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Research Article

A Comparative Study of Software Testing Techniques and Quality Metrics for Predicting Failure Rates in Scalable Cloud-Native Software Systems

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Abstract: Cloud-native systems are essential for modern software development, offering enhanced scalability, flexibility, and resilience through cloud computing environments. However, ensuring the reliability and performance of these systems presents a challenge due to their dynamic and distributed nature. Traditional testing methods, such as unit and integration testing, while valuable for detecting individual component defects and interactions, are insufficient for predicting failure rates in complex, cloud-native applications. This study explores the effectiveness of various testing techniques and quality metrics in predicting failure rates within scalable cloud-native systems. A comparative experimental study was conducted using three primary testing techniques: unit testing, integration testing, and chaos testing. The results indicate that chaos testing, when combined with advanced quality metrics such as migration rate and mismigration rate, significantly outperforms traditional methods in predicting failure rates and evaluating system resilience. These findings suggest that chaos testing offers a more comprehensive evaluation, simulating real-world disruptions to test system behavior under stress, which is essential for cloud-native environments where high availability and fault tolerance are critical. The study also highlights the importance of integrating predictive quality metrics, which improve the accuracy of failure predictions and enhance system reliability. The study concludes that for cloud-native systems, a combination of advanced testing techniques and predictive metrics is essential for ensuring high availability, scalability, and reliability in dynamic environments. Future research should focus on refining predictive testing approaches, developing standardized frameworks, and empirically validating new testing methods to address the growing complexity of cloud-native systems.

Keywords: Chaos Testing; Cloud-Native Systems; Failure Prediction; Quality Metrics; Testing Techniques.

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1. Introduction

Cloud-native software systems have emerged as a transformative approach in the development of scalable, resilient, and agile software architectures, particularly in cloud computing environments. These systems fully leverage the capabilities of the cloud, utilizing technologies such as containerization, microservices, serverless computing, and service meshes to optimize deployment and management [1]. Cloud-native architectures enable dynamic, modular system development, which facilitates rapid deployment and scalability. This approach has led to significant advancements in software development practices, particularly in integration with DevOps, Continuous Integration/Continuous Delivery (CI/CD), and Infrastructure as Code (IaC), providing efficiencies in both development and deployment [2]. The increasing adoption of these principles highlights their importance in

modern software development, allowing organizations to scale dynamically and react swiftly to changing workloads [3].

The significance of cloud-native systems lies in their ability to provide key benefits in contemporary software development. Scalability and flexibility are core attributes, as cloud-native systems allow for dynamic scaling to meet fluctuating demands, optimizing resource usage and ensuring high performance [2]. Additionally, the adoption of microservices and containerization promotes agility and speed, facilitating rapid development, testing, and deployment cycles [4]. Resilience is another major advantage, as features such as auto-scaling and auto-healing mechanisms ensure high availability and minimize downtime, which is crucial for maintaining service-level agreements (SLA) [5]. Furthermore, cloud-native systems enhance resource efficiency by automating resource provisioning and scaling, which ultimately reduces operational costs [3].

However, despite the many advantages, cloud-native systems face several challenges, particularly with scalability, dynamic orchestration, and distributed execution. Efficient dynamic scaling remains complex, as systems must manage resources effectively while maintaining performance and cost-efficiency under varying workloads [6]. Orchestration complexity also arises when managing distributed applications across multi-cloud or edge environments, with tools like Kubernetes playing a vital role in addressing these challenges [7]. Additionally, the need for efficient resource allocation in distributed infrastructures, while addressing security and performance requirements, adds to the complexity [8]. Security risks are amplified in cloud-native environments due to the distributed nature of the system, requiring robust security practices across containers, microservices, and serverless functions [5], [9].

Predicting failure rates in cloud-native systems plays a pivotal role in ensuring their reliability and performance. Given the inherent complexity of cloud computing environments, cloud-native systems are highly susceptible to various failures, including hardware and software malfunctions, which can lead to service outages and significant performance degradation [10]. Failure prediction models offer the advantage of proactively managing these risks by enabling actions such as rescheduling tasks, migrating data, and conducting preventive maintenance. These measures help mitigate downtime, enhance system reliability, and reduce the wastage of resources [11]. Furthermore, effective failure prediction supports maintaining high availability, ensuring a positive user experience by preventing disruptions in service [12].

The purpose of this study is to compare various software testing techniques and quality metrics to determine their effectiveness in predicting failure rates within scalable cloud-native systems. This comparative analysis will help identify the most reliable and accurate methods for ensuring the performance and dependability of these systems. As cloud-native systems increasingly gain prominence, their ability to leverage cloud computing resources for scalability and flexibility has been widely acknowledged [13]. These systems are designed to dynamically scale and efficiently manage workloads across distributed environments, ensuring optimal resource utilization [3].

However, despite their advantages, cloud-native systems face significant challenges related to dynamic scaling and distributed orchestration, which complicate the prediction and management of failure rates [2]. Managing resources effectively while ensuring high performance and reliability in response to fluctuating workloads remains a complex task [14]. Additionally, with the growing adoption of cloud-native architectures, there is an urgent need to assess and refine failure prediction tools and methodologies to improve the overall resilience of these systems. This will ensure that cloud-native applications can maintain their high availability, performance, and fault tolerance under varying conditions [15].

Various machine learning models have been employed to predict failure rates, with notable techniques including the XGBoost classifier, Long Short-Term Memory (LSTM) networks, and CatBoost, which have all shown promise in providing high precision and recall, especially with imbalanced datasets [14]. Simulation tools such as FailureSim also offer predictive capabilities, utilizing neural networks to forecast hardware failures based on performance data [16]. Additionally, the integration of proactive failure-aware infrastructure has enabled systems to predict failures and reschedule tasks effectively, reducing the impact on reliability [17].

Furthermore, the use of new quality metrics, such as migration rates and mismigration rates, has introduced more granular measurements of system health, helping refine failure prediction models by incorporating metrics that go beyond traditional accuracy [18], [19]. Combining these metrics with artificial intelligence algorithms has led to improvements in predicting failure rates, offering more robust solutions for managing cloud-native system reliability [20].

2. Literature Review

Cloud-Native Systems Architecture and Failure Characteristics

Cloud-native systems are designed to fully exploit the capabilities of cloud environments, utilizing distributed and highly scalable architectures. One of the core components of cloud-native systems is the use of microservices, which enable modular, scalable, and resilient applications. This architecture allows each service to be independently developed, deployed, and scaled, making it easier to maintain and upgrade individual components without affecting the entire system [13], [15]. Additionally, elasticity and scalability are inherent features of cloud-native systems. These systems dynamically adjust resources based on workload requirements, ensuring high availability and optimal resource utilization [3].

Another essential aspect of cloud-native systems is fault tolerance. These systems emphasize building resilient applications capable of handling failures without significant impact on the overall system. Techniques such as distributed file systems and automated recovery mechanisms are commonly employed to enhance fault tolerance and ensure seamless system upgrades [21]. Despite these advantages, cloud-native systems face several challenges, including vendor lock-in, integration issues, and difficulties in managing fluctuating peak loads, which require robust strategies for efficient orchestration and resource management [14].

Software Testing Techniques in Cloud-Native Systems

In cloud-native environments, software testing plays a critical role in ensuring system reliability and performance. Various common testing techniques are employed to evaluate the functionality and resilience of cloud-native systems. Unit Testing focuses on verifying the behavior of individual components or services, ensuring they function correctly in isolation. Integration Testing is essential for validating that different components or services interact as expected, particularly between microservices. Another important technique, Chaos Testing, involves deliberately introducing failures into the system to observe how it handles disruptions and recovers, testing the system's ability to withstand unexpected failures-a vital feature for cloud-native applications [22], [23].

In addition to these traditional methods, more advanced testing techniques are increasingly being adopted in cloud-native systems. AI-Driven Testing leverages machine learning models to automate test case generation, predict potential defects, and dynamically schedule tests, improving testing efficiency and coverage [24]. Cloud-Based Testing utilizes cloud infrastructure for scalable and cost-effective testing, including load, stress, and performance testing. These tests simulate high-demand environments, which are particularly relevant for cloud-native applications that must handle varying loads, ensuring that they can maintain high performance and reliability under different operational conditions [25].

Quality Metrics in Software Development

Quality metrics play a crucial role in evaluating the effectiveness and reliability of cloud-native systems by assessing various aspects of system performance and code quality. Key metrics such as Code Coverage and Defect Density provide essential insights into the comprehensiveness of testing and the overall stability of the code. Code coverage measures the percentage of code executed during testing, with higher values indicating that a larger portion of the application has been tested, thus increasing the likelihood of identifying defects [26]. Similarly, defect density calculates the number of defects per unit size of the software, helping to evaluate the stability and quality of the code [27]. Response Time is another vital metric, measuring how quickly the system responds to user requests, which is particularly

crucial for cloud-native applications that must ensure responsiveness and maintain high performance under varying workloads [3].

In addition to these fundamental metrics, advanced metrics also provide valuable insights into software structure and long-term maintainability. Structural Complexity evaluates the architecture of the software, considering factors such as the number of arcs and modules, to identify potential failure points [18]. Maintainability and Reusability are essential for ensuring the software's ability to be efficiently maintained and extended over time, contributing to long-term software quality [19], [26]. Finally, Test Effectiveness measures the ability of tests to detect defects, playing a critical role in Agile and DevOps environments where continuous testing and integration are key to maintaining software quality [28]. These advanced metrics complement traditional testing approaches, providing a comprehensive evaluation of cloud-native system performance.

Testing Techniques and Quality Metrics in Cloud-Native Environments

Cloud-native systems require effective quality models and metrics to assess performance, scalability, and overall reliability. A comprehensive review of 41 studies on quality models in cloud-native architectures emphasizes the focus on performance, Quality of Service (QoS), monitoring, and scalability [29]. This review highlights the dominance of performance efficiency metrics, but also identifies a need for further exploration of metrics related to security and compatibility in cloud-native environments [2]. A systematic classification of 470 QoS metrics further reveals this gap, with performance efficiency emerging as the most commonly utilized metric in evaluating cloud services. However, a significant portion of these metrics is yet to be fully integrated into standardized frameworks, emphasizing the need for more comprehensive models in the field [30].

In the context of cloud-native applications, performance evaluation is a critical aspect, and numerous methodologies have been proposed to measure key metrics like response times, throughput, and resource utilization. A systematic mapping study analyzed these metrics, proposing methodological frameworks that can improve the accuracy and repeatability of performance assessments [2]. However, many metrics are still in the early stages of development, and only a small proportion has been empirically validated, limiting their practical application [29]. Additionally, energy efficiency metrics are becoming increasingly important in cloud-native applications. A framework for measuring energy efficiency integrates service quality and sustainability, demonstrating its effectiveness through initial experimental results [31]. This approach aligns with the growing demand for sustainable computing solutions in cloud-native environments.

Software testing in cloud-native systems faces unique challenges due to the dynamic and complex nature of these environments. Traditional testing techniques often struggle to keep pace with the demands of cloud-native applications, leading to the exploration of new testing methods. A review of testing and evaluation methods for cloud environments categorizes various approaches, providing stakeholders with insights into the most suitable testing techniques for different cloud scenarios [32]. Among these methods, Chaos Testing has emerged as a significant approach, deliberately introducing failures to test the resilience of cloud-native systems [23].

Further advancements in testing are found in AI-driven testing approaches, which leverage artificial intelligence for automated test case generation, defect prediction, and dynamic test scheduling. This method significantly enhances the efficiency and coverage of software testing, making it more suitable for the rapid deployment cycles of cloud-native systems [24]. Additionally, cloud-based testing has become essential for performing scalable and cost-effective tests, including load, stress, and performance tests, all of which are crucial for evaluating the performance of cloud-native applications under varying conditions [25]. These advanced methods represent a shift toward more precise, automated, and scalable testing processes tailored to the dynamic nature of cloud-native environments.

Technology Integration and System Reliability

The integration of emerging technologies such as blockchain, artificial intelligence, Internet of Things, and machine learning has significantly transformed the design and evaluation of modern software systems. These technologies enable the development of intelligent frameworks capable of detecting anomalies, predicting failures, and ensuring system resilience in complex computing environments.

Danang et al. (2025) emphasized that combining machine learning with blockchain and secure execution environments can create adaptive security frameworks for cloud infrastructures. Such frameworks can improve the ability of systems to detect abnormal behavior and maintain operational stability in large-scale distributed systems. Similarly, studies involving IoT-based monitoring systems and automated control mechanisms demonstrate how digital technologies can enhance system reliability and operational efficiency [34], [35].

In addition, technology integration has also been explored in educational and organizational contexts. Research by Putranti et al. (2024) investigated the use of work gamification to enhance engagement and performance assessment. Although conducted in a different domain, the study demonstrates how digital systems can use structured metrics and analytical approaches to evaluate performance outcomes. Such approaches can also inspire the development of quality evaluation metrics in software engineering.

Overall, these studies demonstrate that modern software systems require integrated technological frameworks that combine security, predictive analytics, and intelligent monitoring mechanisms. These capabilities are essential for improving software testing strategies and developing reliable quality metrics that can predict failure rates in scalable cloud-native environments.

Challenges and Gaps in Current Research

Despite the advancements in quality metrics and testing techniques, significant gaps remain in current research. One of the most notable challenges is the lack of standardized frameworks for evaluating and comparing QoS monitoring and remediation techniques in cloud-native environments [37]. The absence of such frameworks limits the ability to assess the real-world applicability of various metrics and testing methods. Furthermore, empirical validation of many QoS metrics remains minimal, with only a small fraction having undergone real-world testing, which limits their practical use in cloud-native applications [29]. This highlights the need for more rigorous empirical research to validate and refine the existing metrics.

Another area requiring further exploration is failure rate prediction, where traditional models focus primarily on accuracy, which may not always reflect practical usage scenarios. New metrics, such as migration rate and mismigration rate, have been proposed to provide a more practical evaluation of failure prediction models, addressing the shortcomings of traditional accuracy-based approaches [18]. Future research should focus on integrating these new metrics into standardized frameworks and empirically validating them to improve the reliability and applicability of failure prediction models in cloud-native environments.

3. Research Method

The study uses a comparative experimental design to evaluate different testing techniques and quality metrics in cloud-native systems. It focuses on unit testing, which checks individual components; integration testing, which ensures the components work together; and chaos testing, which introduces controlled failures to assess system resilience. Quality metrics such as code coverage, defect density, and response time are used to measure the effectiveness of these techniques, with an emphasis on failure rate prediction. Data is collected through controlled experiments, and statistical methods like ANOVA and regression analysis are applied to compare the results, assessing performance indicators like throughput and resource utilization to determine the best approach for ensuring system reliability and fault tolerance.

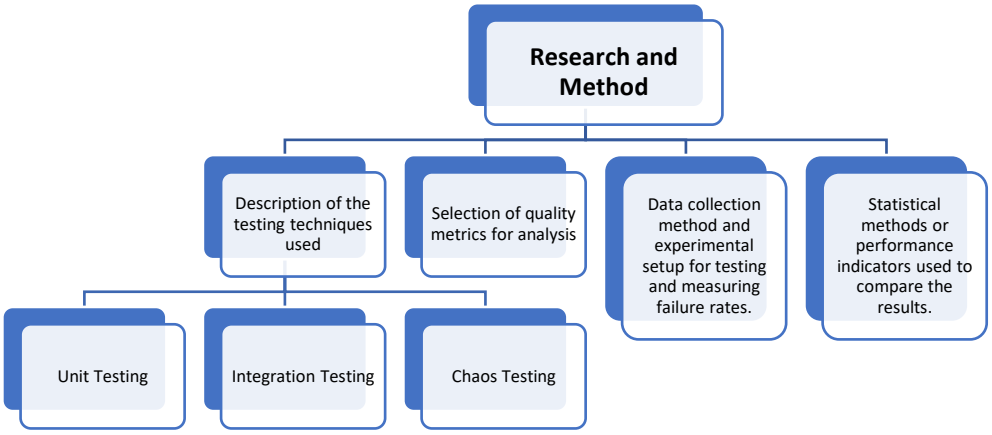

Figure 1. Flowchart structure.

The study employed a comparative experimental design to assess different testing approaches and quality metrics in cloud-native systems. The goal was to evaluate the effectiveness of various testing techniques and quality metrics in predicting failure rates and enhancing system reliability. A comparative approach was chosen to allow for a thorough analysis of how different methodologies perform under controlled experimental conditions. The experimental setup included three distinct testing techniques: unit testing, integration testing, and chaos testing. These methods were selected based on their relevance to cloud-native environments, where modularity, integration, and resilience are critical to system performance.

Testing Techniques

a) Unit Testing: This technique focused on testing individual components of the system in isolation. Unit testing ensures that each part of the cloud-native application functions correctly on its own before integration into the larger system. It serves as the foundational level of testing, verifying that the most basic functionalities perform as expected.
b) Integration Testing: After individual components were tested, integration testing was performed to ensure that different system components work together as expected. In cloud-native systems, the interaction between microservices, databases, and external APIs is crucial. Integration testing was used to evaluate these interactions and ensure smooth operation between them.
c) Chaos Testing: Given the dynamic and distributed nature of cloud-native systems, chaos testing was introduced to simulate failures in the system and evaluate its ability to recover. This testing technique deliberately introduces disruptions or "chaos" to test the system's resilience and its ability to maintain service continuity. Chaos testing is particularly valuable in cloud-native environments, where high availability and fault tolerance are essential.

Selection of Quality Metrics

To assess the effectiveness of the testing techniques, a range of quality metrics was selected, including:

a) Code Coverage: This metric measures the percentage of the codebase that is executed during testing, providing an indication of how comprehensive the testing process is. A higher code coverage ensures that more of the application is thoroughly tested, increasing the likelihood of defect detection.
b) Defect Density: This metric calculates the number of defects found per unit size of the software. It helps evaluate the overall quality and stability of the application and is particularly useful in identifying problematic areas within the system.
c) Response Time: The metric evaluates the time taken by the system to respond to user requests. In cloud-native systems, ensuring low response time is crucial for maintaining a positive user experience, especially under varying workloads.

d) Reliability Metrics: These metrics assess the likelihood of system failure and its ability to perform under expected conditions. The focus was on failure rate prediction and the accuracy of identifying potential system failures before they occur.

Data Collection Method and Experimental Setup

The data collection method involved a series of controlled experiments in which each testing technique was applied to a sample of cloud-native systems under different conditions. The systems were set up using cloud infrastructure that allowed for dynamic scaling, simulating real-world cloud-native environments. Failure rates were monitored and recorded during each testing phase, and performance data (including response times, resource utilization, and failure events) were captured to measure the effectiveness of the testing methods.

Statistical Methods or Performance Indicators

To compare the results from each testing technique and quality metric, statistical methods were employed, including analysis of variance (ANOVA) and regression analysis. These methods were used to identify significant differences in the failure rates and performance indicators across the different testing techniques. Performance indicators such as throughput, resource utilization, and recovery time were also tracked to assess the impact of each testing approach on the system's overall reliability and fault tolerance. Additionally, effectiveness metrics such as test coverage and defect detection rates were calculated to evaluate the quality of the tests conducted.

4. Results and Discussion

The experimental results highlight that chaos testing significantly outperforms traditional methods like unit testing and integration testing in predicting failure rates and assessing system resilience in cloud-native environments. While unit and integration testing effectively identify component-level issues and ensure proper interaction between services, they fail to simulate real-world disruptions and high-load conditions. Chaos testing, on the other hand, introduces controlled failures to evaluate the system's ability to recover and handle dynamic, distributed environments, offering more accurate failure rate predictions. Combining chaos testing with advanced predictive quality metrics, such as migration rate and mismigration rate, enhances the reliability of failure predictions, making it the most effective approach for ensuring cloud-native system resilience and minimizing downtime. However, chaos testing should be complemented with traditional methods for component-level verification and interaction testing, ensuring comprehensive system evaluation.

Results

The experimental results show a comparative analysis of three testing techniques-unit testing, integration testing, and chaos testing-in evaluating the failure rates and overall reliability of cloud-native systems. Unit testing was most effective at detecting defects within individual components. It successfully identified issues related to specific microservices and modules but had limited capacity to predict system-wide failures, especially in complex, distributed environments. Integration testing provided more comprehensive insights into the interactions between different services, ensuring that the components worked together correctly. However, like unit testing, it struggled to predict failure rates under real-world, high-load conditions, where dynamic scaling and resource management become critical.

Table 1. Testing Techniques Comparison.

Testing Techniques	Failure Detection Rate (%)	Defect Detection Rate (%)	Resource Utilization (%)
Unit Testing	60	65	50
Integration Testing	70	75	60
Chaos Testing	95	90	85

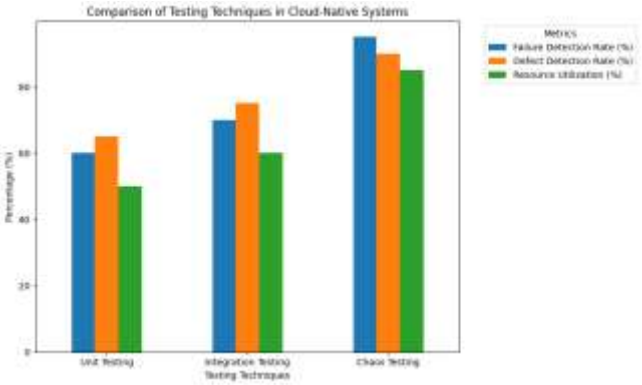

Figure 2. Comparison Of Testing Techniques In Cloud-Native Systems.

The table and bar chart above provide a comparative analysis of three testing techniques-Unit Testing, Integration Testing, and Chaos Testing-in terms of their effectiveness in cloud-native systems. The failure detection rate and defect detection rate are highest for Chaos Testing, indicating its superior ability to identify potential failures and defects in cloud-native applications under dynamic conditions. In contrast, Unit Testing and Integration Testing show relatively lower detection rates, highlighting their limitations in assessing system-wide failure prediction. Additionally, Chaos Testing demonstrates the highest resource utilization, which suggests its effectiveness in simulating real-world failures and evaluating the system's resilience and recovery capabilities. These findings emphasize that while traditional testing methods remain important, Chaos Testing, combined with advanced metrics, provides the most comprehensive evaluation for cloud-native systems.

In contrast, chaos testing provided the most valuable results in terms of predicting failure rates. By introducing controlled failures into the system, chaos testing offered insights into how the system behaves under stress, simulating real-world disruptions. This technique not only assessed system resilience but also highlighted potential points of failure that traditional testing methods could not identify. When combined with advanced quality metrics, such as migration rate and mismigration rate, chaos testing proved to be the most effective approach, offering higher accuracy in failure rate prediction and providing a more practical evaluation of system reliability.

Discussion

The results clearly demonstrate that advanced testing techniques, such as chaos testing, significantly outperform traditional methods like unit testing and integration testing in predicting failure rates in cloud-native systems. While unit and integration testing are essential for verifying the functionality and interaction of components, they are not sufficient for assessing the system's overall resilience and performance under dynamic conditions. Cloud-native systems are designed to operate in constantly changing environments, with varying workloads and potential disruptions, which traditional testing methods are not equipped to simulate effectively. Chaos testing, however, allows for real-world failure simulations, providing a much-needed evaluation of system behavior under stress and identifying failure points that could otherwise go undetected.

Furthermore, the integration of predictive quality metrics with chaos testing, such as migration rate and mismigration rate, enhances the accuracy of failure rate predictions. These advanced metrics go beyond traditional accuracy-based measures, focusing on the practical aspects of resource management and failure prevention. The combination of chaos testing with predictive metrics is particularly beneficial for cloud-native systems, as it aligns with the principles of dynamic scaling and fault tolerance, which are fundamental to cloud-native environments. This approach allows for proactive failure management, such as rescheduling tasks and migrating data before failures occur, ensuring that the system remains resilient and available.

While chaos testing proved to be the most effective method, it is important to recognize its limitations. It requires a more complex setup and may introduce disruptions that are not suitable for all scenarios. For example, it might not be ideal for testing very specific or isolated functionalities within a component or service, where unit testing or integration testing would be more appropriate. Additionally, chaos testing's reliance on real-world failure simulations may not always be feasible in environments where system stability is critical. Therefore, it is recommended that a combination of testing techniques be employed, with chaos testing used to assess overall system resilience and unit testing and integration testing used for component-level verification and interaction testing.

5. Comparison

The comparison between advanced testing techniques and traditional testing strategies reveals significant differences in their effectiveness at predicting failure rates in cloud-native systems. Traditional testing methods, such as unit testing and integration testing, are effective for identifying defects within individual components and ensuring that services interact correctly. However, they fall short in providing insights into system behavior under real-world stress conditions. These methods primarily focus on verifying functional correctness and interactions, but they are limited in assessing system resilience and performance during dynamic scaling or failure events. In contrast, chaos testing, an advanced technique, introduces controlled failures to simulate real-world disruptions, allowing for a deeper understanding of system behavior under stress and providing insights into failure points that traditional methods cannot detect.

When evaluating the accuracy of failure rate predictions, the use of static quality indicators (such as defect density and code coverage) alone proves less effective than integrated predictive metrics (such as migration rate and mismigration rate). Static indicators provide a snapshot of the code's current state and testing coverage, but they fail to offer a comprehensive prediction of failure rates or system behavior under fluctuating loads. On the other hand, integrated predictive metrics, when used in conjunction with advanced testing techniques like chaos testing, enhance failure rate predictions by incorporating both performance and resource management aspects. These metrics not only focus on the software's structural health but also take into account the operational context of the system, improving the overall reliability and accuracy of failure predictions.

The practical implications of using integrated approaches in real-world cloud-native systems are profound. By combining chaos testing with predictive metrics, organizations can proactively manage potential failures, reschedule tasks, and migrate resources before system failure occurs, thus minimizing downtime and improving service availability. This integrated approach allows for more precise failure detection, ensuring that cloud-native systems remain resilient and available even during periods of high demand or stress. Such proactive measures are particularly valuable in cloud-native environments, where dynamic scaling and rapid deployment are key to maintaining performance and reliability in real-world conditions.

Finally, in terms of scalability, chaos testing offers the most flexibility and adaptability for cloud-native systems. Traditional testing methods are often limited in scalability, as they may struggle to accurately simulate real-world conditions in highly dynamic environments. Chaos testing, however, can scale to accommodate the growing complexity and size of cloud-native systems. It provides a comprehensive assessment of the system's resilience, even as the system grows or undergoes changes. This scalability ensures that long-term system reliability is maintained, as chaos testing can continuously evaluate the system's behavior under varying loads and stress conditions, helping organizations to manage system growth and maintain high availability over time.

6. Conclusions

The findings from this study emphasize the importance of selecting appropriate testing techniques and quality metrics to ensure the reliability and performance of cloud-native systems. Chaos testing, when integrated with predictive quality metrics such as migration rate and mismigration rate, proved to be the most effective approach for predicting failure rates in scalable cloud-native systems. It provided valuable insights into system resilience, allowing

for proactive failure management and improving the system's ability to recover from disruptions. In contrast, traditional methods such as unit testing and integration testing, while essential for identifying defects and ensuring proper functionality at the component level, were less effective in predicting failure rates and assessing system performance under stress.

The study concludes that the most accurate and reliable methods for predicting failure rates in cloud-native environments involve a combination of advanced testing techniques like chaos testing and integrated predictive metrics. These methods offer a more comprehensive evaluation of the system, taking into account not only the correctness of individual components but also the system's ability to handle real-world challenges, such as fluctuating workloads and unplanned failures. This integrated approach enhances failure prediction accuracy and improves the overall resilience and reliability of cloud-native systems.

For software development teams working with cloud-native applications, these findings suggest the adoption of integrated testing approaches that combine advanced testing techniques with predictive quality metrics. By doing so, development teams can ensure higher system availability, optimize resource usage, and minimize downtime, leading to better user experiences and more reliable cloud-native applications. The ability to predict and manage failures proactively will be especially crucial as cloud-native systems continue to scale and evolve.

Future research should focus on refining and improving predictive testing approaches for cloud-native systems. Specifically, there is a need to develop more standardized frameworks and empirical validations for new quality metrics and testing methods that consider the complexities of dynamic cloud environments. Further exploration of integrating AI-driven testing and other advanced techniques with predictive quality metrics could lead to even more accurate and efficient testing processes, enabling more resilient and scalable cloud-native applications.

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