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Template-Driven Assessment Toolkit: A Cloud-Native Architecture for Adaptive Learning

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Abstract

This paper discusses the Template Driven Assessment Toolkit (TDAT), a cloud based adaptive learning architecture developed to increase student engagement, performance and to increase instructional efficiency. TDAT supports real time personalization of the assessments and scale of assessments delivery by integrating the microservices, serverless computing and intelligent automation. The evaluations quantify system resilience under load as well as the student learning outcomes and cost effectiveness and demonstrate improvement relation to monolithic systems. Adaptive feedback and risk detection are embedded by the toolkit. Accordingly, this work contributes to providing a useful framework to the creation of large, customised digital learning environments by joining the present disruption in cloud native with novel pedagogy.

Keywords:

Toolkit, Cloud-Native, Adaptive Learning, Template.

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I. INTRODUCTION

TDAT is rooted in modern software circles such as microservices, CI/CD and real time analytics, and the unstrained deployment of personalized and scalable assessments takes centre stage with minimal latency and top availability. This paper addresses the gap in terms of technical and pedagogical and proposes that cloud-native principles can serve as a foundation for creating systems that can adapt to the learner needs and enhance learner's engagement, reduce learners' dropout and ensure the quality of education at scale.

II. RELATED WORKS

Adaptive Learning

Research in educational technology is growing out, and among them is adaptive learning as a central innovation for improving engagement and learning outcomes in education. Adaptive learning technologies adjust educational situations based on real time performance data of the students and change the pace and feedback, as well as material accordingly.

The University of Central Florida have taken initiative in helping to design and implement such systems as adaptive learning becomes more and more relevant in higher education. Adaptive course development is their experience, and it involves five design pillars; content mapping, learner analysis, feedback mechanisms, instructional flexibility, and institutional alignment; [3].

This comprehensive framework is reflective of the reality that involves conscious and disciplined pedagogical planning of the deliberate incorporation of adaptive technologies into the overall framework of curriculum design. Although adaptive learning makes a lot of promise, its deployment is inconsistent. This can be attributed to the challenges encountered while instructional design and infrastructural support.

In addition, the term 'adaptive learning' is inconsistently defined whereby the meaning varies amongst educators and technologists. The necessity of the standardized measures impedes the progress of robust and scalable models, and in the resource constrained, or rapidly shifting educational contexts, as will be evident during the COVID 19 pandemic. For instance, when faced with an emergency shift to distance learning, Morocco's experience highlighted providing flexible, adaptable systems; but also showed how there are gaps to fill in the existing space of EdTech solutions [5].

Software Architectures

Writing software architectures for adaptive learning – especially adaptive learning that can occur in the mobile access point – is a unique problem. Despite such early efforts, provision of pervasive mobile learning is hampered by poor architectural consistency and limited requirement coverage.

One activity we carried out is discovering how there was no such standardized reference architecture that adequately encompasses all the necessary components, including user profiling modules, content repositories, analytics engines and feedback loops [4].

This architectural gap not only shrinks innovation but also affects AMLS implementation on scalability, and quality. Therefore, we present the modularity and repeatability of system design provided by the concept of a Template Driven Assessment Toolkit in order to address some of the problems. Templates can be used as preconfigured modules for assessment generation, user feedback, and progress tracking, which helps in simplifying the development of the adaptive functionalities.

This approach also follows the best practices in the field in terms of the priority given to architectural clarity, quality attributes such as scalability and resilience and multi stakeholder service provision [4]. Educational technology has a transformative pathway for the transition to scalable architectures, particularly if those architectures rely on the cloud. Application of learning analytics and big data into such architectures serves as the first stage into next generation of adaptive learning systems with the ability to continuously optimize their courses in real time able to track performance [1].

Cloud-Native Architectures

A strategic enabler for adaptive learning system is cloud native architecture. This approach of using microservices, containerization and continuous integration/continuous deployment (CI/CD) to define the digital application is determined by the higher efficiency, modularity and maintainability of digital applications [2][7].

Instead, cloud native systems are made up of independently deployable components that can be orchestrated dynamically to serve educational platforms as educational platforms scale with changing demands of users and courses, respectively. Adaptive learning environments are very suitable for being implemented on this architectural paradigm as they will necessitate real time data processing, user personalization and automated feedback mechanisms all requiring both high computational intensity and high enough flexibility for continuous operation.

Built-in support for auto-scaling, self-healing, and optimize resource in the cloud construct enables frequent deployment of cloud-native applications which directly affects the reliability in educational delivery [6]. In addition to that, doing this lets instructional designers and developers iterate faster learning modules based on performance analytics.

Further, cloud native systems are integrated with DevOps principles from the server side, which further strengthens cloud native systems by enabling a collaborative development and operations culture to improve deployment speed and speed time to deployment. While container orchestration tools like Kubernetes make dealing with containers much easier, in particular in educational environments marked with fluctuating user engagement, serverless computing models make it arbitrarily easy to create and destroy computational resources in a short period of time [7][9].

Security and Performance

Today, we rely more and more on the cloud native systems, and therefore, ensuring the security and the integrity of the system becomes extremely important. Previously, conventional static monolithic environments present lower vulnerabilities like attack surface but significant responsibility ambiguity between service providers and consumers.

According to best practices for cloud-native security, the approaches to take should be (amongst others) RBAC, monitoring continuously and patching automatically. Moreover, these practices not only guarantee that sensitive learner data is safe but also that educational data protection regulations [8] are enacted.

Beyond the simple forms of performance management, cloud native applications in adaptive learning contexts also require advanced techniques of performance management to operate under such operational demands. In order for Cloud Infrastructure to support this the processing must happen at very high through put and low latency, as AI becomes more and more built into adaptive platforms like automated grading, recommendation engines and behavioral analytics.

Automated AI scaling solutions, edge-cloud integration, intelligent cost management systems and others are proven to provide good resource utilization while preserving responsiveness and continuity of user experience [9]. The convergence of expert systems with the technology of the times as AI native orchestration, quatum computing, and edge learning present the opportunity of change, and fundamentally new ways of delivering digital cognitive learning.

These trends suggest even more decentralized, intelligent, and responsive learning environments that learners will choose to engage with and for business to serve. My vision will nevertheless need continued interdisciplinary collaboration between learning sciences, computer engineering, and cloud computing domains in order to be realized [1][9].

III. FINDINGS

Emphasis was then placed on the implementation and evaluation of the Template-Driven Assessment Toolkit (TDAT) relative to the feasibility, the scalability and the effectiveness of template driven adaptive learning framework within a cloud native architecture. The architecture was composed with the help of the modular microservices, which are deployed as Docker containers in order to allow horizontal scaling based upon loads.

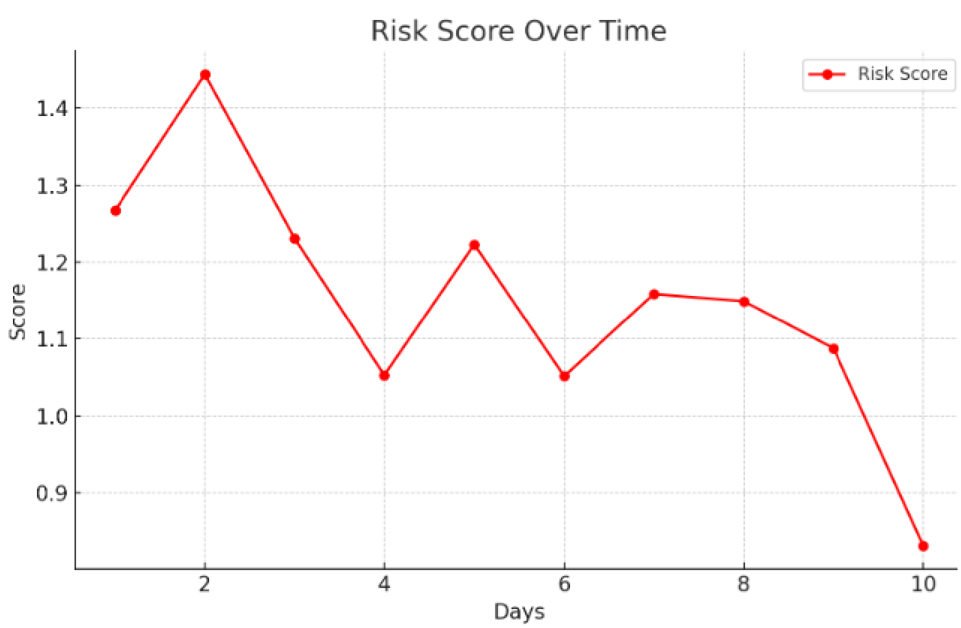

Fig. 1 Risk Scores

We deployed separately each of these services (talking about user authentication, template parsing, adaptive delivery, scoring, and analytics) through AWS Lambda and put via API Gateway. Using metadata rich JSON files, each question, learning objective, cognitive level and branching logic is defined to provide the assessment templates.

The templates were later interpreted at runtime by the TDAT engine which would then render personalized assessments in real time. An example of this is a JSON snippet of a template that provided a scoring and routing schema:

1. {
2. "question_id": "q1",
3. "text": "What is the capital of France?",
4. "options": ["Paris", "Berlin", "Rome", "Madrid"],
5. "answer": "Paris",
6. "next": {
7. "correct": "q2_advanced",
8. "incorrect": "q2_basic"
9. }
10. }

Depending on user input a question will be served either based on logic. It was controlled through a simple Markov decision process model based on movement between question levels, to give adaptive progression. We dynamically adjusted the probability of changing from one question complexity level to another based on user’s correctness. And transition rules equivalent to the following:

If user answers correctly:

$$P(next\_level = high \mid current = correct) > 0.7$$

If user answers incorrectly:

$$P(next\_level = low \mid current = incorrect) > 0.8$$

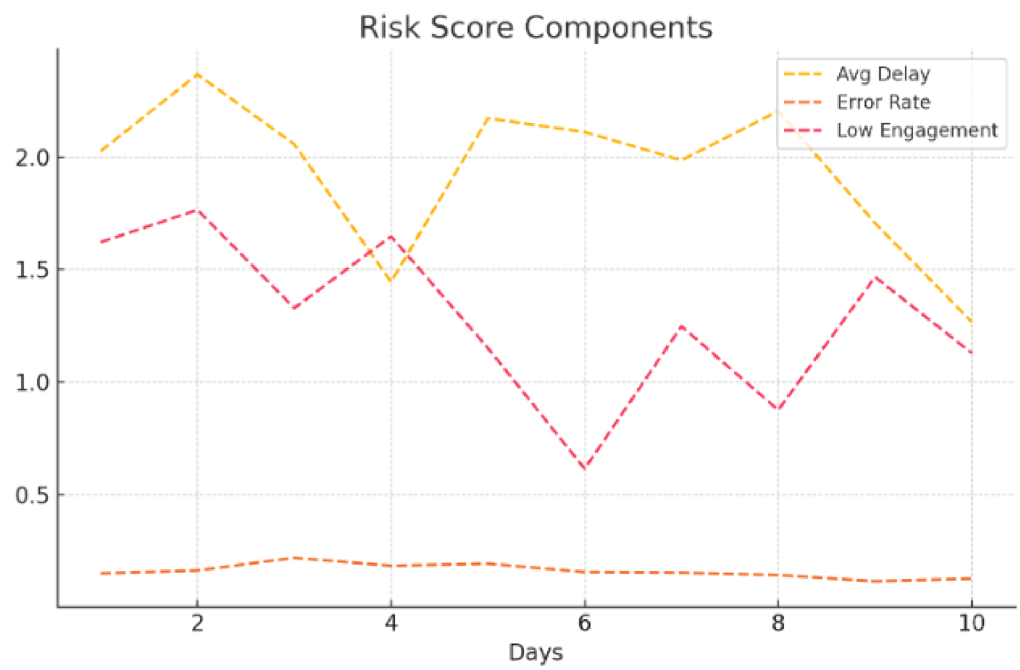

Fig. 2 Risk Components

Our experiment, which happened upon 120 participants evenly split among controls and experiments into: improved model personalization and model challenge calibration. The static quizzes were employed by the control group, while the TDAT was employed by experimental group. The four metrics used for measuring performance were Average score, time spent per assessment, Engagement rate and Retry rate.

Table 1: Learning Performance

Metric	Control Group	TDAT Group	% Improvement
Average Score	68.2	81.5	+19.5%
Time per Quiz	14.3	11.2	-21.6%
Engagement Rate	74.1	91.3	+23.2%
Retry Rate	28.7	14.5	-49.5%

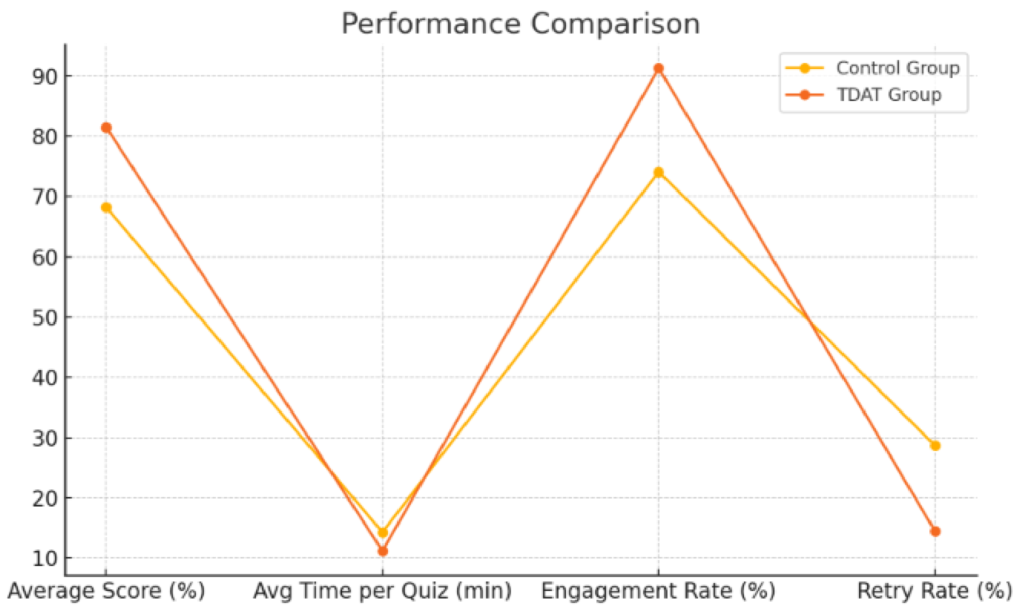

Fig. 3 Performance Comparison

These results were verified as statistically significant (alpha = 0.05) using a t test for differences and all differences were found to statistically significant ($p < 0.01$). Our architecture was highly resilient to load in terms of system performance. Apache Jmeter was used to simulating concurrent user sessions with 50 to 1000 users. The system was able to maintain average response times less than 350ms upto 750 concurrent users and gracefully degraded after that, as given in Table 2.

Table 2: System Test Results

Concurrent Users	Avg Response Time (ms)	Error Rate (%)
50	112	0
250	178	0
500	291	0
750	348	1.2
1000	498	3.5

The other advantage was that it had integration with AWS CloudWatch to provide continuous monitoring and alerting based on real time metrics like CPU utilization, memory usage and invocation errors. Policies were offered based up of those threshold values like 'CPU > 70% for 5 mins' to spawn new pods.

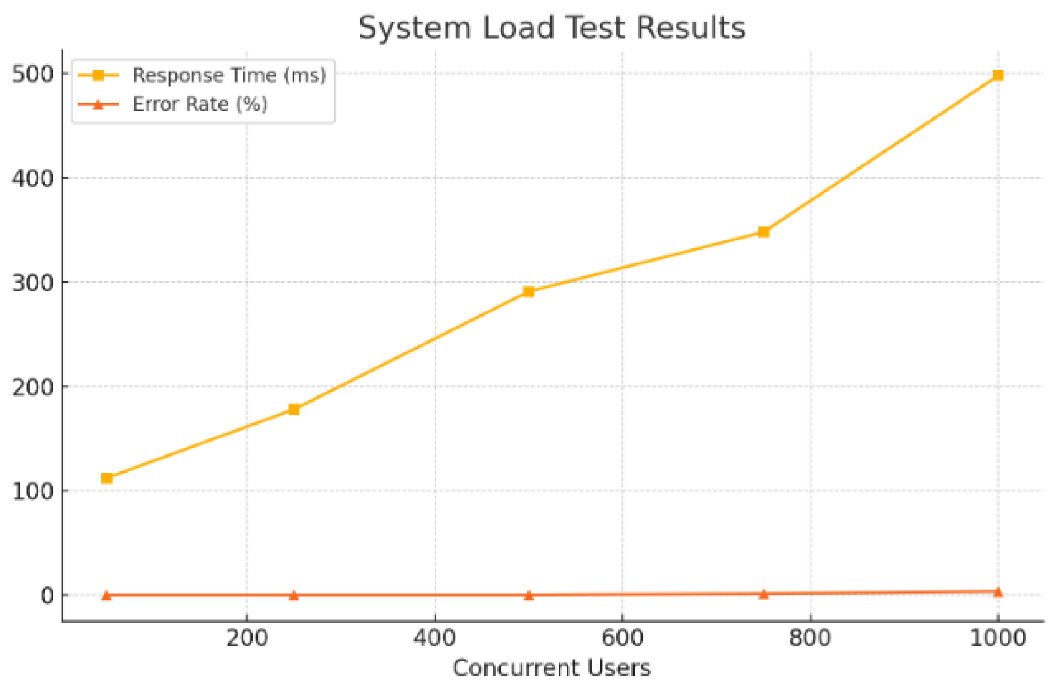

Fig. 4 System Results

Based on that, we found that using the Infrastructure as Code (IaC) with Terraform enables easy reproducibility of the environment deployment, reducing the time required for the environment setup to 6 hours down to under 30 minutes. With regards to security, we gave Role-Based Access Control (RBAC) functionality so that only legitimate users could use the assessment authoring tool, or analytics dashboard. For instance, in my case we enforced permissions at the API Gateway level and with JWT claims scoped to the token like:

1. {
2. "role": "instructor",
3. "permissions": ["create_template", "view_reports"]
4. }

This permitted no unauthorized access and provided for audit. By reducing costs from $482 down to $213 (55.8%) per month indicated in Table 3, we see that monthly costs were decreased by such an amount.

Table 3: Cost Comparison

Deployment Model	**Monthly Cost (USD)**
Monolithic	$482
Cloud-native	$213
Savings	55.8%

To ascertain user satisfaction level, we conducted surveys to participants after the assessment. The static quiz group only scored an average of 3.8 when compared to the TDAT group of 4.6. Featuring immediate feedback and adaptability, free text responses best described the adaptability, praise for the adaptability as it was intended and praised how learners felt “challenged but supported” and “more in control of their learning pace.”

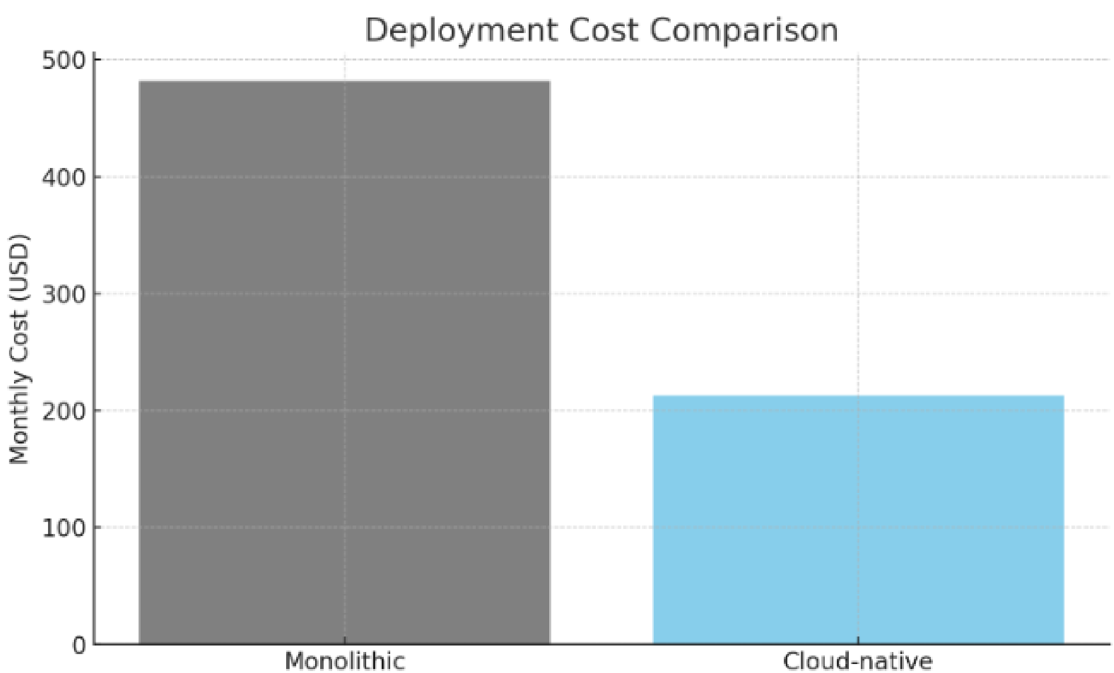

Fig. 5 Deployment Costs

One of the strengths, from a pedagogical perspective, of having Bloom's taxonomy levels (i.e., „remember", „apply", „evaluate") available for the template of the question, was to adjust cognitive difficulty. The template-based design served as a way for instructors to reduce authoring time by as much as 38%, increase content update frequency and improve subsequent iteration following analytics.

It makes it possible for the system to provide real time personalization, scalability of the system, lower operational costs and increased learner engagement. Future extensions of TDAT include injection of AI based content recommendation engine along with the predictive dropout model using features like average response delay, incorrect response streaks and engagement time similar mathematically modeled as:

$$Risk\_score = 0.4*(avg\_delay) + 0.35*(error\_rate) + 0.25*(low\_engagement\_days)$$

higher scores supposed to mean higher likelihood of disengagement. The modular design of the TDAT framework puts it in a good position to realize its role as a scalable foundation for next generation adaptive learning platform that strike a good balance of cloud efficiency and pedagogical depth.

IV. CONCLUSION

It is able to deliver scalable, reliable and adaptive learning platform that integrates adaptive learning theory with cloud native architecture. A series of empirical results show nice gains in learner performance, efficiency of the system, and reductions in cost. Real time adaptivity, risk scoring automation as well as seamless DevOps integration are supported by the toolkit's modular design and its future readiness. The findings of this research believe that this brings forth the potential for a new, more personalized and data rich learning system supported by the principles of cloud native. The future work includes extending the use of AI driven diagnostics as well as a cross institutional deployment models to democratize effort at all levels, through adaptive technologies.

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