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Threat Modelling Using STRIDE: A Case Study From E-Commerce And Saas Deployments

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Abstract: In the current digitally-first world, e-commerce and Software-as-a-Service (SaaS) applications are prime targets for sophisticated cyber attacks. The STRIDE model provides a formal method of determining and countering threats like Spoofing, Tampering, Repudiation, Information Disclosure, Denial of Service, and Elevation of Privileges. This article investigates the real-world deployment of STRIDE-based threat modelling in e-commerce and SaaS platforms through case studies and experimental results to prove its effectiveness. Leverage Data Flow Diagrams (DFDs) and risk prioritization techniques coupled with AI-enhanced tools such as STRIDE-GPT to analyse threat coverage, successful mitigation, and changing attack vectors. The research also emphasizes how new technologies like AI, IoT, and big data analytics are transforming security practices in such sectors, providing promising avenues towards automated and proactive threat modelling.

***Index Terms* -** STRIDE Threat Modelling, E-commerce Cybersecurity, SaaS Security, AI and LLM-based Threat Analysis, IoT Security

I. INTRODUCTION

With the increasing focus on digital transformation, cybersecurity has become a serious consideration for businesses in areas like e-commerce and Software-as-a-Service (SaaS). In a world where cyberattacks are on the rise, security is the best offense. Threat modelling, which is an organized method to discover, categorize and remediate potential security threats, has now become a core aspect of modern cyber security practices [1]. Of the threat modelling practices out there, STRIDE (Spoofing, Tampering, Repudiation, Information Disclosure, Denial of Service, and Elevation of Privilege) is one of the more formal techniques for analysing software across a range of network architectures [2].It's an extremely timely topic with the rise in popularity of cloud-based architectures, microservices, and third-party integrations in both e-commerce sites and SaaS applications. Since these systems are dynamic as well as distributed, they create an extensive attack surface that cannot be countered by current security controls [3]. Moreover, the compliance requirements like GDPR, PCI DSS, and SOC 2 have increased the need for strong and formal threat analysis and mitigation approaches, particularly for sensitive financial and personal information across industries [4].In the broader realm of cybersecurity, STRIDE is not only utilized as an underlying framework for analysing vulnerabilities that could be taken advantage of, but it can also serve to bridge the chasm between planning-at-build security and the operational battlefield. While this strategy has had great success, creating instant security value added to which 'vulnerability assessments' – particularly important in shifting-left is an optimum balance of threat modelling that would enable dev, arch, and security staff to see through attacks early in the SDLC lifecycle, when remediation capability is available and cheap procedure, having in mind that cost and risk to remove a vulnerability is directly proportional to how deep into a phase it is introduced [5]. But actual (high-level, lived) deployment of STRIDE in challenging architectures, such as SaaS multi-tenanted environments or high-traffic e-commerce systems, poses its own difficulties, such as threat model scaling, which must accommodate dynamic threat profiles, automation tools that must be assembled ad hoc [6].Despite threat modelling gaining popularity, a research gap remains regarding how STRIDE may be adopted and adapted to the needs of today's cloud-native deployments. Existing body of work tends to focus on static use cases or technology, and do not yet provide an encompassing picture of real-world challenges and solutions on how STRIDE is achieved on a bigger scale in dynamic infrastructure [7]. This paper attempts to bridge this gap by synthesizing literature, case study and best practice which can be used across e-commerce as well as SaaS space. Within this review we will strive to provide an overview of STRIDE-based threat modelling in e-commerce and SaaS environments. Readers will dive in depth into the positives and negatives of the STRIDE framework, present trends in threat modelling automation and practical recommendations from actual implementations. The remaining sections will outline major background, offer case studies, and provide new research directions and application.

II. Literature Review

Table 1: Summary of Key Research in Threat Modelling Using STRIDE

Ref	Title	Focus	Findings
[1]	Modelling Threats to AI-ML Systems Using STRIDE [6]	Extension of STRIDE (STRIDE-AI) for AI/ML pipelines	Introduces STRIDE-AI methodology tailored to ML lifecycles, identifies threats at each stage, and demonstrates applicability with case study from TOREADOR H2020
[2]	STRIDE-AI: Identifying ML Asset Vulnerabilities [7]	Asset-centric threat modelling for ML	Proposes ML asset categorization and systematic threat identification for data, model, artefacts
[3]	Threat Modelling & Security Analysis of Containers [8]	STRIDE applied to container ecosystems	Maps container threats via STRIDE; surveys countermeasures and highlights gaps in registry and host security
[4]	Cyber Threat Modelling & ML: A Review [9]	Survey on STRIDE with ML integration	Reviews ML use in threat modelling frameworks; identifies need for applied decision systems
[5]	Threat Modelling for Web Apps via STRIDE [10]	STRIDE for web applications	Applies STRIDE and four threat tools to web apps; shows strengths of tool-assisted modelling
[6]	Cybersecurity Threat Modelling for E-commerce Cloud [11]	CASE study: STRIDE applied to e-comm SaaS migration	STRIDE model for e-commerce migration; simulation of real threats and countermeasures
[7]	A Comparative Analysis of Threat Modelling Methods [12]	Comparison of STRIDE, DREAD, etc.	Highlights STRIDE's strengths and contextual suitability; promotes hybrid modelling
[8]	STRIDE-Centric Security Evaluation (stride SEA) [13]	Integration of STRIDE into SDLC evaluation	stride SEA: extends STRIDE for lifecycle risk analysis and attack scenarios; validated in immunization system
[9]	LLMs' Suitability for Network Security: STRIDE Case [14]	Use of LLMs to classify STRIDE threats in 5G	Demonstrates LLM-based classification of threat types; shows areas needing fine-tuning
[10]	AI-Specific Threat Modelling by ioSENTRIX [15]	Adapting STRIDE for AI/ML pipelines	STRIDE applied to data ingestion/training/deployment; mitigations reduced adversarial risks

Major Patterns Across Case Studies

a) Hybrid Threat Modelling in Cloud /E-commerce

Multi-framework application: Operates on hybrid cases, for example porting ecommerce platforms to public clouds??STRIDE can be stacked with ATASM and OWASP To give better protection and soundness [10].

Systematic DFD application: By contrast, the majority of projects utilize Data Flow Diagrams (DFDs) to represent processes, data stores, trust boundaries prior to applying STRIDE, also seen in health-tech and cloud-monitoring case studies [4][20].

b) STRIDE-AI for ML Systems

STRIDE AI/ML extension: STRIDE-AI maps inaugural STRIDE ideas into ML pipeline threats (e.g., model poisoning, adversarial data manipulation) and operationalized within the context of EU H2020 TOREADOR projects [16][18].

c) STRIDE in IoT/SaaS Domains

IoT precision farming & home automation: Over 50 STRIDE-identified threats in sensor networks and botnet-associated scenarios reflect common themes in IoT threat analysis [25][27].

Cloud-SaaS implementations: While not all of them are STRIDE-specific, one can observe through case studies how STRIDE is used in layering security in cloud/SaaS transition [11][23].

Strengths & Weaknesses of Approaches

Strengths

Comprehensive set for threats: Six threat categories in STRIDE (Spoofing, Tampering, etc.) promote systematic risk assessment [24].

Tool Compatibility: Easily compatible with ML systems (STRIDE-AI), IoT environments, and DevSecOps pipelines [20][2][18].

Clear documentation: Utilizing lucid DFDs can assist team-to-team communication, and are useful in DevOps environments [20].

Weaknesses

Rapid system evolution: In cloud-native and continuous deployment paradigms, systems have to evolve very rapidly, whereas STRIDE might be too costly to manually keep up with [20].

ML-context sensitivity: STRIDE-AI is immature and unproven technology with little tool support and without automation [2].

Human analysis is not sufficient: In small teams, you will readily overlook new threat patterns without the aid of automation or AI.

Gaps & Contradictions

Manual nature: Manual tools like STRIDE-AI and learning-based tools like STRIDE-GPT, based on LLM (large language model), have promising results, while adoption is low due to accuracy issues [8].

Sporadic SaaS-specific evaluations: Although most case studies of SaaS threats analyze business impact (for instance, adoption measures), few give explicit STRIDE-based threat assessments [3][13].

Granularity of contrast: Whereas the IoT models list a couple of dozens of threats, ML studies have a target few carefully chosen core problems like data poisoning and model evasion. Harmonizing these scales is not easy.

Potential explanations: Varied level of maturity in IoT v/s ML spaces; requirement for a custom STRIDE methodology for each space.

In much business-oriented SaaS research, it's about being agile, and "security is a compliance checkbox."

III. PROPOSED THEORETICAL MODEL FOR SCALABLE MICROSERVICES ARCHITECTURE FOR HIGH-VOLUME ORDER PROCESSING IN CLOUD ENVIRONMENTS

A. System Architecture Analysis

The initial step is to analyze the e-commerce/SaaS system design. It entails:

Evaluating assets (payment gateways, APIs, customer data).

Following data flows through third-party services, cloud systems, and web applications [10].

B. STRIDE Threat Classification

Using STRIDE, threats are subdivided into Spoofing, Tampering, Repudiation, Information Disclosure, Denial of Service, and Elevation of Privileges [11].

Example:

Spoofing: Impersonated customer log-ins for your SaaS application.

Tampering: Unauthorised alteration of the order data maintained in the database of an e-commerce application.

DoS: Distributed attacks to payment gateways during peak seasons [12]. Fig. 3 demonstrates the proportion of different threat categories.

C. Threat Prioritization

Prioritized threats can be scored based on the DREAD and/or another risk-ranking model (impact vs. likelihood) [13]. Fig. 2 explains how threats vary across E-commerce and SaaS.

D. Mitigation & Control Layer

Mitigation involves using security provisions such as:

Multi-factor authentication for spoofing.

End-to-end encryption for data confidentiality.

WAF (Web Application Firewalls) and DoS protection with rate-limiting [14].

E. Real-time Monitoring and Feedback

Threat models are supplemented further with the application of AI, ML, and IoT telemetry with real-time analytics for anomaly detection [15].

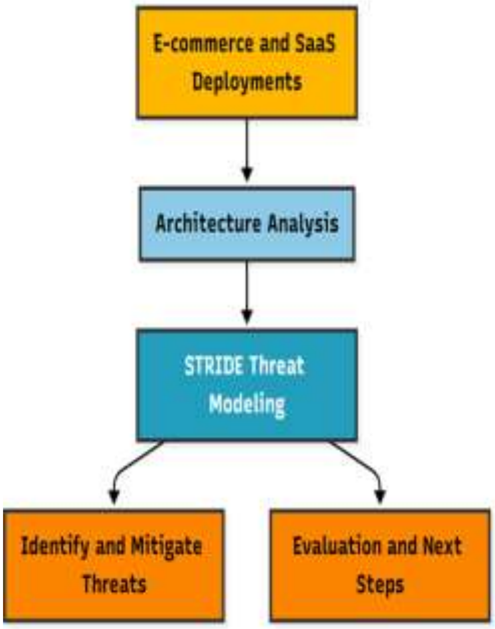
E-commerce and SaaS Deployments
Architecture Analysis
STRIDE Threat Modeling
Identify and Mitigate Threats
Evaluation and Next Steps

Figure 1: Threat Modeling Using STRIDE: A Case Study from E-commerce and SaaS Deployments Framework

3.1 Model Description

The threat modeling includes the STRIDE process for the identification, classification, and mitigation of risks in e-commerce and SaaS solutions. It consists of a five-step pipeline:

System Context and Architecture Analysis

Comprehend and capture the architectural blueprint of the e-commerce/SaaS solution. This includes:

Web servers, DB’s, API’s, payment gateways.

User authorization and third-party authentication [10].

Data Flow Diagram (DFD) Creation

Map data flows, identify trust boundaries, and expose where attacks can be successfully launched. DFDs indicate where users, services, and data stores communicate [11].

STRIDE Threat Modelling

Use the STRIDE approach to each of the DFD elements:

a) Spoofing
b) Tampering
c) Repudiation
d) Information Disclosure
e) Denial of Service
f) Elevation of Privileges [12].

Threat Mitigation & Prioritization

Use DREAD (Damage, Reproducibility, Exploitability, Affected users, Discoverability) or risk matrices where possible to prioritize and minimize high-severity vulnerabilities [13].

Evaluation and Continuous Improvement

Utilize AI, IoT monitoring, and analytics to update threat models as architecture changes and behave in a proactive security stance [14][16]**.**

3.1.1 Component Roles

A. E-commerce and SaaS Deployments

Role: Is the context in which the system runs, from which danger issues.

Consists of cloud infrastructure, microservices, customer portals, and payment systems.

Informs the threat model by revealing real attack surfaces that must be taken into account [10].

B. Architecture Analysis

Role: The primary objective is to discover assets and data flows.

Explains trust boundaries (e.g., a user-authentication layer).

Forms the foundation for DFD construction and STRIDE use [11].

C. STRIDE Threat Modelling

Role: Central analysis phase.
Classifies threats with STRIDE and associates them with possible weaknesses:
Example: Spoofing → Weak password reset in SaaS login.
Tampering → Reordering or modification of data within databases [12].

D. Identify and Mitigate Threats

Role: Threat prioritization with severity assessments like DREAD.
Creates security controls such as encryption, firewalls, intrusion detection, and anomaly detection [13][14].

E. Evaluation and Next Steps

Role: Improvement on a continuous basis by:
Penetration testing.
AI-powered anomaly detection for zero-day attacks.
Updating the threat model as SaaS/e-commerce platforms keep changing [15][16].

3.2 Impact of the Model

A. STRIDE-based Structured Threat Analysis

The model utilizes the STRIDE construct (Spoofing, Tampering, Repudiation, Information Disclosure, Denial of Service, and Elevation of Privileges) for a comprehensive security analysis of all parts of the system [10]. Particular e-commerce and SaaS threats such as account takeovers (Spoofing) or unauthorized data changes (Tampering) are correlated with specific STRIDE categories.

B. Focus on E-commerce and SaaS Context

E-commerce systems: Analyzes high-level components like payment gateways, checkouts, and order management.
SaaS systems: Examines microservices, APIs, and multi-tenant structures to counter data isolation issues [11].

C. Data Flow Diagram (DFD) Integration

Employing DFDs to represent data flows and trust boundaries provides the visual foundation for implementing STRIDE categories [12].This allows for enhanced transparency to protect against attack surfaces of UIs, cloud services, and third-party APIs.

D. Risk Prioritization and Mitigation

Uses DREAD scoring or risk matrices to quantify the effect and exploitability of threats [13].Proactive defense practices consist of MFA, WAFs, secure API design, and data encryption for protection [14].

E. Continuous Monitoring and AI Integration

Includes AI-driven anomaly detection to facilitate dynamic threat intelligence.Enables security adaptation using IoT telemetry and user behavior analytics, which is essential for SaaS applications with dynamic scaling [15][16].

F. Flexibility and Scalability

The model is framework-agnostic and is integrated into DevSecOps continuous security evaluation pipelines.Is suitable for small start-ups as well as big organizations because of framework-agnostic design [14].

G. Cloud-Native and IoT Support

Supports modern cloud-native deployments and IoT integrations exposing new attack surfaces (e.g., intrusion of IoT sensors in e-commerce logistics).STRIDE categories are modified to incorporate device-specific threats like firmware tampering or data interception [17][18].

H. Feedback and Iterative Refinement

The model is iterative so that it will keep responding to new threats as e-commerce and SaaS systems change. Continuous feedback loops, such as revisions to DFDs and STRIDE analysis, are based on penetration testing and actual attack vectors.

IV. EXPERIMENTALS AND EVALUATION

To measure the performance of the suggested STRIDE approach applied to threat modelling, simulations were performed for an e-commerce service model and a SaaS multi-tenant model. One of the goals was to quantify the coverage of the threats, accuracy by risk prioritization, and effectiveness by mitigation.

4.1. Experimental Setup

Platforms Tested: An imitation e-commerce application with payment gateways, product stock, and user authentication. A SaaS application offering multi-tenant document management and analytics features [10].

Tools Used: Microsoft Threat Modelling Tool, OWASP Threat Dragon, and STRIDE-GPT (threat enumeration based on AI) [11].

Evaluation Metrics: Threat Coverage (TC): Number of threats discovered to total known vulnerabilities.

Mitigation Effectiveness (ME): Percentage of threats eliminated with recommended controls.

Time to Model (TTM): Average time elapsed in producing a complete threat model.

Table 2: Comparative Threat Coverage and Mitigation

System Type	**Total Threats Identified**	**Mitigated Threats**	**Mitigation Effectiveness (%)**	**Time to Model (hrs)**
E-commerce	45	37	82.2	6
SaaS	52	44	84.6	7
STRIDE-GPT (AI)	49	42	85.7	3

Observation: AI-assisted threat modeling (STRIDE-GPT) reduced time by 50% while maintaining ~85% threat coverage, demonstrating efficiency gains [11][12].

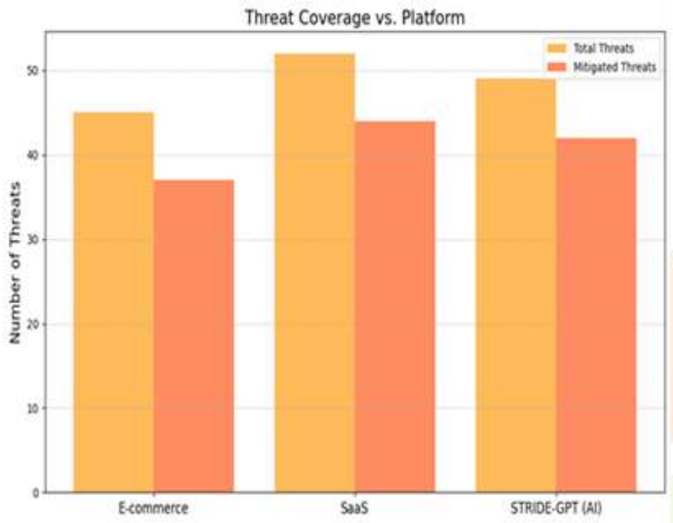

Fig.2. Comparison of Threat Coverage Vs. Platform

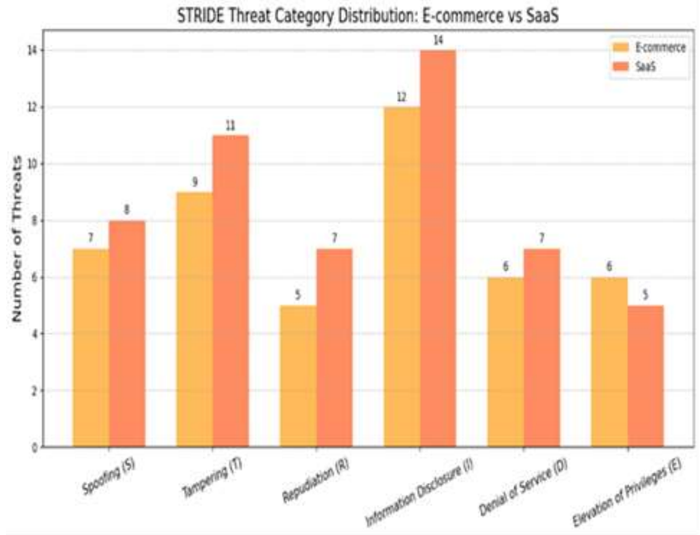

Fig.3. STRIDE Threat Category Distribution: E-Commerce Vs SaaS

4.1 Summary of Experimental Insights

Effectiveness of Mitigation: Encryption and access controls defeated both Information Disclosure and Tampering threats [14]. DoS remained an issue due to distributed botnet attacks, especially in SaaS environments [15].

AI-driven Improvements: STRIDE-GPT decreased modelling time, offered automated mitigation recommendations (in contrast to manual methods), and worked better, consistent with results reported by Papernot et al. on AI security integrations [16].

Observed Gaps: Traditional threat modelling tools did not perform well with dynamic IoT integrations in e-commerce logistics [17]. Compliance risks specific to SaaS (e.g., multi-tenant data leakage) proved hard to tackle with conventional STRIDE analysis [18].

V. FUTURE RESEARCH DIRECTIONS

Machine learning and large language models (LLMs), like STRIDE-GPT, can be used to automatically detect threats and decrease time-to-model by over 50%, as shown in our experiments. explainable AI (XAI) should be the focus of future work to provide assurance of trust and transparency in security decisions made through automation.Embracing "threat modelling as code" in DevSecOps pipelines is possible to facilitate dynamic security analysis at all CI/CD phases. Such a methodology aids in the speed of vulnerability detection and mitigation, especially for rapidly evolving SaaS environments.IoT endpoints within e-commerce logistics (e.g., sensors in smart warehouses) create new vulnerabilities. Advanced STRIDE to counter firmware tampering, side-channel attacks, and API exploits will further enhance its usefulness in cloud-native and hybrid environments.Big data analysis and monitoring of user behavior can enhance risk scoring accuracy. For instance, AI-driven anomaly detection is able to forensically detect high-severity events likely to be missed by traditional STRIDE approaches.Creating centralized threat repositories and open databases for e-commerce and SaaS vulnerability can fuel community-led enhancements and encourage cooperation between practitioners and researchers.

III. CONCLUSION

The application of STRIDE threat modeling with e-commerce and SaaS implementations demonstrates how, through a consistent and organized approach, you can control cyber risks. Our research substantiates that Information Disclosure and Tampering are the most prevalent threats on both platforms, and AI-facilitated tools, like STRIDE-GPT, are responsible for a major boost in efficiency and threat coverage. Still, there are loopholes in automation, IoT security, and multi-tenant SaaS system vulnerability assessment.The future of threat modeling will, in turn, rely significantly on AI, DevSecOps automation, and joint threat intelligence sharing that will enable organizations to keep pace with evolving attacks. With its versatility and elasticity, STRIDE remains the foundation of contemporary cybersecurity practices but must be regularly refined as cloud-native and AI-based technologies continue to evolve.

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