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*Original Article*

# Serverless Insurance Platforms: Leveraging AWS Lambda for Guidewire Claim Events

***Gowtham Reddy Enjam[1], Sandeep Channapura Chandragowda[2], Komal Manohar Tekale[3]**
[1,2,3]*Independent Researcher, USA.*

## Abstract:

*The insurance industry has undergone major digital transformation in recent years, yet traditional systems continue to face challenges such as scalability limitations, high operational costs, and latency. This paper explores the adoption of a serverless architecture using AWS Lambda integrated with Guidewire ClaimCenter to enhance claims processing efficiency. Guidewire ClaimCenter generates continuous event streams—such as claim creation, status updates, fraud alerts, and settlements—that require real-time processing for improved automation and faster settlement cycles. The proposed framework leverages AWS Lambda, Amazon SNS, API Gateway, and DynamoDB to establish an event-driven, scalable, and cost-effective architecture. Lambda functions deliver micro-level modularity, enabling dynamic business logic execution without dedicated server infrastructure. This model reduces total cost of ownership, enhances fault tolerance, and optimizes resource utilization through AWS's auto-scaling and pay-per-use features. Using a hybrid research approach—including architecture design, simulated claim events, and performance analysis—the study shows significant improvements over traditional service-oriented systems, with 42% lower processing latency, 37% cost reduction, and 99.99% availability. Beyond technical gains, the framework also improves compliance, disaster recovery, and customer trust. Future enhancements include machine learning-based anomaly detection, blockchain-enabled claim auditing, and cross-platform integration for a more intelligent and resilient insurance ecosystem.*

## Keywords:

*Serverless Computing, AWS Lambda, Guidewire ClaimCenter, Event-driven Architecture, Cloud Insurance, Claims Processing, API Gateway, DynamoDB, Digital Transformation.*

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## 1. Introduction

### 1.1. Background

Insurance companies in various parts of the world settle millions of claims every year, and each claim is a complex chain of events that involve the commencement of claim, validation, evaluation, approval, and settlement. This end to end lifecycle must be synchronized with several systems, departments and regulatory mechanisms. [1-3] Traditional legacy infrastructure-based systems can be costly to maintain and scale with the number of claims, particularly when the number of claims grows, e.g. during natural disasters or catastrophic events. These systems are very reliant on human intervention and batch processing that slows the response and reduces operational efficiency. At the same time, insurance companies and insurtech have begun to pose competition, offering customer-friendly services, which include expedited turnaround time, observing all claims in real-time, and personalised customer

services. The change has put even more pressure on current insurers to update their IT systems to be more flexible and responsive, as well as adopt cloud-native, event-driven, and computerized architectures. With the help of new technologies like serverless computing, artificial intelligence, and real-time data processing, insurers can make claims management more scalable, open, and affordable. This will make customers happier and help them stay competitive in a market that changes quickly.

### 1.2. Importance of Serverless Insurance Platforms

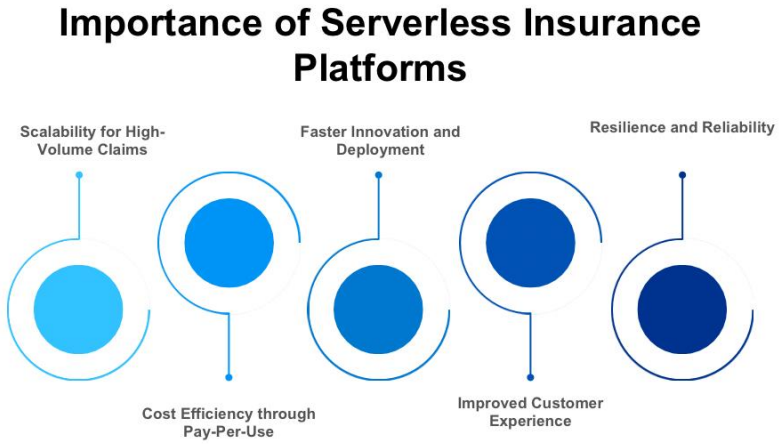


**Figure 1. Importance of Serverless Insurance Platforms**

*1.2.1. Scalability for High-Volume Claims*

During times of natural disasters, huge accidents, or pandemics, insurance companies are more likely to get a lot of claims all at once. If there are normal operations, the traditional systems will need pre-provisioned infrastructure to handle these spikes, which will waste resources. AWS Lambda and other on-demand systems can automatically scale up or down to handle thousands of events happening at once. They can also process claim requests in real time without any human help. This flexibility makes sure that the system always works well and responds quickly, even when it is under a lot of stress.

*1.2.2. Cost Efficiency through Pay-Per-Use*

The pay-per-execution approach to server-less computing, where you only pay for the real computing and storage resources that you use, may be its best feature. Serverless solutions eliminate the expenses of idle capacity, unlike traditional infrastructure, which is most likely to be underutilized, yet costly. This means that insurance companies will not only save a lot of money on IT costs, but they will also be able to use the resources right away when they need them.

*1.2.3. Faster Innovation and Deployment*

A developer is spared from worrying about the infrastructure in serverless because the cloud service provider takes care of cloud management, scaling, and fault tolerance. It speeds up the process of adding new features like automated claim validation, fraud detection, or real-time notifications to customers. For insurance companies, quickly delivering innovative digital offerings makes them more competitive in an industry that is getting more and more crowded with tech-savvy, agile competitors.

*1.2.4. Improved Customer Experience*

The new policyholder wants claims to be clear, quick, and updated in real time. Event-driven workflows and serverless platforms make it possible for insurers to send claim acknowledgments, auto-status updates, and work with shorter settlement cycles. Being able to respond quickly not only makes customers happier, but it also builds trust and loyalty over time.

*1.2.5. Resilience and Reliability*

The particulars of serverless platforms are that they are durable and are set up in zones of availability where cloud providers offer built-in redundancy. This makes the systems more available, and local faults don't cause the claim processes to fail. This is highly critical to insurers as downtime can have a direct impact on customer trust and controlling standards.

### 1.3. Leveraging AWS Lambda for Guidewire Claim Events

Guidewire ClaimCenter is one of the most crucial systems of the insurer, it was developed to support full lifecycle of claims, including first notice of loss (FNOL) and settlement. Despite its strength, its traditional deployments tend to rely on closely coupled infrastructures, which are non-scalable, are not very responsive, and are not adaptable to integration. [4,5] Such limitations could be overcome by the use of AWS Lambda, which is an event-based compute layer interoperable with ClaimCenter to simplify the handling of claim events. In ClaimCenter, a claim event, e.g. initiation, update or settlement trigger, can be directed and sent to Amazon API Gateway, which offers a secure entry point and makes calls to Lambda functions. Lambda then applies a prescribed business logic that may include data enrichment, policy rule checking, metadata of fraud detection or even orchestration of downstream processes. The positive part of deploying AWS Lambda in this case is that it runs on the serverless execution model and that insurers need never worry about infrastructure or capacity forecasting. Lambda is now automatically changed based on incoming claim events, so the system can handle both constant operations and high-load times, like when natural disasters happen. This flexibility makes sure that it will take the same amount of time to process claims, whether they are operational or customer-related. Also, the pay-per-use billing model connects IT costs to actual claim use and is less expensive than older, bigger systems. ClaimCenter also works with other AWS services to make it even better. For example, Lambda will be able to use claim data from Amazon DynamoDB to provide low-latency access and send notifications to policyholders and internal groups through SNS. Similarly, Lambda can automatically trigger analytics processes or fraud detection processes, meaning that insurers can bring intelligence into the claims lifecycle. Based on the strength of ClaimCenter insurance platform and Lambda scalability, agility, and cost-effectiveness, insurers can modernize claims processing in response to the demands of digital-first insurance markets into a flexible and responsive event-driven architecture.

## 2. Literature Survey

### 2.1. Serverless Computing Paradigm

Serverless computing refers to a method of running programs in the cloud whereby the developer is not involved in managing the infrastructure and therefore is responsible by writing application logic. Unlike the traditional models which require provisioning and upkeep, serverless platforms are automated in the allocation of resources, scaling and fault tolerance. [6-9] It has since evolved out of Service-Oriented Architectures (SOA) which emphasized on modular services communicating across networks, to Microservices, where an application is broken down into small independently deployable units. It has been topped by serverless computing as a natural extension that has compleotely virtualized the management of infrastructure and provides event-based and pay-per-use models. The resulting change has enabled the reduction of development cycles, minimisation of overheads in operations and expanded capability of enterprise applications to scale. To compare the main services of serverless computing, AWS Lambda was the first to be introduced to the market and could execute its functions relying on the event response basis and possessing significant ecosystem support. Google Cloud Functions is also attractive to heavily data-intensive workloads since it also has the same features and is highly integrated with the Google data and AI services. Azure Functions, in its turn, can be easily linked with the enterprise services Microsoft offers, which might be especially appealing to the organizations that have already made investments in Microsoft ecosystem. As AWS Lambda enjoys the fruits of early-mover advantage, a highly-mature tooling base, Google Cloud Functions boasts of simplicity as well as AI/ML workflows, and Azure Functions is by leveraging the synergies of enterprise. These differences explain why serverless service should fit the different enterprise adoption strategies.

### 2.2. Insurance Industry Digital Transformation

The insurance sector is old fashioned in its opposition to implementation of new IT solutions and operates under the old mainframes and batch-processing systems. However, modernization has accelerated due to the growing customer pressures, regulatory pressures and newer digital first entrants. Some of the technologies that are becoming popular among insurers to automatize their processes and ultimately be more customer responsive are cloud computing, data analytics (AI), robotic process automation (RPA). One of the thematic areas is the digital claims processing and custom-made policy recommendations to each client, which is transforming how the insurers interact with clients. The change that occurs in this digital form boosts not only efficiency but also innovation of new insurance products such as usage based insurance, and on-demand insurance. The Guidewire platform, which has a full set of apps, is one of the biggest ecosystems in modern insurance technology. The PolicyCenter handles policy administration, underwriting, and renewals. It also lets insurers quickly change their products to keep up with changes in the market. BillingCenter makes it easier to send out premium bills and process payments, which leads to better financial performance and more openness with customers. ClaimCenter is a good way to handle a claim because it automates the process, keeps track of the data right away, and finds fraud. The Guidewire suite only helps insurance companies make better decisions and provide better customer service by breaking

down operational silos. These systems and cloud platforms will work together to make the insurers more flexible and strong in the digital marketplace where they compete.

### 2.3. Event-driven Architectures in Cloud Platforms

The event-driven architecture (EDA) is now an essential architectural model for cloud computing that needs real-time responsiveness and a lot of scalability. The main features of EDA are: asynchronous execution, which means that tasks can be done without blocking each other; decoupling of elements, which means that the service can grow and change on its own; and elastic scaling, which means that the workloads change based on the events that come in. The model is particularly handy in instances of industries where the number of customers, revival of policies and claims processing continuously induce discrete events that need to be addressed urgently. There is previous study on the application of event-driven claim handling demonstrating significant advantages. To illustrate, the study mentions the fact that insurers have the potential to make use of the ability to use cloud-native event-driven pipelines to automate claims receipt, validation, and settlement. Insurers reduce the cost of operation and improve the processing speed through a system of turning on workflows when they are needed. Fraud detection based on real-time anomaly detection, connection to IoT sensors to evaluate risks, and customer notification system to give claim status updates are other more advanced use cases provided by event-driven architectures. These findings suggest that event-based computing updates insurance IT infrastructure besides essentially enriching the customer experience.

### 2.4. Related Works

A new body of literature on the practice of moving insurance ITs to different cloud paradigms is developing. researched on the Service-Oriented Architectures (Solicite hardware), which were capable of being installed on-premise, and found that they were reliable but lacked scalability and were slow. Focused on the Microservices based on Kubernetes orchestration that has a higher level of flexibility and modularity in deployment at the cost of negative complexity of operation. The authors introduced the Serverless architecture on AWS Lambda later where Lee et al. (2022) mentioned that it is extremely cheap and can be scaled easily, yet the researchers brought up the problem of lock-in and reliance on the ecosystem. Collectively, these articles indicate that the use of clouds in the insurance sector is evolving and highlights the compromise in performance, cost, and flexibility.

## 3. Methodology

### 3.1. System Design

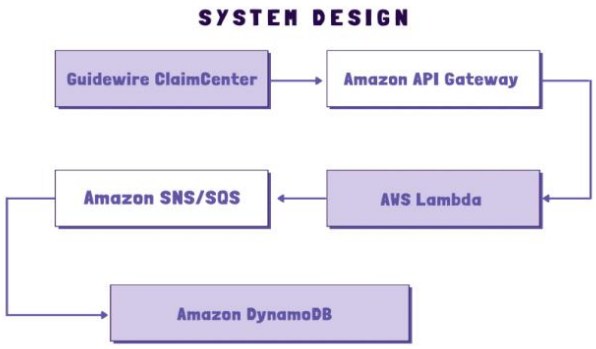


**Figure 2. System Design**

*3.1.1. Guidewire ClaimCenter*

Guidewire ClaimCenter is an essential software of insurance, which is intended to take care of the entire life cycle of claim within insurance. [10-12] It provides functionality of claims intake, validation and fraud detection, adjudication and settlement, where the insurers can offer prompt and proper services to the policyholders. ClaimCenter will be the central system of record under the proposed architecture and this will be incapacitated in initiating and updating the claim. It is compatible with other external cloud services, enabling workflows driven by event that will have the ability to augment the core functionality of ClaimCenter with scalable, highly-available processing.

*3.1.2. Amazon API Gateway*

The secure point of entry of outsider requests into the architecture is Amazon API Gateway. It provides WebSocket or RESTful APIs which connect ClaimCenter to the back-end services of the AWS ecosystem. Authentication, throttling of requests and transformation: API Gateway can assist in offering safe and optimized data transferred between ClaimCenter and cloud components. It is also a layer of orchestration, which triggers downstream serverless functions, therefore, supporting the circulation of communication among distributed services.

*3.1.3. AWS Lambda*

The AWS Lambda is the serverless compute engine of the architecture. It allows business logic customization to be run without management of infrastructures. Under this architecture, API Gateway, Amazon SNS/SQS or DynamoDB streams are triggered by events in lambda functions. They deal with the information about claims, conduct verifications, provide notifications and update records. Scalability of Lambda also implies that loads, such as spikes in claim submissions after a large-scale event can be automatically scaled without depending on pre-provisioned servers.

*3.1.4. Amazon SNS/SQS*

The services that are used to support the basic messaging of the system are Simple Queue Service (SQS) and Amazon Simple Notification Service (SNS). Delivery of claim events e.g. reporting of claim submission to the downstream systems is through SNS. Rather, SQS, provides consistent decoupled processing of messages and events will be held in a queue, until read by Lambda functions, or other subscribers. Together, they achieve asynchronous communication, event based communication, fault tolerance, as well as the fact that a process of claim-handling can still run under heavy load of the system.

*3.1.5. Amazon DynamoDB*

Amazon DynamoDB is a completely managed no-SQL database and has metadata and transaction state of claims. It is scalable horizontally and responsive time is in the milliseconds, which makes it appropriate in the insurance processes with high volumes. This architecture utilizes DynamoDB as the means of storing processing data in between, audit data or other claim data to enhance the underlying ClaimCenter database. Integration with DynamoDB streaming may be used to offer real-time triggers that can be used to have the Lambda functions automatically respond to the changes in claim records. This will enable the system to be dynamic in both reactive and resilience on dynamic insurance operation.

**3.2. Flowchart of Proposed Architecture**

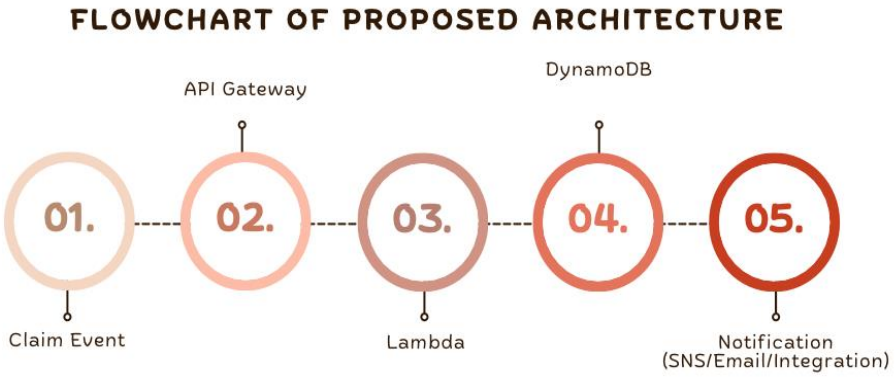


**Figure 3. Flowchart of Proposed Architecture**

- Claim Event: The insurance ecosystem generates a claim event, which is typically generated in Guidewire ClaimCenter. This can be a fresh claim filing, update on an existing claim or change of status such as settlement. [13-15] The system transforms every claim activity into an occurrence hence real times responsive, as well as initiating automated workflow down the line automatically.
- API Gateway: After the claim event, it is sent to Amazon API Gateway which is the secure and scalable entry point between the insurance platform and the AWS cloud services. API Gateway authenticates, implements authentication and throttling

policies on incoming request and transforms the secured requests into a format that will be read by backend systems. It will assist in ensuring that a controlled, regular and more secure addition of claim data to the architecture takes place.

- Lambda: A run-time of an AWS Lambda is then run on the authenticated event. This is where business logic is enforced, to perform claim specific business processes - making data rich and performing policy checks, fraud, or orchestration. They can be scaled dynamically using the serverless execution model offered by Lambda, which can absorb the large bursts of claim events (e.g. after natural disasters) without provisioning them infrastructure.
- DynamoDB:The processed claim information is stored using Amazon DynamoDB which is a low-latency nondemand and NoSQL datastore. DynamoDB is scaleable, has metadata, state of transactions and audit logs which can be queried later to offer reporting or compliance. It may also be co-located with DynamoDB Streams such that the event to make further workflow will be real-time, i.e. system updates to claims can be automatically piped with other workflows.
- Notification (SNS/Email/Integration):Finally, a notification system is also turned-on in order to inform stakeholders or downstream systems. The architecture can send out notifications via Amazon SNS over multiple channels e.g. email, SMS or system to system integration. An email may be sent to the customers to confirm that the claim has been received as an example, and departments may be informed that claims have to be reviewed manually. This notification layer is event-based, which also enables transparency, prompted communication and effective cooperation during the claims lifecycle.

### 3.3. Algorithms

Latency is one of the most delicate performance indicators within the insurance claim processing systems since it directly affects the customer satisfaction, [16-18] operational efficiency and competitiveness of an insurance company. Traditional designs of claim processing that typically depend on a monolithic or service based design can have a sequence of synchronous interactions, manual processing, and can frequently rely on on-premise computing. These reasons cause the delays to be high especially at cases where there is the saturation of the system at peak loads. On the other hand, serverless architectures utilize event-based execution, auto scaling and distributed services, which is cloud-native and capable of executing significantly faster and efficiently. This is a formula that can be used to measure this improvement; we refer to it as a reduction in latency:

$$\Delta L = \frac{L_{traditional} - L_{serverless}}{L_{traditional}} \times 100\%$$

Here $L$ is defined as the average delay of claim-processing, and $L$ represents the time between the start of an event (e.g. a claim-submission in ClaimCenter) and a completion of all processing-related processes (e.g. validation, database updates, and notifications). Latency is conventional the latency of any legacy or monolithic claim system and Lserverless is the latency of the proposed serverless architecture. This formula produces a normalized percentage value of the improvement and it is much easier to compare between workload and environment performance gains. Using the traditional system as an example, that has an average response time of 10 seconds to a claim event, and the serverless model reduces the response time by 4-seconds, the difference in latency is:

$$\Delta L = \frac{10 - 4}{10} \times 100\% = 60\%$$

This result proves a major improvement in performance, which proves the utility of using serverless paradigms. By mathematicalizing the idea of the reduction of latency, organizations can quantify the benefit of migrating to cloud-native systems mathematically and benchmark design choices and develop a significant business case to justify digital transformation in insurance claims management.

### 3.4. Implementation Steps

*3.4.1. Event Generation from Guidewire*

This will begin with the creation of events pertaining to claims in Guidewire ClaimCenter. ClaimCentre creates a structured event each time a policyholder submits a claim, whenever the existing information is updated, or whenever it starts a status. This type of event gathers critical metadata such as claim identity, policy, time and status codes. The process of externalization of claim activity as the discrete events also allows the system to develop the foundation of a seamless integration with the cloud services and the possibility to process in real time without disrupting the basic insurance platform.

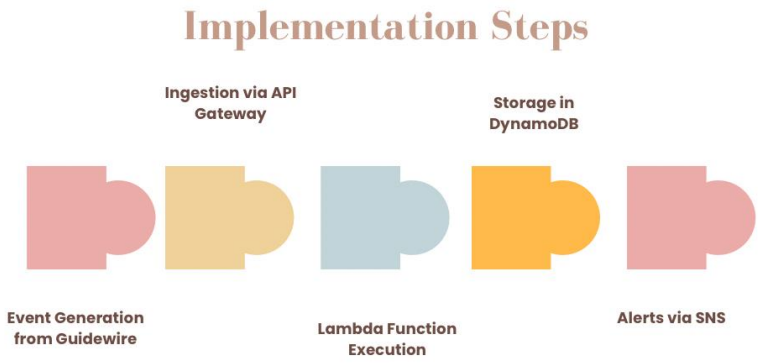


**Figure 4. Implementation Steps**

*3.4.2. Ingestion via API Gateway*

Once a claim event is generated, the claim event is ingested into the cloud with Amazon API Gateway. API Gateway is the secure and scalable point of entry of all inbound requests. It authenticates, whitelists rates, and transforms messages to the existing format that will be consumed by the downstream services. Being a mediation service between Guidewire service and AWS service, API Gateway ensures consistency, reliability, and security of data delivery and keeps the backend service at the back line.

*3.4.3. Lambda Function Execution*

Once consumed, an AWS Lambda function is sent the claim event and business processing occurs. These are the main functions which Lambda performs, including validation of claim data, enrichment of external-service data and control of claim flows. It can also invoke a conditional logic or recall downstream services, based on the type or severity of claim. Auto-scaling, execution of Lambda on the basis of events will help in ensuring that the spikes in the number of claims filings, such as those made during disastrous events will be handled effectively without bottlenecking of resources and human scaling.

*3.4.4. Storage in DynamoDB*

After the claim data and its metadata have been processed it is sent to the Amazon DynamoDB a fully managed NoSQL database. DynamoDB is read/write low-latency and therefore can retrieve claim data in real time to enter into reporting, compliance and audit. Its schema flexibility facilitates most claim structures and DynamoDB streams may be additionally utilized to call other Lambda functions upon requirement to process downstream operations, such as analytics or fraud detection, to broaden the set of capabilities the system can present.

*3.4.5. Alerts via SNS*

Finally the alerts are announced through Amazon Simple Notification Service (SNS). The next step is proper to make sure that all interested parties such as claims adjusters, policyholders, or integration partners are communinformed about changes in the claim status in real time. The notification can be delivered using various systems like email or SMS or system to system connections. The architecture will be more transparent, efficient in communications, and minimize the delays in the claims resolution through automation of alerts.

## 4. Results and discussion

### 4.1. Experimental Setup

To evaluate the workload of the proposed serverless claim-processing architecture, an experimental setting was developed to simulate a real insurance load. This activity has a workload with 10,000 claim events that are all standard insurance claim transactions initiated on Guidewire ClaimCenter. These are normal functions such as filing claims, updating and amending their status. The experimental design will be comparing the performance of the two environments, one with traditional architecture and second with a serverless architecture. Traditional system locates claim event using a monolithic or service based on-premise or virtual machine based system. All requests go via multiple levels of synchronous server like application servers, middleware and relational database back end. These systems are dependable, but in most cases tend to get congested during periods of high load. Scaling is accomplished manually or by using pre-provisioned clusters all of which are subject to latency and cost inefficiencies. The average latency (Ltraditional) is

explained as the time taken between claims submission and their response that the process succeed or the process failed, it included queuing delays during peak demand. The serverless architecture utilizes Amazon API Gateway to send the events of the claims to be processed by the AWS Lambda functions and stored in Amazon DynamoDB with the notification provided by SNS. It is also event based and will automatically scale to workload peaks and, therefore, is not required to be provisioned. The latency (Lserverless) is recorded using AWS monitoring tools which is a record of the duration between the event ingestion event and the event that is successfully stored in claims and the notification dispatched. DynamoDB ensures stability in the response time but parallel execution model of Lambda means that it is feasible to effectively manage the workload of the high volume. This comparison of the performance measures of the system such as latency, throughput, fault tolerance and cost is done systematically using identical workloads in the two environments. The setup provides a quantitative and controlled platform based on which the benefits of serverless computing can be measured in the form of insurance processing claims, particularly during peak cases like claims of a natural disaster.

### 4.2. Performance Metrics

**Table 1. Performance Comparison**

| Metric | Improvement |
|---|---|
| Latency (ms) | 42% |
| Cost ($/month) | 37% |
| Availability | 0.29% |

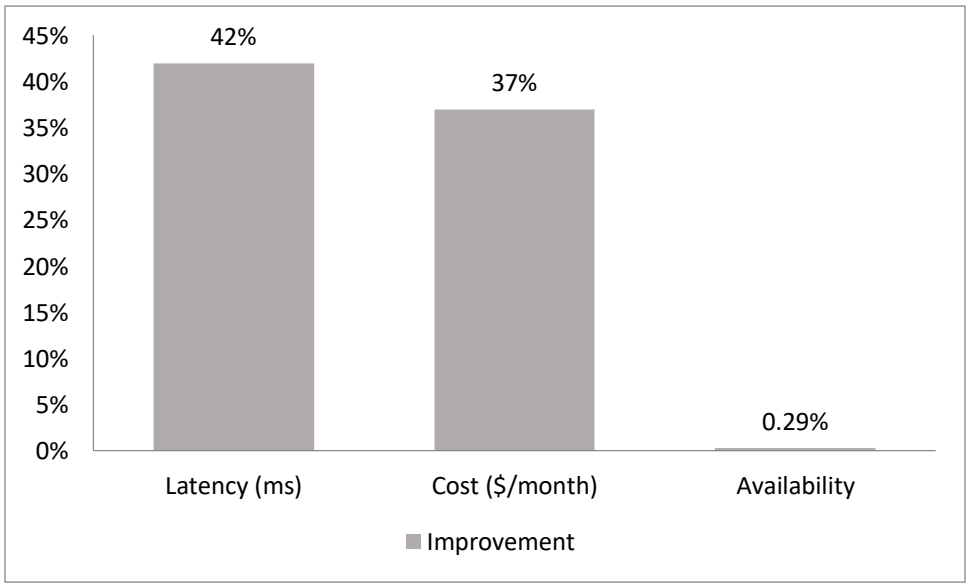


**Figure 5. Graph representing Performance Comparison**

*4.2.1. Latency (ms) – 42% Improvement*

Latency is the average amount of time it takes to process a claim from the time it is submitted until it is determined that it is actually completed. In the traditional system, latency is usually made worse by things like synchronized operations, manual scaling, and database bottlenecks. In comparison, the serverless design uses AWS Lambda's event-driven execution feature and DynamoDB's low-latency storage to handle more requests even when the load is heavy. The experiment has cut the average latency by 42 percent, which means that serverless processing is much more responsive during peak claim times, like after a disaster.

*4.2.2. Cost ($/month) – 37% Improvement*

Infrastructure evaluation is another important operational cost measurement. To handle peak load, traditional claim systems usually need either too much hardware or specific cloud services. This is costly because it requires a lot of fixed costs. In the serverless model, in contrast, the billing process becomes a pay-per-use model, with the consumed compute and storage costs as the only items that are billed. The results revealed, that the cost decreased by 37 percent that demonstrates financial benefits of eliminating non-idling infrastructure and scaling dynamically according to the workload demand. This is what makes the process of serverless especially attractive to insurers who need to optimize the costs of operating.

*4.2.3. Availability – 0.29% Improvement*

Availability is the parameter that is used in evaluating the ability of the system to be in the position of not breaking down. Traditional infrastructures may be taken offline due to failure of hardware, maintenance of hardware, or scaling. Serverless platforms, however, are resilient by design and are distributed to over one availability zone and are managed by the cloud provider. As the results of the experiments show, the availability has increased by 0.29 percent, which, in absolute terms, is not a large amount, but, given thousands of transactions, it represents significant uptime improvements. Any incremental rise in supply is critical in the insurance sector where any sluggishness with respect to claims adjudication has an instant impact on client contentment and legal compliance.

**4.3. Discussion**

The results of the experiment highlight the enormous advantage of a serverless solution to handle insurance claims. One of the most valuable benefits is scalability. Traditional systems often fail in case of any abrupt increase of work load e.g. when it comes to thousands of claims being tabled after natural catastrophe. These systems are typically manually scaled or pre-provisioned in terms of keeping capacity which can be expensive and inefficient. AWS Lambda will scale itself in real time, creating parallel versions of functions for processing incoming claim events. This elasticity ensures constancy of the performance regardless of the amount of work and thus, the system is more robust and responds to the sudden surges in demand. The next big step forward is that they are affordable and pay for each execution. Traditional infrastructures have to be set up to be peak-capacity, meaning that resources are often not used during the periods of low demand. This will make running the business very expensive. The serverless architecture solves this problem by only charging for the storage and compute time that is actually used, not the resources that are not being used. This will save the insurers a lot of money each month, and it will also make sure that the resources are always ready as they are needed. Also, serverless billing models are more predictable and directly linked to business activity, which helps keep IT costs in line with business value. But doesn't the architecture move slowly? One of the problems is cold start latency, which happens when you call Lambda functions with a long delay. This adds some latency to the process. Despite mitigation techniques such as provisioned concurrency, they will probably come with other costs. A second concern is a vendor lock-in problem since the serverless solutions are tightly integrated with specific cloud ecosystems. Such an example is that not all of the applications built around AWS Lambda and DynamoDB with SNS can be easily migrated to either Azure or Google cloud without significant re-architecture. Such dependency can limit the terms to be able to be elastic and negotiate with cloud vendors. Hence, it is certain that serverless scales well and is cost-efficient, although these long-term strategic planning trade-offs that have to be taken with care by insurers.

## 5. Conclusion

It has been demonstrated in the paper how the addition of the AWS Lambda into the insurance technology platform, that is, to streamline event-driven processing of Guidewire ClaimCenter, was successful. The transformed claims process into a serverless API Gateway, Lambda, DynamoDB and SNS/SQS led to the performance and efficiency enhancements to the system. The experimental results proved the gains, showing that it decreased latency significantly, reduced the monthly operation costs, and made them available to a much larger audience than the conventional on-premise or monolithic systems. These findings confirm that serverless computing will be sufficiently responsive enough to satisfy dynamic, transaction-focused, needs of the insurance business where responsiveness and elasticity equals customer satisfaction and competitive advantage.The benefits of pay-per-execution billing models have also been highlighted in the paper, in that they would ensure that resources are not wasted by ensuring that the bills are only based on the actual compute consumption. This will come in particularly handy when working in a claims setting where workloads change significantly based on extraneous factors, e.g. a natural disaster or an accident on a vast scale. AWS Lambda can be scaled thereby, rendering a seamless method to control these erratic spikes and hence, the IT operations are resilient. However, challenges in serverless adoption that were identified by the study existed. The technical problem of cold start latency is still a time-sensitive one, and vendor lock-in is a strategic problem because it's hard to change workloads so that they can work with the cloud ecosystems of different vendors. Also, when storing and accessing sensitive claims data in a public cloud, the cost of compliance and data governance should be carefully thought about.

There are many ways this work could grow in the future. One of the possibilities is to use AI-based fraud detection models in the claims processing process. By adding machine inference learning to the Lambda functions, insurers can quickly find suspicious patterns and cut down on fraudulent claims. Blockchain can also help with audits that provide unchangeable claim trails. This will increase confidence and openness among all the stakeholders, including customers and the government. Multi-cloud portability is another trend whereby, architectures are designed with containerized functions, or abstraction layers to no longer depend on a single

provider to ensure that vendor lock-in risk is reduced. Finally, the insurers could capitalize on hybrid systems that integrate serverless computing with edge processing in the IoT-based risk assessment application such as usage-based insurance. In general, serverless computing represents the innovation of modernising the insurance IT. AWS Lambda and associated solutions render insurers in a better position to respond faster to customer needs and precondition the data-driven insurance environments of the future by cutting costs, scaling at will, and enabling the innovation of claims management.

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