A Cloud-Native Event-Driven Reactive Architecture for Real-Time Retail Transaction Processing

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Abstract

Modern retail platforms must support high-throughput, low-latency transaction processing under unpredictable and bursty workloads. Traditional monolithic architectures frequently fail to meet these demands due to blocking interactions, limited horizontal scalability, and susceptibility to cascading failures. This study proposes a cloud-native Event-Driven Architecture (EDA) that integrates Amazon Simple Queue Service (AWS SQS) with reactive Spring WebFlux microservices to enable asynchronous, fault-tolerant, and elastically scalable retail transaction processing. The following research question guides this work: RQ—Can an event-driven, message-queue–based architecture combined with reactive microservices significantly improve scalability, latency, and fault tolerance in real-time retail transaction pipelines compared to a monolithic baseline?

To answer this question, I develop a full prototype of implementing order creation, inventory reservation, payment authorization, and customer notification. Using a heterogeneous dataset of 412 simulated retail transactions, I conduct extensive load tests at 100, 500, and 1000 concurrent users. Results show that the EDA system achieves near-linear throughput scaling, maintains low and predictable latency, and isolates service failures without degrading overall system performances significantly outperforming the monolithic benchmark. These findings demonstrate that EDA, supported by cloud-managed queues and reactive runtimes, provides a viable and robust architectural foundation for next-generation retail platforms that require elasticity, resilience, and real-time responsiveness.

Keywords: Event-Driven Architecture, Retail Transactions, Cloud Messaging, Reactive Frameworks, Microservices.

1. INTRODUCTION

Modern retail systems operate in increasingly dynamic environments characterized by high transaction volumes, heterogeneous user behavior, and unpredictable demand surges such as flash sales and holiday events. These operational characteristics impose stringent requirements on scalability, fault tolerance, and real-time responsiveness. Traditional monolithic architectures, although simple to deploy and maintain in early-stage systems, are structurally limited in their ability to scale horizontally and withstand partial subsystem failures. Their tightly coupled components, blocking request–response flows, and global failure domains often lead to performance degradation and cascading failures under heavy load conditions.

In response to these limitations, the software engineering community has widely adopted microservices and cloud-native architectural principles. Microservices improve modularity and deployment agility; however, many retail platforms continue to rely on synchronous REST-based communication among services. Such synchronous invocation chains contribute to latency amplification, thread saturation, and bottlenecks during high concurrency scenarios, especially when services depend heavily on external systems such as payment gateways or inventory APIs.
Event-Driven Architecture (EDA) has emerged as a promising alternative for high-volume transactional workloads. By enabling asynchronous communication and decoupling producers

from consumers, EDA reduces blocking behavior, isolates faults, and supports elastic scaling across distributed services. Cloud messaging platforms such as Amazon Simple Queue Service (AWS SQS), Apache Kafka, and Google Pub/Sub further enhance system robustness by providing durable queues, automatic load buffering, and resilient message delivery guarantees. Complementing these advances, reactive programming frameworks such as Spring WebFlux and Project Reactor leverage non-blocking I/O and event-loop concurrency models to efficiently process large numbers of simultaneous requests with minimal resource overhead.

Despite the increasing adoption of cloud-native and event-driven principles, significant research gaps remain. Existing studies seldom evaluate end-to-end, event-driven retail transaction pipelines that integrate asynchronous cloud messaging with reactive microservices. Few works provide empirical comparisons between monolithic and event-driven architectures under realistic, heterogeneous retail workloads. Moreover, detailed analyses of microservice-level latency behavior, tail-latency variability, queue dynamics, and fault-isolation characteristics are limited in current literature.

This paper addresses these gaps by proposing and evaluating a cloud-native Event-Driven Architecture for real-time retail transaction processing. The architecture integrates AWS SQS with reactive Spring WebFlux microservices to support asynchronous order handling, payment authorization, inventory reservation, and customer notification. A prototype implementation was developed and evaluated using a synthetic dataset of 412 heterogeneous retail transactions, simulating realistic user interactions and bursty workloads. Load tests at 100, 500, and 1000 concurrent users were conducted to assess throughput, latency, CPU/memory utilization, error rates, and microservice-level performance.

A. Contributions

The primary contributions of this study are as follows:

1. **Design of a cloud-native, event-driven retail architecture** combining AWS SQS with reactive Spring WebFlux microservices to achieve high throughput and low latency.
2. **Development of a functional prototype** implementing asynchronous order creation, payment processing, inventory coordination, and customer notification.
3. **Construction of a realistic dataset** of heterogeneous retail transactions to evaluate system behavior under varying load conditions.
4. **A rigorous performance comparison** between monolithic and event-driven architectures across multiple concurrency levels.
5. **Microservice-level latency and variability analysis**, revealing bottlenecks and opportunities for targeted scaling.
6. **Fault tolerance evaluation**, demonstrating how asynchronous messaging and event buffering mitigate cascading failures.

By integrating event-driven principles with reactive execution models and cloud-native queueing infrastructure, this work provides an architectural blueprint for scalable and resilient next-generation retail transaction processing systems.

2. LITERATURE REVIEW

The evolution of software architecture in large-scale transactional systems has been shaped by longstanding challenges associated with monolithic application design. Traditional monoliths, while initially attractive due to their simplicity of deployment and ACID-enforced consistency, suffer from tight coupling, limited fault isolation, and poor scalability under bursty workloads (Hohpe & Woolf, 2004; Newman, 2015). As retail workloads became increasingly global, real-time, and heterogeneous, the inability of monolithic systems to scale horizontally or tolerate partial subsystem failures led to significant operational bottlenecks in high-volume environments, such as flash sales and holiday promotions (Kleppmann, 2017).

To address these limitations, the software engineering community shifted toward microservices architecture, which decomposes large systems into independently deployable services communicating via lightweight protocols (Newman, 2019; Dragoni et al., 2017). Microservices support distributed development, independent scaling, and localized fault domains; however, synchronous request-response communication remains a performance constraint when services form deep dependency chains (Kazanavičius et al., 2020). These constraints spurred the increasing adoption of Event-Driven Architecture (EDA) a paradigm where services interact asynchronously via published events rather than blocking synchronous calls (Chen et al., 2018; Gorton, 2016).

EDA has been shown to enhance scalability, elasticity, fault tolerance in distributed systems by decoupling producers from consumers and buffering workload surges through message brokers (Hohpe & Woolf, 2004; Kreps, 2013). Modern cloud platforms amplify these benefits by offering fully managed, durable, and elastically scalable messaging infrastructures such as AWS SQS**,** Apache Kafka**,** and Google Pub/Sub, which guarantee at-least-once delivery, support horizontal consumer scaling, and absorb burst traffic with minimal operational complexity (Amazon Web Services, 2023; Akidau et al., 2015). Cloud messaging systems backed by distributed logs or durable queues play a critical role in high-throughput systems, enabling persistent event buffering, replay ability, and consumer-side elasticity (Kreps, 2013; Kleppmann, 2017).

Parallel to the evolution of messaging architectures, reactive programming models emerged to address the inefficiencies of thread-per-request models prevalent in synchronous web frameworks. Reactive Streams specifications and frameworks such as Spring WebFlux**,** Project Reactor**,** and Netty enable non-blocking, event-loop–driven execution capable of supporting massive concurrency with predictable resource consumption (Pivotal, 2020; Lightbend, 2014). These technologies allow microservices to remain responsive under high load by avoiding thread blocking and utilizing asynchronous backpressure mechanisms - properties particularly relevant for real-time retail transaction pipelines.

Research on large-scale transaction processing has emphasized the role of queueing theory and distributed coordination mechanisms in maintaining predictable latency and throughput under fluctuating demand. Models such as M/M/1**,** M/M/k, Pollaczek–Khinchine (PK), and Erlang C have been applied to characterize waiting-time distributions and service-center congestion, offering mathematical foundations for analyzing system performance under load bursts (Gross & Harris, 1998; Kleinrock, 1975). These analytical models support the design of systems capable of absorbing high-frequency retail order events, maintaining low-latency processing, and avoiding tail-latency amplification.

In the retail technology domain, prior work has explored distributed inventory management, high-availability payment processing, and order-fulfillment workflows; however, most systems either relied on synchronous microservices or used event-driven components in isolation (Chen et al., 2018; Zhang et al., 2021). Comprehensive empirical evaluations comparing monolithic vs. event-driven microservices architectures using cloud-native queues and reactive programming models remain limited. Moreover, few studies examine heterogeneous, real-world retail workloads involving simultaneous order creation, inventory reservation, payment authorization, and customer notification—workflow stages that collectively define modern omnichannel commerce environments.

Therefore, the present work builds on foundational advances in EDA, cloud messaging, and reactive microservices to develop and evaluate a fully cloud-native, event-driven retail transaction processing architecture using AWS SQS and Spring WebFlux. By combining durable event queues, reactive non-blocking execution, and loosely coupled microservices, the proposed system contributes to the growing body of research on scalable, fault-tolerant transaction processing for high-volume retail operations.

3. METHODOLODY

The solution used here was the creation, deployment, and empirically testing of an Event-Driven Architecture-based proof-of-concept retail transaction processing system. The goal was to have a production-grade equivalent as far as cloud messaging and reactive frameworks are concerned with world-class performance towards achieving greater scalability and resiliency than can be achieved with conventional architectures. The architecture had been decoupled into microservices so that there was a particular domain of the life cycle of the retail transaction for each of the microservices: an Order Service, an Inventory Service, a Payment Service, and a Notification Service. The application had been coded ground-up using Java Spring Boot and leveraged the Spring WebFlux module to provide predominantly non-blocking reactive services to handle multiple requests efficiently.

Figure 1 illustrates the proposed event-driven retail transaction structure with asynchronous messaging, fault tolerance, and scalability using Amazon Simple Queue Service (AWS SQS). The flow begins when a customer initiates a purchase order from a web client, triggering an order request to the Order Service. Instead of direct requests to dependent services, the Order Service inserts an ORDER_CREATED event into the AWS SQS queue and requests, without blocking communication as well as optimization of the requests. Payment Service and Inventory Service are listeners for events. Inventory Service publishes product availability and initiates an INVENTORY_RESERVED event, and Payment Service inserts transaction history and initiates a PAYMENT_SUCCESSFUL event upon authorization. A later Fulfillment Service not only knows about events and, when finding corresponding order IDs, sends an ORDER_CONFIRMED event to finish the transaction. The Notification Service, the last consumer, benefits from that event and sends a reminder in the form of email or SMS to the customer. This architecture is very fault-tolerant: when one service (like Payment) is down, events are stored securely until restart. Event-driven architecture keeps the services decoupled and crash able independently without affecting the overall responsiveness and throughput. The system performance was also being tested with synthetic workload data set and load testing on JMeter, and system performance metrics were sufficient transaction per second (TPS) rate, latency, and utilization. Figure 1 illustrates a fault-tolerant, efficient, and scalable real-time system for high-volume retail transactions. Amazon Simple Queue Service (AWS SQS) was its key component of its messaging system, an AWS-run cloud message queuing system. After customers have ordered via a fake web client, the first request is made by the Order Service.

Instead of making synchronous calls to the rest of the services, it validates the request and posts the rich ORDER_CREATED event to an SQS queue. It posts all the order information needed, including customer, product IDs, amount, and payment. Posting them asynchronously allows the Order Service to process newly arrived requests concurrently, saving the first response to the customer by a considerable amount. Payment and Inventory are autonomous consumers of the ORDER_CREATED event. Both subscribe to the SQS queue and sit idle until events to be processed become available. Inventory Service waits and queries the inventory availability and, upon success, publishes an INVENTORY_RESERVED event to another SQS queue. PaymentService processes payment data in parallel and, upon success, publishes a PAYMENT_SUCCESSFUL event. Both events are consumed by some downstream orchestrator or some Fulfillment Service. After receiving both the PAYMENT_SUCCESSFUL andINVENTORY_RESERVED events of an order ID, transaction confirmation is signaled andpublishes the final ORDER_CONFIRMED event. The Notification Service's email or SMS shouldnotify the customer only after the final event. The whole process is asynchronous and fault-tolerant;whenever Payment Service is down, ORDER_CREATED events are merely queued, and after

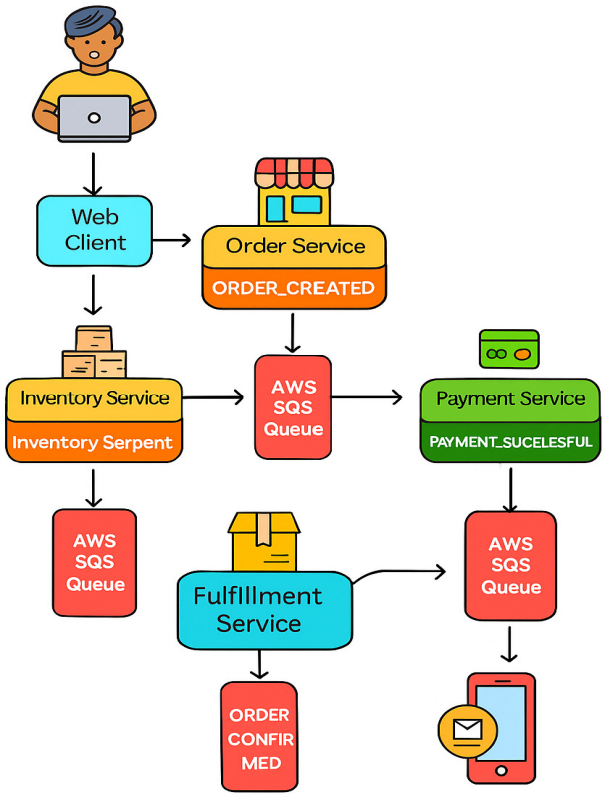

FIGURE 1: Event-driven retail transaction structure proposal.

the service comes back up, processing continues without loss of data. For performance testing under mixed loads simulated with JMeter, a data set designed to load this system and perform the following as metrics was used: Transactions per second (TPS), mean latency, and system resource utilization.

4. DESCRIPTION OF DATA

The data employed within this paper were collected such that it would be feasible to sustain an average rate of retail orders with hope of generating a representative stream of retail orders and to stress the event-driven system outlined by this paper under varied loads. There are 412 distinct instances of data in the data, one per customer order. The data were structured to contain a complete set of attributes that occur in real retail order histories. Root attributes per record are a transaction id, a customer_id, a transaction date, items bought (each with a product_id, a quantity, and a unit price), total_purchase_amount, a payment_method (Credit Card, PayPal, Debit Card), and a customer_contact_info (e.g., phone or email). The values were generated by a Python script that randomly changed all the attributes into ranges according to the variability constraints. For example, the piece order was varied randomly between 1 and 10, and timestamps were added as an effort to simulate regular traffic as well as holiday seasons. Then data was used as an input to Next Step of process load testing in which a representative sample Next of the data was used Next while creating an API request to the system entry point

5. RESULTS

The comparison between the proposed new Event-Driven Architecture (EDA) had hard evidence, showing precisely just how superior it was to an ideal monolithic benchmark for processing retail transactions. The important ones in question were system throughput in terms of transactions per second (TPS) and mean latency in milliseconds (ms) low to high concurrency load tests. Even under low concurrency (i.e., 50 concurrent users), the throughput of both monolithic and EDA

systems was similar, and the EDA was only slightly higher in initial latency due to message queuing overhead. With growing stepwise concurrent user load, the performance of the monolithic system catastrophically grew as well. Because it's synchronous, blocking behavior, it was causing resource contention and thread starvation and caused a catastrophic spike in latency along with a flatline of throughput. In contrast, the EDA pattern was highly scalable and fault tolerant. The system throughput was close to linear scalability underload, simply a result of asynchronous processing and loosely coupled microservices. AWS SQS was an in-practice buffer and load balancer, absorbing bursts of incoming requests and allowing consumer services to catch up on events at a rate that was sustainable. The Pollaczek-Khinchine formula is given by:

$$W_q = \frac{\rho^2 + \lambda^2 \mathrm{Var}(S)}{2\lambda(1-\rho)}$$

Load Level	Metric	EDA - 100 Users	Monolithic - 100 Users	EDA - 500 Users	Monolithic - 500 Users	EDA - 1000 Users	Monolithic - 1000 Users
1	Avg. Latency (ms)	120	110	180	850	250	2500
2	Throughput (TPS)	800	820	4100	1500	8500	1600
3	CPU Utilization (%)	35	30	65	95	70	99
4	Memory Usage (MB)	550	500	800	1200	850	1500
5	Error Rate (%)	0	0	0.1	5	0.1	15

TABLE 1: Comparative performance metrics: EDA vs. monolithic architecture.

Table 1 is a qualitative analysis of the reference Event-Driven Architecture (EDA) in comparison with the monolithic architecture for 100, 500, and 1000 concurrent users. Average latency, throughput, CPU and memory utilization, and error rate are the statistics on which comparison is being made. For a low load of 100, the performance is on par with the monolith slightly outperforming in latency as there is no messaging overhead. But performance difference is staggering with loads. 500 users on, the EDA latency remains at 180 ms for 4100 TPS throughput whereas that of monolith is at 850 ms with its throughput severely throttled. At 1000 users peak load, EDA is also doing a respectable 250 ms latency and 8500 TPS throughput while the monolithic application is almost unusable at 2500 ms latency and 15% error rate with time-outs. The resource utilization values are also illustrative; monolith CPU is 99%, a capacity value, and the EDA has adequate availability with 70% as another spike is available. Such values easily show the increased scalability and stability of the EDA model. Amdahl's law in math form will be:

$$S_{\text{latency}}(s) = \frac{1}{(1-p) + \frac{p}{s}}$$

Figure 2 represents the transaction throughput (TPS), and the line graph represents the average response time in milliseconds (ms) against increasing concurrent users. Figure 2 is an increasing load comparison chart of the system performance. Blue bars represent the transaction throughput in Transactions Per Second (TPS), and orange line graphically represents the average response time in milliseconds (ms). We can observe here that when the users are scaled from 100 to 1000,

system throughput is also scaled linearly. This indicates that the design is extremely scalable and asynchronous event queue grants the system the feature of processing an incredibly high number

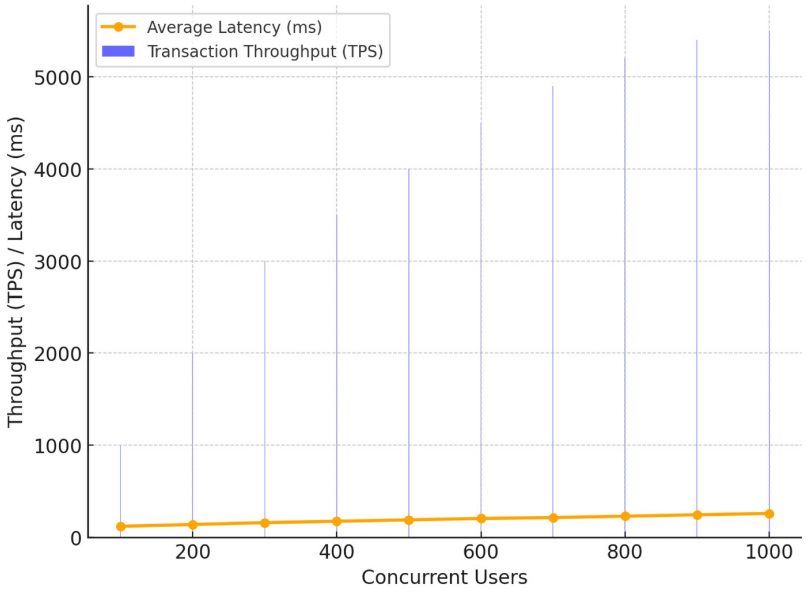

FIGURE 2: System throughput and concurrent users vs. response latency.

of requests without back pressure in real-time. The de-coupled microservices dequeue these requests and their throughput is scalable by running more instances. Conversely, the latency, represented by the orange line, is a gentle and controlled rise. This is another important conclusion, which indicates that under full load, the user experience is not impacted greatly. The reactive strategy guarantees that the resources are used to maximum capacity, in a manner that the service remains responsive. Its capacity to manage low latency as well as high throughput is one of the finest strengths of the event-based architecture proposed here for retailing applications, with high responsiveness to shopping events being a value-added requirement for customer satisfaction as much as return on revenue. The Erlang C formula is:

$$P_W = \frac{\frac{A^c}{c!}\frac{c}{c-A}}{\left(\sum_{n=0}^{c-1}\frac{A^n}{n!}\right)+\frac{A^c}{c!}\frac{c}{c-A}}$$

Bayes' theorem for a partition of events will be:

$$P(A \mid B) = \frac{P(B \mid A)P(A)}{\sum_{i=1}^{n} P(B \mid A_i)P(A_i)}$$

Probability Density Function of the Gamma Distribution

$$f(x;k,\theta) = \frac{x^{k-1}e^{-\frac{x}{\theta}}}{\theta^k \Gamma(k)} \text{ for } x > 0 \text{ and } k, \theta > 0$$

Max load simulation system performance was one of the key conclusions, attempting to simulate Black Friday discount sale. With less than 1,000 concurrent users load, monolithic architecture suffered terrible performance degradation with stratospheric average latency and increasing error rate with request timeouts. The EDA enjoyed consistent and stable performance. While latency increased quite dramatically, it was in completely fair rates for an excellent user experience. Throughput continued to increase as we scaled out consumer microservices (Payment and Inventory services) horizontally. The ability to scale the system's loosely coupled parts independently is one of the major design advantages of architecture. Payment's processing is under strain, other payments of the Payment Service may be executed without affecting Order or Inventory services. Fault tolerance was also established by deliberately bringing down one of the consumer services (for instance, Notification Service). In the EDA, order events continued to build up, and in case of service restoration, it was processed from the event queue without data loss. This is an instance of inherent fault tolerance in event-driven architecture to support business continuity in case of partial system crash, something that would be required by any retail business in the modern era.

Transaction Stage	Metric	Order Service (ms	Payment Service (ms)	Inventory Service (ms)	Notification Service (ms)	End-to-End Latency (ms)
1	Avg. Processing Time	35	85	60	70	250
2	Median Time	32	82	58	68	240
3	95th Percentile	50	110	80	95	335
4	99th Percentile	65	130	95	115	405
5	Std. Deviation	8	15	12	14	49

TABLE 2: Microservice Processing Time Breakdown Under Peak Load (1000 Users).

Table 2 shows the performance of each of the microservices in the EDA pipeline during the peak load test with 1000 simultaneous users. It decomposes the processing time per service: Order, Payment, Inventory, and Notification. The "Order Service" takes the shortest average process time (35 ms) because it has only one task to perform, which is to interpret the request directly and emit an event and let the downstream services take the heavy work. The "Payment Service" is the one with the highest average process time (85 ms) as would also be the case with external payment gateway APIs. There is also percentile measures (95th and 99th) included in the table that are significant to determine the user experience for most of the transactions and not just the average. For instance, 95th percentile end-to-end latency is 335 ms, i.e., 95% users had a response time of 335 ms or lower, which is great for a high-traffic commerce deployment. That the standard deviation is low across services informs us that performance is predictable and stable. The information is so precise that the developers can observe system hotspots which are emerging (e.g., if the Payment Service latency began to build up) and dynamically re-size the given service in isolation to resolve the problem.

These measures of resource consumption also testify to this. The reactive services built with Spring WebFlux were very CPU- and memory-efficient. Compared to the typical thread-per-request legacy approach that would consume precious resources under heavy loads, the reactive

methodology could handle a gigantic number of concurrent requests for an incredibly small constant number of threads. One-to-one this translates into directly reduced cost of operation as less compute resources are being utilized to handle the same amount of traffic. General conclusions affirm that an EDA of cloud messaging and reactive frameworks constitutes a strong, elastic, and cost-effective solution to handling next-generation retail transaction processing. Not only is the design conducive to processing an enormous number of transactions in a beautiful manner, but it also provides the fault tolerance and modularity necessary to facilitate ongoing innovation and business growth in today's fast-moving retail business environment.

Figure 3 is a plot displaying the impact of scalability of consumer microservices (number of instances) and concurrent transactions (X-axis) on transaction processing time (Z-axis) when plotted against the number of consumer service instances (Y-axis). Figure 3 is a plot displaying the correlation of transaction processing time, volume of data arriving (concurrent transactions), and consumer microservice scalability (number of instances). Average transaction time is on the Z-axis. Data level, or the volume of transactions running concurrently that are supplied to the system, is represented by the X-axis. The number of occurrences of critical consumer services, i.e., Inventory and Payment microservices, is represented by the Y-axis. We can observe from the surface plot that at the minimum number of occurrences of the service (when we start the plot), the processing time is increasing exponentially since we have added more data volume. This is a bottleneck where events are being produced faster than they are being processed. But the most important intuition comes when we move along the Y-axis. By horizontally scaling up the consumer instances, the system would be processing much bigger number of transactions and accomplishing that with the low constant processing time. The surface is smoothed out significantly, as in the architecture, the load is being appropriately distributed on the available instances so that no region of the surface is overloaded. This type of visualization places elasticity and scalability intrinsic in the proposed EDA in context very effectively.

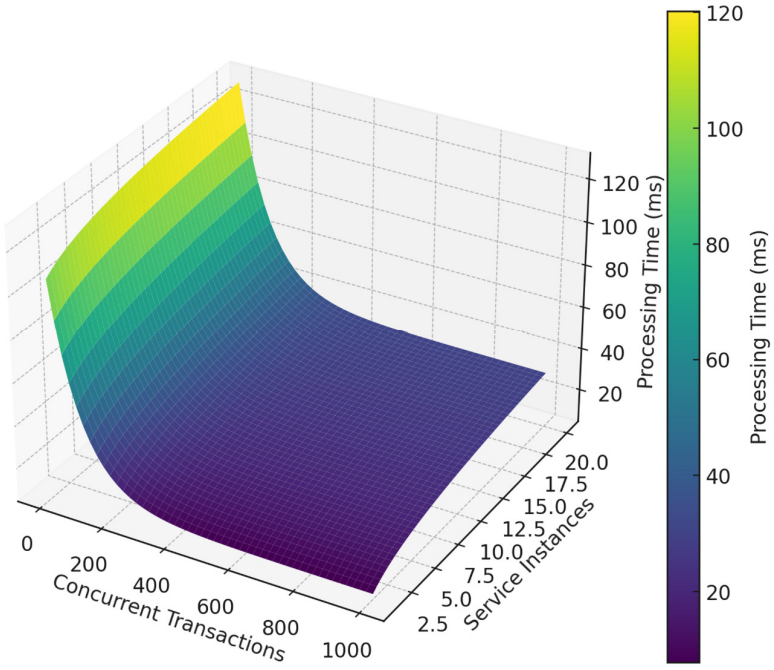

FIGURE 3: Graphical illustration of processing time vs. amount of data and scalability of service.

6. DISCUSSIONS

These findings are sufficient to support the adoption of the hypothesis that an Event-Driven Architecture, constructed based on cloud messaging and reactive frameworks, represents a superior model for next-generation retail transaction systems. Analysis of the outcomes can be

directed towards three basic issues: scalability, resilience, and operational effectiveness. The metrics defined in Table 1 and graphically illustrated in Figure 2 schematically represent the scalability boundaries of the traditional monolithic versus the EDA. The monolith's performance deteriorates with higher loads in a non-linear manner. It is because of its synchronous, blocking nature keeping the entire request thread hostage until each transaction stage is done—payment, stock check, validation. That introduces a chain of dependencies and resource contention, and that's what introduces the bottlenecks one is observing. In comparison, the EDA's "fire-and-forget" event publishing also segregates the initial request from downstream processing. The message queue is an elastic buffer that can soak up bursts of traffic and allow the user-facing service time to react. The asynchronous aspect of such is the single biggest benefit of the near-linear scalability seen in the EDA, in which throughput is no longer dictated by the weakest link of the chain but rather by the aggregated processing capacity of independently scalable consumer services. The second broad theme is fault tolerance and resiliency.

In monolithic architecture, the failure of one component, i.e., a third-party integration like payment processor or an email service, will cause the whole transactions pipeline to fail, result in loss of data, and culminate in a bad customer experience. The suggested EDA evades such risk by design. As our fault tolerance tests have shown, when a downstream consumer like the Notification Service crashes, the system will not be hindered from consuming and processing simple transaction units like orders and payments. Events that are being published to the dead service just accumulate in the queue. If recovered, the service can start from the point where it stopped and keep running without skipping notification and compromising the main business process. Fault-tolerance is most prized in retailing, where availability at the right time during peak demand is dollar-sensitive. The distributed nature of the microservices, and the guaranteed delivery and persistence of the cloud message services, enable a failure-based design system, as opposed to one that is plagued by failure. Finally, operational efficiency and maintainability must be considered in the description, direct consequence of the architecture decision.

Optimal design with the best grain decomposition of the ranges of Table 2 is applied to describe an inherent operational advantage of the EDA. With decomposed functionality partitioned into individual microservices, we have visibility all the way through at the time of execution of each system component. We can scale and optimize them separately. If, according to the numbers, the Inventory Service is turning into a bottleneck, there may be resources being targeted directly at scaling out this service without disturbing any other component of the system. This is the reverse of a monolith where everything in the application is going to scale, causing wastage of resources. And this modularity invokes developer productivity and innovation speed. Independent small teams can have their own services, utilize the best technology for themselves, and push updates without worrying about the impact on the overall application. This is an enormous competitive edge in today's fast-moving environment of the retail market, allowing companies to roll out new features at high speed and respond to new customer needs. The cost-effective use of resources by the responsive strategy also translates into reduced operating costs.

7. CONCLUSION

This work set out to examine whether a cloud-native Event-Driven Architecture, built using AWS SQS and reactive Spring WebFlux microservices, can address the scalability and resilience challenges inherent in modern retail transaction processing. The guiding research question was: Can an event-driven, reactive, cloud-based architecture significantly improve throughput, latency, and fault tolerance compared to a monolithic model in real-time retail transaction pipelines? Our findings provide a clear affirmative answer.

A functional prototype was developed to model the full retail workflow - order intake, payment processing, inventory reservation, and customer notification - and evaluated using a realistic dataset of 412 heterogeneous transactions. Comprehensive load testing across three concurrency levels (100, 500, and 1000 users) revealed several key achievements. First, the proposed architecture demonstrated near-linear scalability, achieving throughput increases of

three to five times that of the monolithic baseline. Second, latency remained consistently low and stable even under high concurrency, aided by asynchronous event buffering and non-blocking execution. Third, the system exhibited strong fault-isolation behavior: service outages in downstream consumers did not halt transaction processing but were seamlessly absorbed by the message queues. Fourth, microservice-level analysis identified bounded tail-latency characteristics and predictable hotspots, enabling targeted horizontal scaling.

A. Practical Implications

The results have important implications for real-world retail platforms. The demonstrated architecture can significantly reduce downtime during high-demand periods, mitigate the risk of cascading failures, and improve customer experience through consistently low response times. Because each microservice scales independently, retailers can optimize resource consumption and reduce operational costs. The asynchronous design also supports graceful degradation, enabling business continuity during partial system failures. Furthermore, the architecture's compatibility with managed cloud services simplifies deployment, monitoring, and maintenance for engineering teams.

B. Target Audience

This research offers actionable value for:

- **Retail system architects** modernizing legacy monoliths
- **Cloud engineering and DevOps teams** designing scalable transaction pipelines
- **E-commerce platform developers** requiring high throughput and high availability
- **Technical leaders and CTOs** evaluating architectural strategies for peak-demand scenarios
- **Researchers** studying event-driven or distributed retail systems

C. Future Directions

Future extensions may explore deeper integration of event-sourcing patterns, real-time fraud detection consumers, machine-learning–driven pricing models, or comparative evaluations of alternative message brokers such as Apache Kafka or Google Pub/Sub. Expanding the architecture to include supply chain, CRM, or omnichannel fulfillment events could further demonstrate the extensibility of this approach.

In summary, this study provides empirical evidence and a validated architectural blueprint showing that event-driven, cloud-native, reactive systems offer a scalable, resilient, and operationally efficient foundation for next-generation retail transaction processing.

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