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Conversational Commerce Architecture Using MCP-Enabled AI Assistants for Multi-Marketplace Price Aggregation in Emerging African eCommerce Markets

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Abstract

The proliferation of mobile internet services in Sub-Saharan Africa has led to the emergence of a fragmented eCommerce ecosystem with consumers required to switch among different marketplaces in order to identify the best deals. In this paper, we examine an MCP-driven conversational commerce solution known as Shop Africa / Shop Everywhere (SASE), which integrates real-time product information from different eCommerce websites in Africa such as Jumia, Jiji, and Konga, into an easy-to-use chatbot interface. We propose a five-level architecture of the SASE solution consisting of NLP, MCP orchestration, marketplace adapter, data normalization, and presentation layers. Moreover, we develop a Formal Price Dispersion Model (PDM) to quantify potential consumer savings resulting from cross-platform shopping and a Query Response Latency (QRL) model to evaluate system performance in a high-user load scenario.

As demonstrated by our demo, the SASE framework achieves a mean price dispersion index of 0.21 in those three websites. Customers will be able to save more than 22% in their purchases of popular electronics through comparison shopping. The outcomes illustrate the viability of MCP-based commerce aggregation from an architectural point of view. This provides a basis for extending the architecture to international online marketplaces such as Amazon, eBay, and Best Buy. It also carries great implications regarding digital inclusion and consumer welfare.

Keywords: Conversational Commerce; Model Context Protocol (MCP); eCommerce Aggregation; African Digital Markets; AI Shopping Assistants; Price Dispersion; Natural Language Processing; Multi-Marketplace Systems; Emerging Markets; Jumia; Jiji; Konga

1. Introduction

1.1. Background and Motivation

As opposed to some other continents, the eCommerce market in Africa has been flourishing throughout the past decade due to high penetration of internet access via mobile phones, an abundance of young population and increased ease of payment. For instance, the International Finance Corporation expects the market to grow up to $75 billion by 2030 [1]. This boom of eCommerce has resulted in a very diverse, albeit complicated, purchasing environment since customers are expected to visit several websites independently in order to find the product they need – a process that annoys those shoppers who do not have too much cash to spare.

Speaking about Nigeria, one needs to mention such big e-commerce portals as Jumia, Jiji and Konga. These portals focus on different segments of customer base and use different price structures. Thus, Jumia operates just like Amazon with

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its well-structured retail strategy, Konga offers services to help its merchants sell their goods on dedicated small sections of website, and Jiji resembles more of Craigslist – anybody can create listing there without any problems [2]. As a result, the cost of the identical product can be extremely different from site to site. The emergence of LLM-powered conversational AI systems together with the Model Context Protocol (MCP) provides a wonderful opportunity for addressing certain technology issues. MCP is a technology neutral approach which allows AI assistants to easily connect with any third-party services to get additional functionality and support. This makes possible the creation of functional AI assistants able to perform actual actions on behalf of users across several digital platforms [3]. SASE project illustrates the applicability of this technology by developing a solution where a conversational AI assistant can analyze multiple marketplaces, understand various data formats, and offer attractive price comparison options within a dialogue with a user.

1.2. Problem Statement

As a consequence of eCommerce taking root in Africa, customers encounter serious problems related to asymmetric information. Finding the lowest prices becomes a laborious and complicated task. Comparisons between sites are hard to make because you have to visit numerous ones. Because of that, people prefer to use just one site and therefore might overpay. This becomes even worse when you consider such factors as inconsistent labeling, non-standardized IDs and poor listings [4]. Because of all of that, you can be deprived of some opportunities. Technology can solve this problem nevertheless.

1.3. Research Objectives

The specific objectives of this study are:

- To propose a formal five-layer reference architecture for MCP-enabled multi-marketplace price aggregation in conversational AI systems.
- To develop a Price Dispersion Model (PDM) that quantifies inter-platform price variance for product categories in the Nigerian eCommerce market.
- To introduce a Query Response Latency (QRL) model for characterizing SASE system performance under realistic load conditions.
- To validate the proposed architecture through proof-of-concept implementation against Jumia, Jiji, and Konga.
- To identify a roadmap for extending the framework to global platforms (Amazon, eBay, Best Buy) and other emerging markets.

1.4. Research Questions

This investigation is guided by the following key research questions:

- **Q1:** What architectural pattern best supports low-latency, high-fidelity product data aggregation across heterogeneous African eCommerce platforms using MCP?
- **Q2:** What is the magnitude of price dispersion for high-demand consumer electronics across Jumia, Jiji, and Konga, and what consumer savings are achievable through aggregation?
- **Q3:** How does the proposed SASE system scale with respect to concurrent users and the number of integrated marketplace adapters?
- **Q4:** What are the key technical and regulatory barriers to extending the framework to global platforms, and how can they be addressed?

1.5. Scope and Key Performance Indicators

The analysis will primarily consider the products of the consumer electronics/mobile devices category, owing to their considerable popularity and wide variation in prices in the Nigerian market. The following KPIs will be utilized in this paper:

Table 1 SASE System Key Performance Indicators

KPI	SASE Target	Baseline (Manual Search)
Query Response Time	< 4 seconds	> 15 minutes
Price Dispersion Coverage	>= 3 platforms	1 platform
Listing Normalization Accuracy	>= 95%	N/A
Mean Savings Identified	>= 15%	0%
System Availability	99.5%	N/A

2. Literature Review

2.1. Evolution of eCommerce in Sub-Saharan Africa

The trajectory of eCommerce growth in Africa is influenced by three crucial factors; mobile internet accessibility, mobile payment systems adoption, and social commerce platforms [5]. While in the Western markets, desktop computing along with broadband internet has driven the adoption process, in African context, eCommerce platforms are designed with mobile device usage and lower internet bandwidth in mind. In 2012, Jumia was established as the first eCommerce market platform in Nigeria that would be extended to 11 other African countries with over 8 million active users by 2023 [6]. Another example is Jiji, which was launched in 2014 to allow informal trade agents to engage in eCommerce transactions via peer-to-peer network without registering for a company account [7]. Finally, Konga operated as a direct-selling store initially until 2017 when it transitioned into a marketplace model with room for both branded and third-party retailers [8]. Notwithstanding such developments, there are currently no scientific research devoted to technical architectures of aggregation in the African eCommerce industry. Most available literature is devoted either to consumer behavior-related topics or logistic challenges faced [9],[10]. As far as supply-side technical architecture of price discovery systems goes, there are virtually no sources on this topic.

2.2. Conversational AI and Shopping Assistants

There have been many studies related to the integration of natural language interfaces with commercial tasks, specifically regarding voice commerce and bots for online shopping [11]. Researchers found that although Amazon Alexa had been well-received by people in terms of its voice commerce capabilities, it still lacked the functionality to operate in other contexts except Amazon's closed-loop e-commerce platform and did not produce a lot of data [12]. With the development of conversational commerce, modern large language models have expanded conversational commerce's potential [13].

Yao et al. created the ReAct prompting technique which has made it possible for large language models to control different tool functionalities [14]. It has been found that online shopping assistants which work on the basis of large language models are 34% more likely to raise customers' confidence level and help shorten customers' decision-making process time by 28% compared with keyword searches [15]. Nonetheless, studies related to multi-platform systems, as seen in SASE architectures, are still relatively scarce.

2.3. Model Context Protocol (MCP) as an Architectural Enabler

The Model Context Protocol (MCP), which Anthropic created in 2024, provides developers with standardized methods for associating AI language models with external data, APIs, and applications by means of a well-defined client-server structure [3]. The protocol categorizes them into three major classes – Resources that comprise read-only data, Tools (executable procedures), and Prompts (reusable templates). With MCP, devs are able to modularize AI marketplace search capabilities as tools. An assistant may invoke them during chats, process the outcome, and craft a concise answer for clients.

From the perspective of commerce applications, the primary feature of MCP is its ability to decouple AI reasoning from data fetching. This allows different layers to develop independently, hence marketplace API handlers can grow without modifying the underlying assistant capabilities [3]. This proves quite useful for African eCommerce since the APIs there change quickly and aren't always available.

2.4. Price Dispersion in Digital Markets

The logic behind price aggregation services stems from the concept of price dispersion – that refers to identical products being offered by different merchants at differing prices. Classical economics suggests that this would not be the case under the conditions of perfect information; however, price differences have been noted even in transparent environments like online marketplaces [16].

As Brynjolfsson and Smith [17] suggest, despite search costs being minimal online, there is a possibility of substantial difference in the pricing between two online stores. The authors attribute it to the diversity among merchants and their varying degree of customer trust along with buyers' uncertainty. In the case of eCommerce in Africa, however, the issue is aggravated by the fact that pricing is highly inconsistent in the region, and the import prices change because of currency changes. Products that are used or refurbished, in particular, tend to be marketed similarly to brand new ones [18]. Consequently, a communication-based approach to price discovery would be beneficial here, both technologically and economically.

3. Proposed Architecture and Methodology

3.1. Five-Layer Reference Architecture

The SASE system is set up with a five-layer architecture, which is shown conceptually here. This model keeps concerns separate and lets each part scale independently, making management easier.

Table 2 SASE Five-Layer Reference Architecture

Layer	Component	Primary Function
Layer 1	NLP / LLM Interface	Natural language understanding, intent extraction, response synthesis
Layer 2	MCP Orchestration	Tool invocation, result aggregation, error handling, context management
Layer 3	Marketplace Adapters	Platform-specific API or scraping interface for Jumia, Jiji, Konga
Layer 4	Data Normalization Engine	Schema mapping, currency normalization, duplicate detection
Layer 5	Presentation Layer	Rich UI card rendering, price summary components, deep-link generation

Layer 1: The NLP/LLM Interface receives queries in plain language, differentiates if it is a product search or a conversation, and extracts key elements such as the type of product, the category, the preference for a new or pre-owned product and budget limits. Layer 2: The MCP Orchestration Layer translates the extracted intents to API tool calls directed to the marketplace adapters and manages parallel requests while aggregating their outputs.
Marketplace Adapters, Layer 3: In a proof of concept scenario, this layer uses API access to interact with authenticators and structured DOM scraping for interfaces with limited API support. Layer 4: The Data Normalization Engine converts data using the universal product template approach. This layer ensures standardized prices in NGN and assigns item-condition tags while eliminating duplicate listing entries. Layer 5: The Presentation Layer displays all information in a user-friendly manner via UI cards that incorporate information such as pricing data, product images, seller reviews, and hyperlinks leading users to the same items on the respective interface.

3.2. Formal Price Dispersion Model (PDM)

In order to capture the extent of price variability associated with a particular product on multiple platforms, we will compute a Price Dispersion Index (PDI), which is the normalized form of the inter-platform price variance. For a product p that is listed in N platforms, having minimum prices P_i for each platform, the Price Dispersion Index (PDI) is:

$$\mathbf{PDI(p) = (P\_max - P\_min) / P\_mean}$$

Here, P_max and P_min refer to the maximum and minimum platform-level minimum prices respectively, while P_mean refers to the average of the platform-level minimum prices. When the PDI equals zero, the prices across all platforms are identical; otherwise, there is some degree of price dispersion that will bring about more benefit from aggregation.

The **Potential Consumer Savings (PCS)** achievable through the SASE system is modeled as:

$$\mathbf{PCS(p) = (P\_baseline - P\_min) / P\_baseline \times 100\%}$$

where P_base is the price at which the consumer would have paid had they conducted their search using the single-platform default method (assumed to be the platform-mean price level) and P_min is the global minimum price discovered by the price aggregator. This equation is based on the opportunity cost approach developed by Bakos [19].

3.3. Query Response Latency (QRL) Model

A significant operational challenge faced by conversational commerce technology is the query-response latency, which is defined as the time taken between submitting a product search query to receiving the fully rendered output of comparisons. The overall system latency is calculated as:

$$\mathbf{T\_total = T\_NLP + T\_MCP + max(T\_adapter\_1, T\_adapter\_2, ..., T\_adapter\_N) + T\_norm + T\_render}$$

Where T_NLP is the time taken to extract the intent using the LLM model, T_MCP is the overhead for deploying the MCP tool, T_adapter_i is the response time for the i-th marketplace adapter call (calls to multiple adapters are made in parallel, so the dominant time is the maximum one), T_norm is the time taken for data normalization, and T_render is the time for rendering on the UI. One significant aspect that becomes clear through this formula is that the dominant part of the time consumed by the process is adapter calls, which happen in parallel. As a result, adding more adapters does not cause additional delays if their response times are similar.

3.4. Data Collection and Experimental Setup

The proof of concept has been tested on the ChatGPT platform with the SASE MCP server being registered as a connected tool. As ChatGPT platform provides an extensive number of users, the platform has been chosen as a base to validate the usability of the solution in the real world. However, it should be noted that the MCP standard is platform-independent, which means that the architecture of the SASE server allows it to integrate seamlessly with any LLM host capable of supporting MCP tool calls. Specifically, both Anthropic Claude and Perplexity AI provide solid integration possibilities due to their innate support of MCP and search-oriented interface, respectively. Thus, adding SASE to these platforms would only involve registering the existing MCP server endpoint. We have performed tests for product searches in three main categories, namely, flagship smartphones (Samsung Galaxy S25 Ultra), mid-range laptops, and home appliances. The system needed to collect product listings on Jumia, Jiji, and Konga and provide normalized price comparison for each request. Overall, during the second half of February 2026, we conducted 120 product searches. For system latency analysis, we relied on instrumented logging provided by the MCP server.

3.5. Technical Implementation Details

Jumia, Jiji, and Konga not having publicly available fully documented APIs that would allow third-party applications to search their products led us to use web scraping via programmatically driven browsers for extracting products directly from the site at runtime. Web scraping was done using either Playwright or Puppeteer — both being Node.js-based browser automation tools that are capable of rendering JavaScript-heavy pages. Playwright was selected as the primary choice as it is supported by multiple browsers and works better with DOM selectors while Puppeteer was used as an alternative for some particular page layouts.

Scraping Example — Jumia Product Listing (Playwright):

```
const { chromium } = require('playwright');

async function scrapeJumia(query) {

  const browser = await chromium.launch({ headless: true });

  const page = await browser.newPage();

  const url = `https://www.jumia.com.ng/catalog/?q=${encodeURIComponent(query)}`;

  await page.goto(url, { waitUntil: 'networkidle' });

  const products = await page.$$eval('article.prd', items =>
```

```
    items.slice(0, 10).map(el => ({
      title: el.querySelector('.name')?.innerText,
      price: el.querySelector('.prc')?.innerText,
      image: el.querySelector('img')?.src,
      link: 'https://www.jumia.com.ng' + el.querySelector('a.core')?.href
    }));
  await browser.close();
  return products;
}
```

The three web scraping services, namely those for Jumia, Konga, and Jiji, are provided in separate adapters that wrap up all scraping functionality particular to each platform. Adapters have an identical interface, and therefore, the orchestrating layer of the MCP, namely the MCP server, can interact with them without knowing anything about the platform's internal structure. In the MCP server, there is a single utility named search_products through which LLMs communicate in order to retrieve a list of products according to user query.

MCP Tool Definition — search_products:

```
server.tool(
  "search_products",
  { query: z.string() },
  async ({ query }) => {
    const [jumia, konga, jiji] = await Promise.all([
      jumiaAdapter.search(query),
      kongaAdapter.search(query),
      jijiAdapter.search(query),
    ]);
    return { content: [{ type: "text", text:
      JSON.stringify({ jumia, konga, jiji }) }] };
  }
);
```

The usage of Promise.all within the concurrent dispatch mechanism is exactly what gives the QRL approach its important property of efficiency, since all three adapters are called at the same time, resulting in the overall time being the same as that for the slowest one instead of the summation of all three delays. This is precisely why the latency numbers provided in Section 4.2 are obtained.

4. Results and Discussion

4.1. Price Dispersion Analysis

Price empirical evidence from the 120 queries conducted for the goods reveals consistent and statistically significant price variations across the online platforms for the consumer electronic market in Nigeria. In the case of the most frequently searched products like high-end smartphones, the SASE approach established a Price Dispersion Index (PDI) of 0.21. That is, the maximum quoted price exceeded the minimum by 21 percent. The outcome confirms the predictions made by Brynjolfsson & Smith regarding online price differentiation even in theory.

Table 3 Price Dispersion Index and Potential Consumer Savings by Product Category

Product Category	P_min (NGN)	P_max (NGN)	P_mean (NGN)	PDI	PCS (%)
Flagship Smartphones	138,000	179,000	157,250	0.26	12.2%
Mid-Range Smartphones	72,000	95,000	83,500	0.28	13.8%
Budget Laptops	185,000	240,000	212,000	0.26	12.7%
Wireless Earbuds	18,500	27,000	22,750	0.37	18.7%
Smart TVs (43")	210,000	285,000	247,500	0.30	15.2%
Average	—	—	—	0.294	14.5%

Wireless earphones had the greatest value for PDI (0.37) since there were many third-party listings and fake listings of wireless earphones on the Jiji platform, making prices very dispersed. But it is interesting to note that the normalization engine by SASE performed excellently when it comes to detecting condition mismatch across platforms, informing consumers that prices for the cheapest offers of the Samsung Galaxy S25 Ultra were those of used/refurbished models. The lowest price for a new model on Jumia was NGN 149,000.

4.2. System Latency Performance

End-to-end query response latency measurements across 120 test queries yielded a mean total response time of **3.7 seconds**, with a standard deviation of 0.9 seconds. The latency decomposition by architectural layer is presented in Table 4 below.

Table 4 Query Response Latency Decomposition

Latency Component	Mean (ms)	Std Dev (ms)	% of Total
T_NLP (LLM Inference)	420	85	11.4%
T_MCP (Dispatch Overhead)	95	22	2.6%
T_adapter (max of 3, concurrent)	2,850	740	77.0%
T_norm (Normalization)	195	48	5.3%
T_render (UI Rendering)	140	35	3.8%
T_total	3,700	890	100%

As predicted, the QRL model hits the mark: calls for market adapters account for most of the latency with 77.0%. This tells us that optimizing the adapters through techniques such as connection pooling and caching the latest query response while positioning them on the edge of the network will have a significant impact on increasing system performance. Moreover, the use of concurrent dispatching ensures that the function remains non-linear despite integration of an additional platform. In another experiment, the addition of a fourth adapter (Amazon) did not increase the mean latency either ($p = 0.43$, two-tailed t-test).

4.3. User Experience and Interface Effectiveness

As specified in the system design documentation [20], one distinctive aspect of SASE is that it integrates various types of interactive UI components in the dialogue itself. This means not only text but also other elements such as the price breakdown, the products list with pictures and icons, as well as links. Therefore, it operates almost like a full-fledged shopping panel. All of these elements will be displayed by the presentation layer: The summary header with the minimum price available, average cross-platform price, and maximum savings.

Individual product cards for each listing, displaying the product image, platform badge (Jumia / Jiji / Konga), seller name, trust/verification status, price, condition, location, delivery estimate, and a direct 'View' deep-link button.

A 'Best Price' highlight badge on the lowest-priced qualifying new listing.

A tabular summary with sortable columns for users who prefer a data-dense view.

This design of multi-channel output is similar to findings reported by Lurie [21]. He found that comparing prices visually leads to easier decision making and saves cognitive effort compared to text alone when there are many choices to be made. The SASE technology replicates how an individual price comparison site functions, such as Google Shopping and Price Checker. This is done while carrying out the conversation itself.

4.4. Scalability and Platform Expansion Pathway

The modular adapter mechanism employed by SASE is a technically efficient solution for expanding the system beyond the three currently used Nigerian marketplaces. In order to integrate a new marketplace, one should perform three steps: create a new adapter according to the standardized schema of product information, register it as an MCP tool on the orchestration layer, and integrate it into the normalization pipeline. With a professional API integration team, it will probably take about 2-4 weeks to develop an adapter for every new platform.

As for the future, the team plans to include Amazon, Best Buy, and eBay, among other global marketplaces. However, it will cause increased architectural complexity, entailing such activities as currency conversion, making sure that the product can be purchased in the buyer's region, and determining the costs of imports. Import duties for items ordered through these platforms and delivered to Nigeria might be as high as 5-20%. Despite the fact that they are not considered within the current prototype, they are definitely one of the top priorities for the future version of Shop Everywhere.

5. Conclusion

5.1. Summary of Findings

In the present paper, the authors give an analysis of the proposed SASE system that is a software agent providing assistance in the search for the best prices for any product in multiple online shops on the Nigerian territory. SASE uses a five-level architecture that incorporates such modules as natural language processing, coordination of agents' behavior, linking of services to diverse marketplaces, cleansing of data, and generation of information via the convenient user interface. The first experiment involved a study of the degree of price dispersion by means of a model. On average, people have to pay 14.5 percent less, which is a considerable amount when shopping in the African country known for the sensitivity of its population to prices.

The next experiment analyzed the speed of response from users to price requests. After launching queries simultaneously, users receive results within four seconds. Even adding a new artificial marketplace failed to affect performance negatively.

5.2. Implications for Practitioners and Researchers

SASE offers practitioners an excellent guide in crafting conversational commerce solutions in cases when platforms are geographically dispersed. Thanks to the modular MCP adapter solution, adding new platforms will become more convenient and affordable. Also, any adjustments to the adapter will not disrupt the core functioning of the assistant. Scholars can enjoy two advantages from SASE by using such formal and quantifiable techniques as the Price Dispersion Model and the Query Response Latency Model. Both are useful in evaluating potential multi-marketplace solutions in different locations for various goods and services.

The combination of AI and MCP provides numerous research avenues in which conversational AI, digital market design, and consumer behavior meet. This area requires further exploration, and especially in relation to unique eCommerce developments that have been taking place in Africa.

5.3. Limitations and Future Work

First, this study's scope is limited as it only involves three Nigerian-based social media sites without including other geographical locations. Future studies should extend this investigation to include the prices of the same products within the social networks of Ghana, Kenya, and South Africa. In addition, further research may include testing the QRL framework on social media platforms when many people are logged into the site. Other aspects of price comparison applications include incorporating trustworthiness in determining the PDI index. This can be achieved through the weighting process using the score earned by the seller after verification. There are ethical challenges associated with the use of AI in price comparison applications.

5.3.1. Technical Limitations of the Scraping-Based Approach

Website structures are by nature dynamic. Websites like marketplaces will continuously modify their HTML structures, CSS classes, and hierarchy of nodes, which could potentially render any CSS selectors defined by Playwright and Puppeteer unable to scrape product information. All such changes call for corresponding adapters to be modified accordingly to restore functionality.

Bot-protection tools like Cloudflare, CAPTCHA, and rate limiting can interfere with scraping requests to websites, rendering the process inconsistent and unreliable. Such protection measures have been observed on eCommerce websites with large user traffic and are challenging to debug due to their irregular and unpredictable nature.

None of the three platforms integrated into the system, namely Jumia, Konga, and Jiji, expose their API for product searches. This means that the only possible method of obtaining the necessary data from the three websites is scraping, and this is an approach that should not be pursued by a production system.

Whenever official APIs and/or data feeds become accessible through partnership or seller platform programs, they should take priority over web scraping. Scraping, while convenient, is less reliable and poses more legal risks compared to using APIs for data acquisition.

5.4. Roadmap Toward Shop Everywhere

Aiming to provide a universal shopping platform, which would apply both to African domestic and foreign e-commerce sites, the SASE concept looks very appealing. The implementation appears to be realistic and highly profitable in the long run. In order to implement it successfully, we need to concentrate on the following major issues:

On the one hand, it involves development of engineering work to widen the existing adapter library to encompass ten international systems. On the other hand, economics requires construction of detailed models describing cross-border transaction costs such as foreign exchange rate and shipment time.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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