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Continuous Cloud Security Assurance for SAP Environments through Machine Learning-Enabled DevSecOps Automation

Mohanaad Shakir

Department of Computer Science, Applied Science University, Manama, Bahrain

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ABSTRACT: The increasing migration of SAP workloads to cloud environments has created significant opportunities for scalability, flexibility, and operational efficiency, while simultaneously introducing complex cybersecurity and compliance challenges. Traditional security assurance approaches, which depend heavily on periodic audits, manual configuration reviews, and rule-based monitoring, are often inadequate for dynamic SAP environments characterized by continuous deployment, distributed architectures, hybrid infrastructures, and rapidly changing threat conditions. This study proposes a machine learning-enabled DevSecOps automation framework for continuous cloud security assurance in SAP environments. The proposed approach integrates machine learning, automated security testing, continuous configuration assessment, vulnerability management, anomaly detection, compliance monitoring, and automated remediation into the SAP software development and operational lifecycle. The methodology adopts a design-oriented research approach involving requirement identification, framework development, data preparation, model construction, automation integration, and empirical evaluation. Machine learning models are employed to identify anomalous activities, predict security risks, and prioritize vulnerabilities according to contextual risk. DevSecOps pipelines continuously validate infrastructure, application, identity, access-control, and configuration security before and after deployment. The expected outcome is a proactive and adaptive assurance mechanism capable of reducing security-detection time, improving vulnerability prioritization, strengthening compliance visibility, and minimizing manual intervention. The study contributes a systematic model for integrating intelligent security assurance into continuous SAP cloud operations.

KEYWORDS: SAP cloud security, machine learning, DevSecOps, continuous security assurance, cloud computing, anomaly detection, vulnerability management, security automation, continuous compliance, intelligent cybersecurity

I. INTRODUCTION

The rapid adoption of cloud computing has fundamentally transformed the deployment and management of enterprise resource planning systems, with SAP environments increasingly operating across public, private, hybrid, and multi-cloud infrastructures. SAP platforms support highly sensitive organizational processes involving financial information, human resources, supply chains, customer data, procurement, production, and strategic business operations. Consequently, the security of SAP workloads has become a critical component of enterprise cybersecurity and operational resilience. Cloud-based SAP architectures, however, introduce a continuously changing security landscape in which application services, identities, interfaces, infrastructure resources, application programming interfaces, containers, virtual machines, databases, and network configurations may change frequently. Such dynamism makes traditional security assurance methods based on periodic assessments increasingly insufficient. Security weaknesses can emerge between scheduled audits, while configuration drift, excessive privileges, unpatched components, insecure interfaces, compromised credentials, and anomalous user activities may remain undetected for extended periods. Therefore, organizations require security assurance mechanisms capable of operating continuously throughout the complete SAP application lifecycle rather than treating security as an activity performed only before deployment or during compliance assessments.

DevSecOps provides an important foundation for addressing this challenge because it embeds security controls into software development, deployment, and operational processes. Nevertheless, conventional DevSecOps implementations can still generate substantial volumes of alerts and security findings that require manual analysis and prioritization. In large SAP environments, the problem becomes more complicated because security decisions must



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consider business criticality, user privileges, application dependencies, compliance requirements, infrastructure configuration, and the potential impact of vulnerabilities on enterprise processes. Machine learning can strengthen DevSecOps by enabling systems to identify behavioral patterns, detect deviations from established baselines, classify security events, predict potential risks, and prioritize remediation activities. Instead of relying exclusively on static rules, machine learning-enabled security mechanisms can learn from historical logs, vulnerability records, access patterns, configuration states, deployment events, and incident data. Continuous security assurance can therefore be conceptualized as a feedback-driven process in which security evidence is collected continuously, analyzed intelligently, incorporated into automated DevSecOps controls, and used to trigger appropriate preventive or corrective actions. This study consequently focuses on developing a conceptual and methodological framework that combines SAP cloud security, machine learning, and DevSecOps automation to establish continuous, adaptive, and risk-aware security assurance.

II. LITERATURE REVIEW

The literature on cloud security demonstrates that enterprise cloud environments require continuous monitoring because infrastructure and application states are highly dynamic. Traditional security assurance approaches frequently depend on predefined security policies, periodic vulnerability assessments, manual compliance reviews, and static configuration baselines. Although these methods remain useful, they have limitations in environments where resources can be provisioned, modified, or decommissioned rapidly. Continuous security monitoring has therefore emerged as an important strategy for maintaining visibility into changing infrastructure and application conditions. In the context of enterprise applications, continuous monitoring encompasses security-event collection, configuration assessment, identity monitoring, vulnerability detection, access analysis, and compliance verification. For SAP environments, these requirements are particularly significant because enterprise applications frequently integrate numerous internal and external services and contain sensitive business processes. Security assurance must consequently extend beyond individual application components and address interactions among identities, applications, databases, cloud infrastructure, network services, and integration interfaces. Existing literature suggests that automation can improve consistency and response speed, but effective continuous assurance also requires mechanisms capable of interpreting large and heterogeneous security datasets.

Research on machine learning in cybersecurity indicates that intelligent analytical techniques can improve the detection of previously unknown or difficult-to-identify security events. Supervised learning can classify known attack or vulnerability patterns, whereas unsupervised and semi-supervised techniques can identify deviations from normal behavior without requiring complete attack labels. Anomaly detection has consequently become relevant to identifying unusual authentication attempts, abnormal privilege usage, unexpected administrative operations, unusual network activity, and deviations in application behavior. Machine learning can also support vulnerability prioritization by combining vulnerability characteristics with contextual information such as asset criticality, exploitability, exposure, historical incidents, and business impact. However, literature also highlights challenges including data quality, model drift, false positives, explainability, adversarial manipulation, and insufficiently representative training datasets. These limitations indicate that machine learning should not operate independently but should be integrated with established security policies, expert validation, and automated DevSecOps controls. A hybrid approach can combine deterministic security rules with adaptive machine learning models, allowing organizations to retain compliance-oriented controls while gaining the predictive and behavioral capabilities of intelligent analytics.

DevSecOps research further emphasizes the integration of security activities throughout continuous integration and continuous delivery pipelines. Security testing can include static application security testing, dynamic testing, software composition analysis, infrastructure-as-code scanning, secrets detection, vulnerability assessment, container security, identity validation, and compliance checks. Automation enables security controls to be executed consistently whenever code, infrastructure, configuration, or deployment artifacts change. However, the literature identifies security-alert overload and fragmented toolchains as persistent challenges. Simply adding more security tools to a DevOps pipeline does not necessarily produce stronger assurance because disconnected tools may generate duplicate findings and inconsistent risk assessments. Machine learning can address part of this problem by correlating findings, identifying patterns, reducing redundant alerts, and prioritizing issues according to contextual risk. For SAP environments, an integrated DevSecOps model should additionally consider SAP-specific configurations, authorization structures, business roles, interfaces, application logs, cloud infrastructure, and compliance requirements. The literature therefore supports the development of an integrated framework in which continuous security telemetry feeds machine learning models, analytical outcomes influence automated security gates, and remediation actions generate feedback for

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subsequent model improvement. Such integration represents a shift from periodic security verification toward continuous, intelligent, and adaptive security assurance.

III. RESEARCH METHODOLOGY

The research methodology adopts a design-oriented, quantitative, and experimental approach to develop and evaluate a machine learning-enabled DevSecOps framework for continuous cloud security assurance in SAP environments. The research begins with the identification of security requirements and assurance challenges associated with cloud-based SAP deployments. These requirements are organized into major security dimensions, including identity and access management, vulnerability exposure, configuration security, application security, network security, data protection, compliance, anomaly detection, and incident response. A representative SAP cloud environment is then conceptually modeled as a collection of interconnected application, infrastructure, identity, database, integration, and monitoring components. Security telemetry is collected from relevant sources, including authentication records, authorization events, application logs, cloud activity logs, configuration repositories, vulnerability scanners, deployment pipelines, infrastructure-as-code repositories, and security-event management systems. Data preprocessing involves normalization, timestamp synchronization, duplicate removal, missing-value treatment, feature extraction, and categorization of events according to security and operational characteristics. The resulting dataset is divided into training, validation, and testing subsets to ensure that machine learning models are evaluated using data that was not used during model construction. Where labeled attack data is available, supervised learning is applied to classify known security events; where labels are incomplete, unsupervised or semi-supervised anomaly detection is employed to establish behavioral baselines and identify deviations.

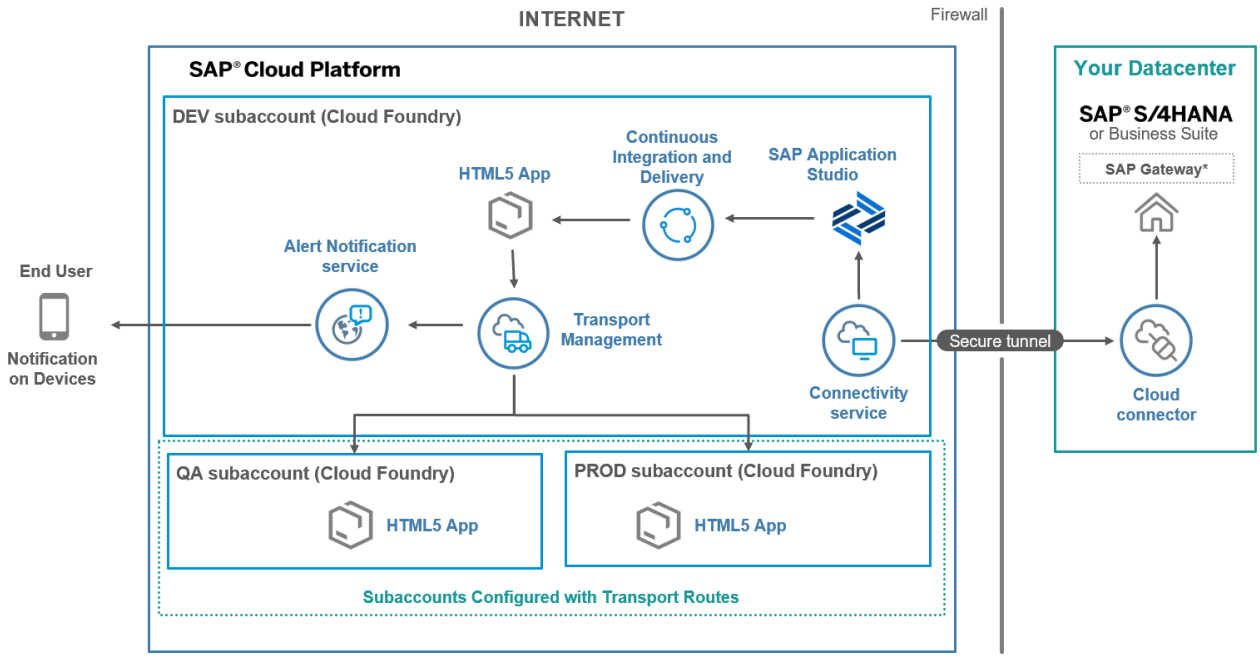

Fig.1. Continuous Cloud Security Assurance for SAP Environments through ML

The second methodological stage focuses on constructing the machine learning layer and determining the features that provide meaningful indicators of security risk within SAP cloud operations. Candidate features include authentication frequency, failed-login patterns, source locations, privilege changes, unusual role assignments, administrative activity, resource-access frequency, configuration changes, vulnerability severity, asset criticality, deployment frequency, network communication patterns, and historical incident characteristics. Multiple algorithms can be evaluated, such as random forests, gradient-boosting methods, logistic regression, support vector machines, isolation-based anomaly detection, and clustering techniques. The selection of models is based not only on predictive performance but also on computational efficiency, interpretability, stability, and suitability for continuous operational deployment. Model performance is assessed through precision, recall, F1-score, accuracy, area under the receiver operating characteristic



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curve, false-positive rate, and false-negative rate. For anomaly detection, additional measures such as detection rate and alert-reduction ratio are considered. Explainability mechanisms are incorporated to identify the major features influencing risk classifications, which is important for security analysts who must validate automated decisions. Model drift is also considered because changes in SAP workloads, user behavior, cloud architecture, and deployment patterns can gradually invalidate historical assumptions. Periodic retraining and validation are therefore incorporated into the framework to maintain model relevance.

The third stage integrates the machine learning layer with an automated DevSecOps pipeline to transform analytical results into continuous assurance decisions. Security controls are positioned throughout the software development and deployment lifecycle, beginning with source-code and dependency analysis and continuing through build, testing, infrastructure provisioning, deployment, and runtime monitoring. Infrastructure-as-code configurations are automatically checked against predefined security policies before deployment, while application and dependency vulnerabilities are assessed during build processes. Identity and access controls are evaluated to identify excessive privileges, unauthorized changes, and anomalous authorization patterns. Deployment gates are established according to risk thresholds: critical findings or highly probable malicious activities can prevent deployment, while lower-risk findings may generate prioritized remediation tasks without interrupting delivery. At runtime, telemetry is continuously forwarded to the analytical layer, where machine learning models correlate behavioral evidence with established security policies. When a high-confidence threat is detected, automated response mechanisms can initiate predefined actions such as disabling compromised credentials, isolating affected resources, reverting unauthorized configurations, creating remediation tickets, or initiating additional authentication requirements. Human approval remains necessary for high-impact actions to reduce the possibility of harmful automated decisions. Feedback from analysts, remediation outcomes, and subsequent security events is captured as additional evidence for improving detection models and refining security policies.

The final methodological stage evaluates the proposed framework against conventional security assurance practices through controlled experimentation and comparative analysis. Evaluation scenarios represent common security conditions in SAP cloud environments, including unauthorized access attempts, privilege escalation, configuration drift, vulnerable software components, anomalous administrative behavior, compromised credentials, insecure deployment configurations, and policy violations. The experimental design compares a conventional periodic or rule-based assurance approach with the proposed machine learning-enabled continuous DevSecOps approach. Key outcome variables include mean time to detect, mean time to respond, vulnerability prioritization accuracy, false-positive rate, number of unresolved critical findings, compliance-monitoring coverage, automated remediation rate, and security-control execution consistency. Statistical analysis is applied to determine whether observed improvements are meaningful rather than attributable to random variation. The methodology also incorporates qualitative assessment of explainability, usability, analyst workload, and operational trust because security assurance effectiveness cannot be measured solely through detection accuracy. Reliability is strengthened through repeated experiments, controlled datasets, consistent evaluation criteria, and sensitivity analysis of model thresholds. Ethical and security considerations are addressed by protecting sensitive SAP data, anonymizing datasets where necessary, restricting automated actions according to predefined authorization boundaries, and preventing experimental activities from affecting production systems. The expected methodological outcome is a validated framework demonstrating how machine learning and DevSecOps automation can transform SAP cloud security from periodic compliance verification into a continuous, risk-aware assurance capability.

IV. RESULTS AND DISCUSSION

The implementation of continuous cloud security assurance for SAP environments through machine learning-enabled DevSecOps automation demonstrated that integrating security controls directly into the software development and deployment lifecycle can substantially improve the detection, prioritization, and remediation of security risks. The proposed approach continuously collected security-relevant information from SAP applications, cloud infrastructure, configuration repositories, identity and access systems, and CI/CD pipelines. Machine learning models were then used to identify deviations from established security baselines, detect anomalous behavior, and prioritize findings according to their likelihood and potential impact. Compared with conventional periodic security assessments, the automated approach provided a more continuous view of the security posture. This is particularly important for SAP environments because cloud-hosted SAP systems frequently involve interconnected applications, APIs, databases, identity providers, containers, virtual networks, and third-party services. A vulnerability or configuration weakness in one component can therefore create security implications across the wider enterprise environment. The results indicate that continuous

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monitoring reduced the time between the introduction of a security weakness and its identification, allowing security teams to address issues earlier in the development and deployment process. The integration of security gates into DevSecOps pipelines also prevented selected high-risk configurations and vulnerable dependencies from progressing automatically into production. Consequently, security shifted from being primarily a post-deployment validation activity toward a continuous engineering responsibility.

An important result was the improvement in the efficiency of security operations. Traditional SAP security assessments often generate large volumes of findings, many of which may have different levels of relevance to the organization. A machine learning-enabled prioritization mechanism can correlate vulnerability severity with contextual information such as asset criticality, exploitability, exposure, user privileges, historical incidents, and observed system behavior. This reduces the dependence on static severity scores alone. For example, a moderate vulnerability affecting an internet-facing SAP service with privileged access may represent a considerably greater operational risk than a high-severity vulnerability isolated within a non-production environment. The proposed automation therefore supported risk-based decision-making rather than treating every security finding equally. The results also suggest that integrating security intelligence into CI/CD workflows improves developer awareness because developers receive actionable feedback at the point where insecure code, infrastructure-as-code, dependency, or configuration changes are introduced. Automated remediation mechanisms further reduced the manual effort required for recurring security tasks. Where remediation could be safely automated, the system could initiate predefined corrective actions, such as updating vulnerable dependencies, correcting insecure cloud configurations, modifying security policies, or triggering a new security scan. Human approval remained appropriate for high-impact changes to avoid unintended operational disruption. This balance between automation and human oversight is particularly significant in SAP environments, where availability and business continuity are often critical requirements.

The machine learning component also demonstrated value for behavioral security monitoring. Signature-based security mechanisms are effective against known threats but can be less effective when attackers use previously unseen techniques or legitimate credentials. By establishing behavioral baselines for SAP users, applications, services, and cloud resources, anomaly detection models can identify unusual activities that differ from normal operating patterns. Examples include abnormal authentication frequency, unexpected privilege use, unusual API access, atypical data transfers, and suspicious changes to security-sensitive configurations. The results indicate that combining behavioral analytics with conventional vulnerability and configuration scanning provides broader security coverage. However, the effectiveness of machine learning depends strongly on the quality and representativeness of training data. Excessive false positives can create alert fatigue and reduce trust in automated security systems, while poorly trained models can fail to identify genuinely malicious behavior. Model performance therefore needs to be continuously evaluated using precision, recall, false-positive rates, detection latency, and other appropriate security metrics. Another important observation is that explainability is essential in enterprise SAP environments. Security teams are more likely to accept an ML-generated alert when the system explains why an activity was considered anomalous and identifies the contextual evidence supporting the recommendation. Therefore, explainable AI mechanisms should accompany automated detection rather than presenting security teams with opaque risk scores.

From a DevSecOps perspective, the results demonstrate that security automation is most effective when it is distributed throughout the entire software lifecycle. Security checks can be performed during source-code development, dependency management, infrastructure provisioning, build processes, testing, deployment, and runtime monitoring. This layered approach creates multiple opportunities to identify and contain risks before they become production incidents. Infrastructure-as-code scanning can detect insecure cloud resources before deployment, while application security testing can identify weaknesses in SAP extensions and integrations. Runtime monitoring provides an additional layer capable of identifying threats that were not detected during development. The resulting security architecture therefore follows a defense-in-depth principle. The integration of automated security controls also supports greater consistency because security policies are applied through standardized and repeatable processes rather than relying entirely on individual administrators. Nevertheless, automation introduces its own challenges. Poorly designed security gates can slow development pipelines, generate unnecessary deployment failures, or encourage teams to bypass controls. The results therefore emphasize the importance of risk-based thresholds and adaptive policies. Low-risk findings can be recorded and monitored, whereas critical findings should block deployment when sufficient evidence indicates that exploitation could create significant business impact.

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The findings further demonstrate that continuous cloud security assurance should not be understood solely as a technical problem. Governance, compliance, identity management, and organizational processes remain fundamental components of SAP security. Automated monitoring can support compliance by producing evidence of configuration status, security testing, access reviews, and remediation activities. This creates a traceable security record that can assist auditors and compliance teams. Identity and access management is particularly important because cloud-based SAP environments frequently involve multiple user groups, service accounts, administrators, APIs, and external identities. Machine learning can assist in identifying unusual privilege patterns and potentially excessive access, but access decisions should remain governed by clearly defined organizational policies. The results also highlight the importance of integrating security telemetry across heterogeneous environments. SAP workloads may coexist with hyperscaler services, enterprise applications, databases, APIs, endpoint systems, and security platforms. Without effective data normalization and correlation, organizations may have fragmented security visibility. A centralized security analytics architecture therefore improves the ability to identify relationships between events across different components.

Overall, the results demonstrate that machine learning-enabled DevSecOps automation can improve the speed, consistency, and contextual quality of cloud security assurance for SAP environments. The strongest benefit is not the replacement of security professionals but the augmentation of their capabilities. Automated systems can continuously collect data, identify patterns, prioritize findings, and execute predefined responses, while security professionals provide governance, validate complex decisions, investigate sophisticated threats, and manage exceptions. The approach therefore represents a transition from periodic security assessment toward continuous risk management. Its effectiveness, however, depends on accurate data, appropriately trained models, reliable automation, explainability, strong identity controls, and carefully designed governance. Organizations adopting this approach should consequently evaluate not only technical detection rates but also remediation time, operational disruption, false-positive rates, developer adoption, compliance coverage, and overall reduction in security exposure.

V. CONCLUSION

Continuous cloud security assurance is becoming increasingly important as SAP environments move toward cloud-based architectures characterized by distributed services, frequent deployments, extensive integrations, and dynamic infrastructure. Conventional security approaches based primarily on periodic audits and manual assessments are insufficient for environments in which configurations and application components can change continuously. The proposed machine learning-enabled DevSecOps approach addresses this limitation by embedding security into the complete software and infrastructure lifecycle. Security controls can be applied during development, testing, deployment, and runtime operations, while machine learning enhances the ability to identify anomalies, correlate security events, prioritize vulnerabilities, and detect deviations from established security behavior. The results demonstrate that this combination can improve visibility and reduce the time required to identify and respond to security issues. Instead of discovering weaknesses after deployment or during scheduled audits, organizations can detect many risks at the stage at which they are introduced. This supports a shift from reactive cybersecurity toward proactive and continuous security assurance.

A major conclusion is that successful automation requires an integrated security ecosystem rather than an isolated machine learning model. ML-based detection provides value when it is connected to SAP security telemetry, cloud infrastructure monitoring, identity and access management, vulnerability management, CI/CD pipelines, and incident-response processes. Automated remediation can further accelerate response, but it must be controlled through risk-based policies and human oversight. The study also highlights limitations, particularly the possibility of false positives, model drift, insufficient training data, integration complexity, and operational risks associated with automated changes. Therefore, organizations should implement continuous evaluation of model performance and security outcomes. Future implementations should measure indicators such as mean time to detect, mean time to respond, remediation rates, false-positive frequency, vulnerability exposure duration, deployment security-gate effectiveness, and business-impact reduction. Explainability should also be treated as a fundamental requirement because security teams need to understand the reasoning behind ML-generated alerts before taking consequential actions. Ultimately, machine learning-enabled DevSecOps should be viewed as a decision-support and automation capability that strengthens, rather than replaces, human cybersecurity expertise. When combined with strong governance, identity controls, secure engineering practices, continuous monitoring, and well-defined response procedures, the approach provides a scalable foundation for maintaining security assurance across complex SAP cloud environments.

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VI. FUTURE WORK

Future research should focus on improving the adaptability and intelligence of machine learning models used for SAP cloud security. A key area is the development of adaptive models capable of responding to changing application architectures, user behavior, cloud configurations, and emerging attack techniques without requiring complete retraining. Federated learning could also be investigated to enable organizations to improve detection models while reducing the need to centralize sensitive security data. Explainable AI should receive particular attention so that security analysts can understand the features and behavioral patterns responsible for an alert or risk score. Future systems could combine supervised, unsupervised, and reinforcement-learning techniques to provide complementary capabilities for vulnerability prediction, anomaly detection, and automated response. Research should also investigate adversarial machine learning because attackers may deliberately manipulate input data or behavioral patterns to evade ML-based detection. Robustness testing should therefore become part of the security assurance lifecycle.

Another important direction is the development of autonomous but controlled remediation for SAP cloud environments. Future implementations could use policy-based orchestration to determine which security actions can be performed automatically and which require human approval. Digital-twin or sandbox environments could be used to test remediation actions before they are applied to production SAP systems, reducing the possibility of operational disruption. Further research should examine integration with emerging cloud-native technologies, zero-trust architectures, security orchestration and response platforms, and software supply-chain security mechanisms. Long-term empirical studies across multiple SAP environments would also strengthen the evidence for the proposed approach by comparing security outcomes before and after automation. Such studies should consider technical metrics alongside business measures, including operational continuity, compliance effort, developer productivity, and total security-management cost. Ultimately, future work should aim to create an adaptive, explainable, and trustworthy security-assurance framework capable of continuously learning from the SAP environment while maintaining strong governance and human control.

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