuring that these suggestions are in line with current trends and weather conditions. In addition, the report offers customized guidelines for developing marketing content that fits both the products being promoted and the specific local context, in order to maximize the effectiveness of promotional activities.

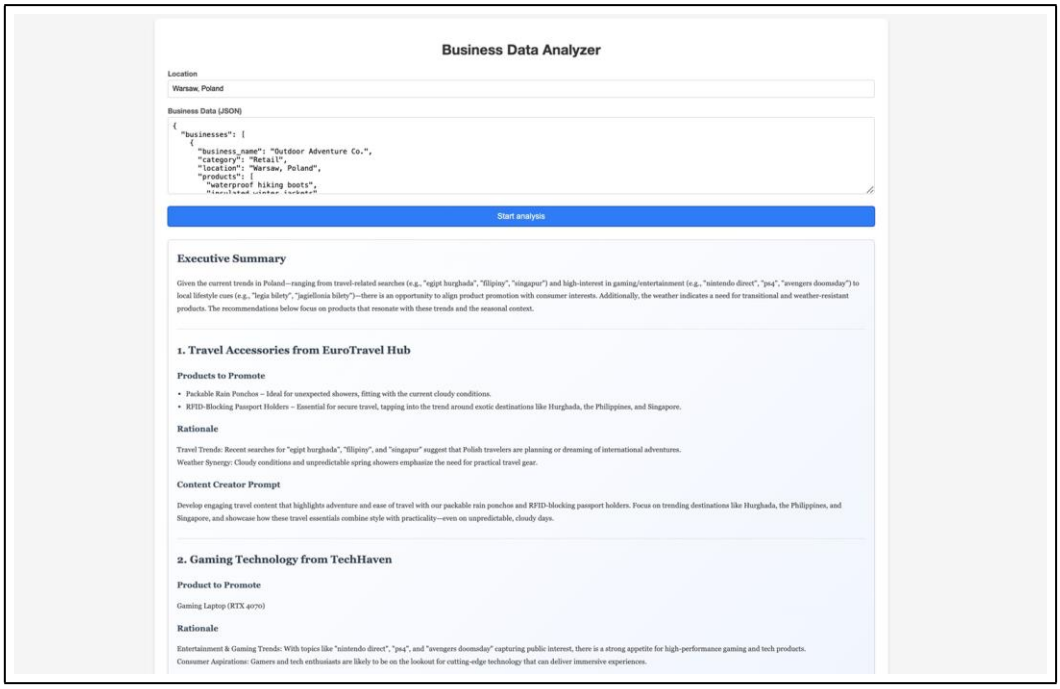
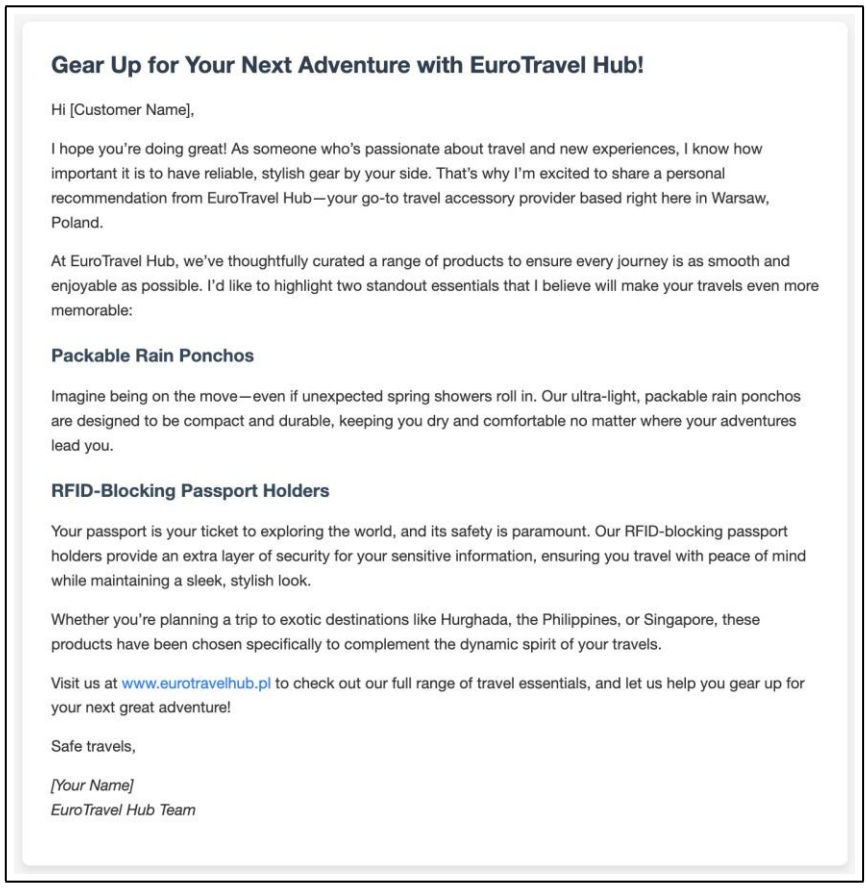



**Fig. 5. Analyst's response based on the data collected at the time**

Fig. 5 is an example of the analyst's response based on the data collected at the time and illustrates the output generated by the Analytical Agent. The example demonstrates the platform's capability to integrate diverse data sources and convert them into actionable insights that support effective, real-time decision making.

Personalized content creation: In this case the system generates marketing content automatically, having to prepare a fully personalized message. After analyzing real-time weather data, trending topics, and business-specific details, the Analytical Agent prepares a prompt describing what should be promoted. This prompt is passed to the Content Creator Agent, which uses it to produce personalized marketing messages tailored to current local conditions and audience interests. The final result is content which can be used in the marketing campaign.



## Gear Up for Your Next Adventure with EuroTravel Hub!

Hi [Customer Name],

I hope you're doing great! As someone who's passionate about travel and new experiences, I know how important it is to have reliable, stylish gear by your side. That's why I'm excited to share a personal recommendation from EuroTravel Hub—your go-to travel accessory provider based right here in Warsaw, Poland.

At EuroTravel Hub, we've thoughtfully curated a range of products to ensure every journey is as smooth and enjoyable as possible. I'd like to highlight two standout essentials that I believe will make your travels even more memorable:

### Packable Rain Ponchos

Imagine being on the move—even if unexpected spring showers roll in. Our ultra-light, packable rain ponchos are designed to be compact and durable, keeping you dry and comfortable no matter where your adventures lead you.

### RFID-Blocking Passport Holders

Your passport is your ticket to exploring the world, and its safety is paramount. Our RFID-blocking passport holders provide an extra layer of security for your sensitive information, ensuring you travel with peace of mind while maintaining a sleek, stylish look.

Whether you're planning a trip to exotic destinations like Hurghada, the Philippines, or Singapore, these products have been chosen specifically to complement the dynamic spirit of your travels.

Visit us at www.eurotravelhub.pl to check out our full range of travel essentials, and let us help you gear up for your next great adventure!

Safe travels,

*[Your Name]*
*EuroTravel Hub Team*

**Fig. 6. Content Creator Agent response based on received from analyst prompt**

Fig. 6 is an example of the Content Creator Agent's response, generated based on a prompt received from the Analytical Agent. Using this contextual input, the Content Creator generates content suggestions tailored to the product, location, and current consumer interests. The example demonstrates the platform's ability to automate content generation and ensure that the resulting messages are personalized, relevant, and aligned with the live marketing context. Real-time campaign optimization: A marketer uploads their campaign content into the system. Once the campaign is submitted, the platform uses its LLM-powered analysis tools to evaluate the text on several levels, including clarity, tone, grammar, and alignment with current market data. The system then generates a comprehensive report that offers targeted recommendations for improvement. This feedback highlights strengths as well as areas where the campaign could be enhanced.

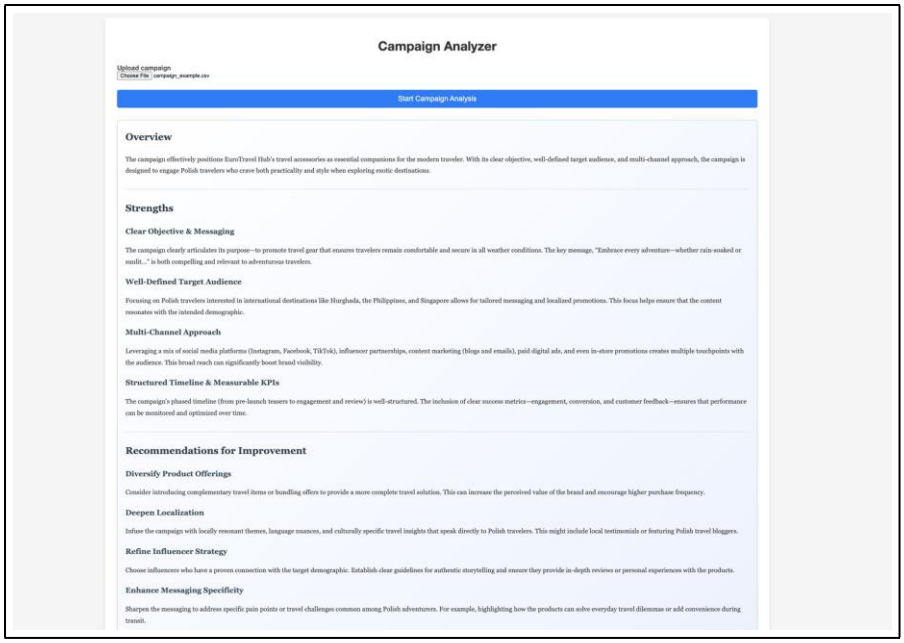



Fig. 7. Campaign analyst response based on received from marketer campaigns

Fig. 7 is an example of the campaign analyst response based on received from marketer campaigns. Feedback from the example guides marketer to enhance aspects such as audience engagement and message clarity.

## Discussion

During the development of the platform, several challenges were faced. One issue was the lack of an official API for Google Trends, which led us to rely on third-party Python libraries like Pytrends (Pytrends, no date). While useful, these tools required additional adjustments to fit our platform's needs. Another limitation was the high cost of accessing the GPT-4o API (OpenAI Platform, no date), which restricted the number of experiments we could run during testing. We also found that only a limited group of companies have product sales that are strongly influenced by weather and trending topics, which narrowed the range of realistic validation scenarios. Another limitation was the use of synthetic business data during testing, as it cannot fully replicate the complexity and unpredictability of real-world business environments (Sirkin, 2024). Future work should include field validation with real business input to better assess practical performance.

Evaluating the quality of generated marketing content remains a challenge. Metrics such as clarity or relevance can be partially assessed using language models, but understanding actual user engagement and conversion potential requires A/B testing and feedback from marketing professionals (Fatouros et al., 2025).

The platform's usability and user experience have not yet been systematically evaluated with marketing practitioners. Future work should include user testing to refine the interface and improve the guidance given by agents, especially for non-technical users.

Since the platform depends on real-time external APIs for weather and trend data, its responsiveness and reliability can be affected by third-party service availability. Mitigating API limitations and introducing fallback strategies will be key to improving robustness (OpenWeather, no date; Google Trends, no date).

Currently, the system operates in English and focuses on general search trends. Expanding to support other languages and region-specific data sources would increase its applicability in diverse international markets (Aydin, 2024).

We also tried alternative solutions such as DeepSeek (DeepSeek-AI, 2024). It was considered as an LLM for agent communication, but its request limits made it unsuitable for consistent testing (Bloomberg, 2025). Other agent orchestration frameworks, such as LangGraph, were also reviewed. Although they offered different features compared to CrewAI, CrewAI was ultimately selected for its simplicity and flexibility (Aydin, 2024).

Future work will focus on extending the variety of real-time data sources. There are also plans to collaborate with real companies in order to evaluate campaign performance in actual marketing environments. These changes will help improve the platform.

## Conclusion

This paper introduced a LLM-based multi-agent system designed for real-time marketing adaptation through the integration of weather and consumer trend data. The platform addresses key challenges faced by modern marketers - such as seasonality, dynamic demand fluctuations, and the need for hyper-personalization by enabling automated, context-aware campaign generation in response to rapidly changing external conditions.

This paper contributes to the field of intelligent marketing systems by presenting an end-to-end architecture in which large language models collaborate through specialized agents to collect, process, analyze, and operationalize real-time data streams. The system's modular design supports scalability and adaptability, allowing for further integration of diverse data sources and business constraints.

Through practical use cases, we demonstrated how the system can support data-driven decision-making by generating targeted recommendations and marketing content aligned with both consumer interest and environmental context. Future work may focus on enhancing agent collaboration using reinforcement learning, expanding domain knowledge integration, and evaluating the system in live marketing deployments.

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