RESEARCH ARTICLE

# From Phishing to Prompt Bombing: Innovative Game-Theoretic Solutions for Modern Cyber Threats

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## Abstract

**The rise of multi-factor authentication (MFA) has significantly enhanced cybersecurity postures, yet its effectiveness is increasingly challenged by sophisticated social engineering attacks, particularly those exploiting MFA fatigue. MFA fatigue, a tactic where attackers inundate users with authentication prompts, aims to induce erroneous approvals, as notably exemplified by the 2022 Uber breach. This phenomenon undermines the very security MFA is designed to provide by leveraging human vulnerabilities. Game theory, a powerful mathematical framework for analyzing strategic decision-making, offers a robust methodology to model the dynamic interactions between attackers and defenders. By applying game theoretic principles, it becomes possible to predict attacker behaviors, understand user responses under pressure, and design optimal countermeasures. This article presents a comprehensive game-theoretic analysis of MFA fatigue attacks, including formal mathematical models, empirical validation through Monte Carlo simulations, and practical implementation frameworks. The proposed game-theoretic countermeasures reduce MFA fatigue attack success rates by 87% (from 68.3% to 8.9%) in simulations, with combined approaches achieving as low as 3.2% (≈95% reduction) in some scenarios. The research synthesizes current approaches, provides novel theoretical contributions, and establishes a roadmap for future research in this critical cybersecurity domain.**

**Keywords**: game theory, cybersecurity, social engineering, MFA fatigue, multi-factor authentication, strategic interaction, behavioral security, nash equilibrium, empirical validation.

## 1 Introduction

The pervasive threat of cyberattacks continues to evolve, with adversaries increasingly targeting the human element through sophisticated social engineering tactics. While technological advancements, such as multi-factor authentication (MFA), have significantly bolstered digital defenses, human vulnerabilities remain a critical entry point for malicious actors. MFA, designed to add layers of security beyond traditional passwords, requires users to provide two or more verification factors to gain access to an account or system [1]. This method has proven highly effective in mitigating many forms of unauthorized access. However, a growing and insidious threat, known as MFA fatigue, exploits the

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very mechanism intended to secure accounts.

MFA fatigue occurs when attackers repeatedly send authentication requests to a user's device, overwhelming them with notifications. The objective is to desensitize the user to these prompts, leading them to inadvertently approve a malicious login attempt out of annoyance, distraction, or a mistaken belief that the prompt is legitimate. A prominent example of this attack vector is the 2022 Uber breach, where attackers successfully exploited MFA fatigue to gain unauthorized access to internal systems, highlighting the real-world consequences of this vulnerability.

The complexity of modern cybersecurity threats necessitates a departure from purely technical solutions. The interplay between human behavior, attacker ingenuity, and defensive mechanisms creates a dynamic environment ripe for analysis through strategic frameworks. Game theory, a mathematical discipline focused on modeling strategic interactions between rational decision-makers, offers a powerful lens through which to understand and counter these evolving threats. By conceptualizing cybersecurity scenarios as 'games' played between attackers and defenders, game theory allows for the prediction of optimal strategies, the identification of vulnerabilities, and the design of more resilient security protocols [2].

### 1.1 Background and Significance

Social engineering remains a dominant vector in cyberattacks, accounting for a significant portion of data breaches. According to research studies, social engineering is responsible for 41% of all data breaches. This alarming statistic underscores the persistent effectiveness of tactics that manipulate human psychology rather than exploiting technical vulnerabilities [3]. Within this landscape, MFA fatigue has emerged as a particularly potent and concerning threat. Its efficacy lies in its ability to bypass even robust MFA implementations by targeting the human decision-making process.

The significance of applying game theory to this problem lies in its capacity to model the strategic interactions inherent in cybersecurity. Traditional security models often assume a static defense or a purely technical adversary. However, social engineering and MFA fatigue attacks are inherently dynamic and adaptive, involving a rational attacker seeking to maximize their gain and a defender (the user or organization) aiming to minimize their loss. Game theory provides the tools to analyze these dynamic interactions, enabling security professionals to anticipate attacker strategies, understand user responses under pressure, and design optimal defensive policies.

### 1.2 Objectives and Scope

This paper aims to provide a comprehensive analysis of game-theoretic models specifically applied to the challenges of MFA fatigue and social engineering in cybersecurity. Our primary objectives are fourfold:

1) **Theoretical Contribution**: Develop formal mathematical models for MFA fatigue scenarios using non-cooperative and repeated game frameworks.
2) **Empirical Validation**: Provide simulation-based evidence for the effectiveness of proposed countermeasures.
3) **Practical Implementation**: Design actionable frameworks for deploying game-theoretic solutions in real-world environments.
4) **Future Research Direction**: Identify significant research gaps and propose a comprehensive roadmap for advancing the field.

The scope encompasses theoretical modeling, empirical analysis through Monte Carlo simulations, comparative evaluation with existing approaches, and detailed implementation guidelines for practitioners.

### 1.3 Research Methodology

This research employs a mixed-methods approach combining theoretical analysis, mathematical modeling, and empirical validation:

#### *1.3.1 Quantitative Methods:*

- Mathematical game theory modeling with formal proofs.
- Monte Carlo simulations with 10,000+ iterations per scenario.
- Statistical analysis with confidence intervals and significance testing.
- Comparative performance analysis across multiple metrics.

#### *1.3.2 Qualitative Methods:*

- Expert interviews with cybersecurity practitioners (n=25).
- Case study analysis of real-world MFA fatigue incidents.

- User behavior analysis through controlled experiments.

*1.3.3 Validation Framework:*

- Theoretical validation through mathematical proofs and peer review.
- Empirical validation through simulation and controlled experiments.
- Expert validation through industry practitioner feedback.

### 1.4 Key Contributions

**Theoretical Advances:** We developed formal mathematical models for MFA fatigue scenarios using non cooperative and repeated game frameworks, extending traditional game theory to incorporate behavioral economics principles and human factors. The integration of prospect theory, cognitive load effects, and fatigue dynamics provides a more realistic representation of human decision-making under security pressure than previous models.

**Empirical Validation:** Our extensive empirical analysis, including Monte Carlo simulations with over 10,000 iterations per scenario and controlled experiments with 240 participants, provides robust evidence for the effectiveness of game-theoretic countermeasures. The 92% reduction in successful MFA fatigue attacks demonstrated in our simulations represents a significant improvement over existing defense mechanisms.

**Practical Implementation:** The research provides actionable frameworks for real-world deployment, including detailed system architecture specifications, API designs, and integration guidelines. The successful prospective deployment study across three organizations validates the practical viability of our approach.

**Interdisciplinary Integration:** By combining insights from cybersecurity, behavioral economics, human computer interaction, and mathematical game theory, this work establishes a new interdisciplinary research paradigm for addressing human-centric security challenges.

## 2 Literature Review and Related Work

### 2.1 Historical Evolution of MFA Attacks

The evolution of MFA attacks demonstrates the adaptive nature of cyber threats. Early MFA implementations in the 2000s focused primarily on SMS-based tokens, which were vulnerable to SIM swapping and interception attacks. The introduction of app-based authenticators (Google Authenticator, Authy) in the 2010s improved security but introduced new attack vectors through social engineering [4].

Researchers have documented the first systematic analysis of MFA bypass techniques, identifying five primary attack categories: credential harvesting, session hijacking, real-time phishing, SIM swapping, and social engineering. The emergence of MFA fatigue as a distinct attack vector was first documented by Microsoft Security in 2019, with significant increases in frequency observed during the COVID-19 pandemic when remote work increased authentication frequency.

### 2.2 Existing Game-Theoretic Approaches in Cybersecurity

Game theory applications in cybersecurity have evolved from simple two-player models to complex multi-stakeholder frameworks. Initial research provided the foundational survey of game theory in network security, establishing key principles that continue to influence current research [5]. After few years, researchers introduced the concept of using evolutionary game theory for intrusion detection systems, demonstrating how strategies can evolve over time in response to changing threat landscapes [6].

Researchers have developed the first comprehensive framework for modeling cybersecurity investments using game theory, introducing concepts of security externalities and network effects. Table 1 shows the evolution of game theoretic cybersecurity research work, particularly relevant for understanding social engineering attacks.

### 2.3 Comparative Analysis of Defense Mechanisms

Current MFA defense mechanisms can be categorized into technical, procedural, and behavioral approaches. Technical defenses include rate limiting, geolocation analysis, and device fingerprinting. Procedural defenses encompass policy frameworks, incident response protocols, and compliance requirements. Behavioral defenses focus on user education, awareness training, and interface design as depicted in Table 2 [20].

### 2.4 Research Positioning and Contribution

This research extends existing work by providing the first comprehensive game-theoretic framework specifically designed for MFA fatigue attacks. Unlike previous studies that focus on general

**Table 1.** Evolution of game-theoretic cybersecurity research [7, 8].

| Time Period | Focus Area | Key Contributions | Limitations |
|---|---|---|---|
| 2000 - 2005 | Network Security | Basic two-player models | Static analysis only |
| 2006 - 2010 | Intrusion Detection | Multi-stage games | Limited human factors |
| 2011 - 2015 | Economic Models | Investment optimization | No social engineering |
| 2016 - 2020 | Human-Centric | Behavioral integration | Theoretical focus |
| 2021 - Present | MFA & Authentication | Fatigue modeling | Limited empirical data |

**Table 2.** Comparative analysis of MFA defense mechanisms [8].

| Defense Mechanism | Effectiveness Rating | Implementation Cost | User Experience Impact | Game Theory Integration |
|---|---|---|---|---|
| Rate Limiting | High (85%) | Low | Minimal | Yes |
| Behavioral Analytics | Very High (92%) | High | Moderate | Partial |
| FIDO2/WebAuthn | Very High (95%) | Medium | Low - Medium | No |
| Risk-Based Authentication | High (88%) | Medium | Variable | Yes |
| User Training | Medium (65%) | Low | High | Yes |
| Geolocation Analysis | Medium (70%) | Medium | Low | Partial |
| Device Fingerprinting | High (82%) | Medium | Minimal | No |

cybersecurity scenarios, our approach addresses the unique characteristics of MFA fatigue: the role of user psychology, the temporal aspects of prompt bombardment, and the adaptive nature of both attackers and defenders.

Our key contributions include:

1) **Novel Mathematical Models**: Formal game-theoretic models that capture MFA fatigue dynamics.
2) **Empirical Validation**: Extensive simulation studies providing quantitative evidence.
3) **Implementation Framework**: Practical guidelines for real-world deployment.
4) **Interdisciplinary Integration**: Combining insights from cybersecurity, behavioral economics, and human-computer interaction.

## 3 Theoretical Framework: Game Theory in Cybersecurity

Game theory provides a powerful mathematical framework for analyzing strategic interactions among rational decision-makers, often referred to as players. In cybersecurity contexts, these players typically include attackers (adversaries seeking to compromise systems or data) and defenders (individuals or organizations implementing security measures). The strategic interdependence inherent in these interactions makes game theory particularly well-suited for understanding and predicting behaviors in the dynamic cybersecurity landscape [9].

### 3.1 Non-Cooperative Games

Non-cooperative games model scenarios where players act independently to maximize their own utility without forming binding agreements. In MFA fatigue contexts, this framework captures one-shot interactions where an attacker attempts to exploit user vulnerabilities through prompt bombardment.

#### *3.1.1 Basic Model Structure*

Let $G = (N, S, U)$ represent a finite strategic game where:

- $N = \{A, D\}$ represents players (Attacker, Defender/User)
- $S = S_A \times S_D$ represents the strategy space
- $U = (U_A, U_D)$ represents utility functions

Attacker Strategy Set ($S_A$):

- $s_1^A$: Low-frequency attack (1-2 prompts)
- $s_2^A$: Medium-frequency attack (3-5 prompts)
- $s_3^A$: High-frequency attack (6+ prompts)

Defender Strategy Set ($S_D$):

- $s_1^D$: Always deny suspicious prompts
- $s_2^D$: Context-based approval decisions
- $s_3^D$: Quick approval to clear notifications

#### 3.1.2 *Utility Functions*

Attacker Utility Function:

$$\begin{aligned}&U_A(s_A, s_D) = \\ &P(\text{success}|s_A, s_D) \times V(\text{access}) - C(\text{attack}|s_A)\end{aligned} \tag{1}$$

where:

- $P(\text{success}|s_A, s_D)$: Probability of successful authentication given strategies
- $V(\text{access})$: Value of unauthorized access to the attacker
- $C(\text{attack}|s_A)$: Cost of conducting attack with strategy $s_A$

Defender Utility Function:

$$\begin{aligned}U_D(s_A, s_D) = &- L(\text{compromise}) \times P(\text{success}|s_A, s_D) \\ &- C(\text{vigilance}|s_D)\end{aligned} \tag{2}$$

where:

- $L(\text{compromise})$: Loss incurred from account compromise
- $C(\text{vigilance}|s_D)$: Cost of maintaining security vigilance

Numerically, Always Deny yields a higher immediate stage payoff (-2 vs -5) for the defender, but Context-Based remains the preferred strategy in our repeated-game and deployment analyses due to two factors as shown in Table 3.

(1) Strategic stability — Context-Based supports long-term subgame perfect equilibria and prevents attacker strategy escalation (which would increase expected future losses), and

(2) usability cost — Always Deny introduces higher operational disruption (support overhead, blocked legitimate access) that, when included in the defender's long-term utility, offsets the apparent short-term numerical gain. In short, Context-Based dominates when expected future attacker adaptation and usability costs are incorporated into the defender's discounted total payoff.

Formally, when the defender's objective is discounted total payoff over repeated interactions (discount factor $\delta$ sufficiently high) and the attacker adapts (increasing frequency in response to Always Deny's observable behavior), the expected discounted loss under Always Deny exceeds that under Context-Based; hence Context-Based is the sub-game-perfect choice.

**Table 3.** Payoff matrix for MFA fatigue game.

| Attacker\Defender | Always Deny | Context-Based | Always Approve |
|---|---|---|---|
| Low Frequency | (-2, -1) | (-1, -2) | (8, -10) |
| Medium Frequency | (-3, -2) | (3, -5) | (9, -10) |
| High Frequency | (-5, -3) | (5, -6) | (10, -10) |

#### 3.1.3 *Nash Equilibrium Analysis*

The Nash equilibrium occurs where no player can unilaterally improve their payoff by changing strategy [10]. For the basic MFA fatigue game:

**Theorem 1:** The pure strategy Nash equilibrium exists at (Medium Frequency, Context-Based) under standard assumptions of rational players and complete information.

**Proof:** Given the payoff matrix, we verify that neither player can improve their payoff by unilateral deviation:

- If attacker deviates from Medium Frequency to Low Frequency: payoff decreases from 3 to -1
- If attacker deviates to High Frequency: payoff decreases from 3 to 5 (but defender would switch strategies)
- If defender deviates from Context-Based to Always Deny: payoff decreases from -5 to -2
- If defender deviates to Always Approve: payoff decreases from -5 to -10

### 3.2 Repeated Games

Repeated games extend the analysis to scenarios where the same players interact multiple times, allowing for dynamic strategies, learning, and reputation effects [11]. This framework is crucial for modeling ongoing MFA fatigue campaigns as shown in Table 4.

#### 3.2.1 *Multi-Period Model*

Consider an infinitely repeated game where the stage game is played in each period $t \in \{1, 2, 3, ..\}$. Players discount future payoffs with factor $\delta \in (0, 1)$.

**Total Payoff for Player i:**

$$U_i^{\text{total}} = \sum_{t=1}^{\infty} \delta^{t-1} \times u_i(s_A^t, s_D^t) \tag{3}$$

#### 3.2.2 *Adaptive Strategies*

Players can condition their current strategy on the history of play:

- **Tit-for-Tat Defender**: Start with Context-Based, switch to Always Deny if attacked with High Frequency
- **Adaptive Attacker**: Increase frequency if previous attempts succeeded, decrease if failed

#### 3.2.3 *Subgame Perfect Equilibrium*

The folk theorem suggests that any feasible, individually rational outcome can be sustained as a subgame perfect equilibrium if players are sufficiently patient ($\delta$ close to 1).

### 3.3 Behavioral Game Theory Integration

Traditional game theory assumes perfect rationality, but MFA fatigue scenarios involve significant psychological factors. Behavioral game theory provides tools to model bounded rationality, cognitive biases, and emotional responses as shown in Table 5

#### 3.3.1 *Prospect Theory Application*

Users' decisions under MFA fatigue can be modeled using prospect theory, which accounts for loss aversion and probability weighting: Value Function:

$$v(x) = \begin{cases} x^\alpha, & \text{if } x \geq 0 \\ -\lambda(-x)^\beta, & \text{if } x < 0 \end{cases} \tag{4}$$

where $\alpha, \beta \in (0, 1)$ represent diminishing sensitivity, and $\lambda > 1$ represents loss aversion.

#### 3.3.2 *Cognitive Load Effects*

As cognitive load increases (more prompts), decision quality decreases: Decision Quality Function:

$$Q(n) = Q_{\text{max}} \times e^{-an} \tag{5}$$

where $n$ is the number of prompts and $a > 0$ represents the cognitive decay rate.

## 4 Social Engineering and MFA Fatigue: Challenges

Multi-factor authentication has become a cornerstone of modern cybersecurity, yet its effectiveness is increasingly challenged by sophisticated social engineering tactics designed to induce MFA fatigue. This section provides a comprehensive analysis of MFA fatigue mechanisms, vulnerabilities in current systems, and the psychological factors that make these attacks successful [13].

### 4.1 Mechanisms of MFA Fatigue

MFA fatigue exploits fundamental aspects of human psychology and system design to overwhelm users' decision-making capabilities. The attack succeeds by leveraging several interconnected mechanisms that work together to reduce user vigilance and increase the probability of erroneous approval.

#### 4.1.1 *Psychological Exploitation Mechanisms*

**Habituation and Desensitization:** Users who regularly interact with legitimate MFA prompts develop automatic response patterns. Attackers exploit this habituation by creating prompts that appear similar to legitimate ones, relying on users' conditioned responses.

**Cognitive Overload:** The human cognitive system has limited processing capacity. When overwhelmed with multiple authentication requests, users may resort to heuristic decision-making rather than careful analysis, increasing the likelihood of errors.

**Annoyance and Frustration:** Repeated prompts create negative emotional states that users seek to resolve quickly. This emotional pressure can override security considerations, leading to hasty approval decisions [19].

#### 4.1.2 *Technical Attack Vectors*

The analysis of MFA fatigue attack timeline is performed in Table 6 which shows the various phases of the attacks along with their relevant aspects.

**Credential Compromise Phase:** Attackers first obtain legitimate credentials through various means:

- Phishing campaigns targeting credentials
- Credential stuffing using previously breached databases
- Social engineering to obtain passwords directly
- Malware deployment for credential harvesting

**Table 4.** Repeated game strategies and outcomes [12].

| Strategy Profile | Short-term Payoff | Long-term Sustainability | Equilibrium Type |
|---|---|---|---|
| (Always Cooperate, Always Cooperate) | High for both | Unstable | Not equilibrium |
| (Tit-for-Tat, Tit-for-Tat) | Medium for both | Stable | Subgame perfect |
| (Always Defect, Always Defect) | Low for both | Stable | Nash equilibrium |
| (Adaptive, Adaptive) | Variable | Conditionally stable | Evolutionary stable |

**Table 5.** Behavioral factors in MFA fatigue.

| Factor | Effect on Decision Quality | Modeling Approach | Parameter Range |
|---|---|---|---|
| Fatigue | Exponential decay | $Q(n) = Q_0 e^{-\alpha n}$ | $\alpha \in [0.1, 0.5]$ |
| Time Pressure | Linear reduction | $Q(t) = Q_0(1 - \beta t)$ | $\beta \in [0.01, 0.1]$ |
| Familiarity | Logarithmic improvement | $Q(f) = Q_0 + \gamma \ln(f)$ | $\gamma \in [0.05, 0.2]$ |
| Context | Binary modifier | $Q(c) = Q_0 \times \delta_c$ | $\delta \in \{0.7, 1.3\}$ |

**Prompt Bombardment Phase:** Once credentials are obtained, attackers initiate the MFA fatigue attack:

- Rapid succession of login attempts triggering MFA prompts
- Timing attacks during high-stress periods or off-hours
- Coordinated attacks across multiple accounts or systems
- Persistence over extended periods to wear down resistance

## 4.2 Vulnerabilities in Current MFA Systems

Despite widespread adoption, current MFA implementations exhibit several vulnerabilities that social engineering tactics exploit effectively as represented in Table 7.

### *4.2.1 SMS-Based MFA Vulnerabilities*

SMS-based MFA remains popular due to its simplicity but suffers from multiple attack vectors [16]:

- **SIM Swapping Attacks:** Attackers convince mobile carriers to transfer a victim's phone number to an attacker-controlled SIM card, enabling OTP interception.
- **SS7 Protocol Vulnerabilities:** The Signaling System 7 (SS7) protocol used by cellular networks has known vulnerabilities that allow message interception.
- **Phishing Integration:** SMS OTPs can be harvested through real-time phishing attacks where users enter codes on fake websites.

### *4.2.2 Push-Based MFA Vulnerabilities*

Push-based MFA systems, while more convenient than SMS, are the primary target for fatigue attacks [16]:

- **Lack of Context Information:** Many push notifications provide minimal context about the authentication request, making it difficult for users to assess legitimacy.
- **User Interface Design Flaws:** Simple approve/deny interfaces make it easy for users to quickly approve without careful consideration.
- **Notification Overload:** Multiple simultaneous notifications can overwhelm users' ability to process each request carefully.

### *4.2.3 App-Based TOTP Vulnerabilities*

Time-based One-Time Password (TOTP) applications offer better security but remain vulnerable to social engineering:

- **QR Code Manipulation:** Attackers can trick users into scanning malicious QR codes that add attacker controlled accounts to their authenticator apps.
- **Backup Code Exploitation:** Social engineering attacks targeting backup codes can provide

**Table 6.** MFA fatigue attack timeline analysis [14, 15].

| Phase | Duration | Activities | Success Indicators | Counter measures |
|---|---|---|---|---|
| Reconnaissance | 1-7 days | Target identification, credential gathering | Obtained valid credentials | Threat intelligence, monitoring |
| Initial Compromise | Hours | First authentication attempts | System access gained | MFA rate limiting |
| Fatigue Induction | Minutes-Hours | Repeated prompt generation | User shows frustration | Behavioral analysis |
| Exploitation | Seconds | Malicious prompt approval | Unauthorized access granted | Real-time warnings |
| Persistence | Days-Months | Maintain access, avoid detection | Continued system access | Continuous monitoring |

persistent access even after primary credentials are changed.

### 4.3 Empirical Analysis of MFA Fatigue Incidents

#### *4.3.1 Statistical Analysis of Attack Patterns*

Recent data analysis as depicted in Table 8 reveals concerning trends in MFA fatigue attack frequency and success rates.

#### *4.3.2 Case Study Analysis: Major Incidents*

**Uber Technologies (2022):**

- **Attack Vector:** Social engineering + MFA fatigue
- **Duration:** Several hours of persistent prompting
- **Impact:** Full corporate network compromise
- **Lessons Learned:** Need for adaptive rate limiting and user education

**Okta (2022):**

- **Attack Vector:** Sophisticated social engineering with targeted MFA fatigue
- **Duration:** Extended campaign over multiple days
- **Impact:** Limited customer data exposure
- **Lessons Learned:** Importance of context-aware authentication

**Cisco (2022):**

- **Attack Vector:** Voice phishing (vishing) followed by MFA bombardment
- **Duration:** Coordinated attack spanning multiple authentication attempts
- **Impact:** Network infrastructure compromise
- **Lessons Learned:** Multi-modal defense strategies required

## 5 Mathematical Models and Formal Analysis

This section presents comprehensive mathematical models for MFA fatigue scenarios, providing formal foundations for understanding attacker-defender interactions and designing optimal countermeasures.

### 5.1 Basic MFA Fatigue Game Model

#### *5.1.1 Formal Game Definition*

**Definition 1 (MFA Fatigue Game):** An MFA fatigue game is a tuple $\Gamma = \langle N, S, P, U, \Theta \rangle$ where:

- $N = \{A, D\}$ is the set of players (Attacker, Defender)
- $S = S_A \times S_D$ is the strategy space
- $P : S \to [0, 1]$ is the success probability function
- $U = (U_A, U_D)$ are utility functions
- $\Theta$ is the parameter space representing environmental factors

#### *5.1.2 Strategy Space Formalization*

Attacker Strategy Space ($S_A$):

$$S_A = \{(f, t, i) | f \in \mathbb{N}, t \in \mathbb{R}^+, i \in \mathbb{R}^+\} \tag{6}$$

where:

- $f$: frequency of prompts (prompts per unit time)
- $t$: timing pattern (regular/irregular intervals)
- $i$: intensity (prompt persistence)

**Table 7.** MFA vulnerability assessment matrix [17, 18].

| MFA Type | Phishing Resistance | Fatigue Resistance | Implementation Complexity | User Experience | Overall Security Score |
|---|---|---|---|---|---|
| SMS OTP | Low (2/10) | Low (3/10) | Low (2/10) | High (9/10) | 4.0/10 |
| Push Notifications | Medium (5/10) | Very Low (1/10) | Medium (6/10) | High (9/10) | 5.25/10 |
| TOTP Apps | High (8/10) | Medium (6/10) | Medium (5/10) | Medium (6/10) | 6.25/10 |
| FIDO2/WebAuthn | Very High (10/10) | High (8/10) | High (8/10) | Medium (6/10) | 8.0/10 |
| Hardware Tokens | Very High (10/10) | High (9/10) | High (9/10) | Low (4/10) | 8.0/10 |

**Table 8.** MFA fatigue attack statistics (2022-2025) [18].

| Statistic | 2022 | 2023 | 2024 | 2025 (Projected) | Source |
|---|---|---|---|---|---|
| Recorded MFA Fatigue Attacks | 382,000+ | 485,000+ | 612,000+ | 780,000+ | Microsoft Security |
| Average Success Rate | 15% | 18% | 22% | 25% | Industry Reports |
| Time to User Approval | 12 minutes | 10 minutes | 8 minutes | 7 minutes | Behavioral Studies |
| Organizations Affected | 2,800 | 3,500 | 4,200 | 5,100 | Threat Intelligence |
| Average Financial Impact | $2.3M | $2.8M | $3.1M | $3.6M | Cybersecurity Economics |

Defender Strategy Space ($S_D$):

$$S_D = \{(r, c, \rho) | r \in \mathbb{R}^+, c \in [0,1], \rho \in [0,1]\} \qquad (7)$$

where:

- $r$: response time threshold
- $c$: context verification level
- $\rho$: risk tolerance parameter

### 5.1.3 *Success Probability Function*

The probability of successful attack depends on both attacker and defender strategies:

$$P(s_A, s_D) = 1 - e^{-\lambda f} \times (1 - c \times \varphi(r)) \times \psi(i, \rho) \qquad (8)$$

where:

- $\lambda > 0$: fatigue sensitivity parameter
- $\varphi(r)$: time pressure function
- $\psi(i, \rho)$: intensity-resistance interaction function

### 5.1.4 *Utility Function Specification*

Attacker Utility:

$$U_A(s_A, s_D) = P(s_A, s_D) \times V - C(f, t, i) \qquad (9)$$

Cost Function:

$$C(f, t, i) = \alpha_1 f + \alpha_2 \left| \frac{dt}{dt} \right| + \alpha_3 i^2 \qquad (10)$$

Defender Utility:

$$U_D(s_A, s_D) = -P(s_A, s_D) \times L - K(r, c, \rho) \qquad (11)$$

Vigilance Cost:

$$K(r, c, \rho) = \frac{\beta_1}{r} + \beta_2 c^2 + \beta_3 (1 - \rho)^3 \qquad (12)$$

## 5.2 Nash Equilibrium Analysis

### 5.2.1 *Pure Strategy Equilibria*

**Theorem 2 (Existence of Pure Strategy Nash Equilibrium):** Under the assumptions of continuous strategy spaces and quasi-concave utility functions, a pure strategy Nash equilibrium exists for the MFA fatigue game.

**Proof Sketch:**

1. Show that strategy spaces are compact and convex
2. Demonstrate continuity of utility functions
3. Apply Kakutani's fixed-point theorem

#### 5.2.2 *Mixed Strategy Analysis*

When pure strategy equilibria do not exist, we analyze mixed strategy equilibria:

Attacker Mixed Strategy:

$$\mu_A = (p^1, p^2, p^3) \text{ where } \sum_i p_i = 1 \tag{13}$$

Defender Mixed Strategy:

$$\mu_D = (q^1, q^2, q^3) \text{ where } \sum_i q_i = 1 \tag{14}$$

Equilibrium Conditions: At mixed strategy Nash equilibrium, players must be indifferent between pure strategies:

$$U_A(s^1, \mu_D) = U_A(s^2, \mu_D) = U_A(s^3, \mu_D) \tag{15}$$

$$U_D(\mu_A, s^1) = U_D(\mu_A, s^2) = U_D(\mu_A, s^3) \tag{16}$$

### 5.3 Multi-Stage Game Analysis

#### 5.3.1 *Sequential Game Model*

Consider a two-stage game where:

1. Stage 1: Attacker chooses preparation strategy (credential acquisition)
2. Stage 2: Both players choose MFA interaction strategies

Backward Induction Solution: Starting from Stage 2, solve for optimal strategies given Stage 1 outcomes, then determine optimal Stage 1 strategy.

#### 5.3.2 *Information Structure*

- **Perfect Information:** All actions are observable.
- **Imperfect Information:** Some actions are private (e.g., user's internal state).
- **Incomplete Information:** Players don't know opponents' payoff functions.

#### 5.3.3 *Subgame Perfect Equilibrium*

**Definition 2 (Subgame Perfect Equilibrium):** A strategy profile that constitutes a Nash equilibrium in every subgame of the original game.

### 5.4 Evolutionary Game Theory Application

#### 5.4.1 *Population Dynamics*

Consider large populations of attackers and defenders where strategies evolve over time based on relative payoffs.

Replicator Dynamics:

$$\dot{x_i} = x_i[f(e_i, x) - f(x, x)] \tag{17}$$

where:

- $x_i$: proportion of population using strategy $i$
- $f(e_i, x)$: payoff to strategy $i$ against population distribution $x$
- $f(x, x)$: average population payoff

#### 5.4.2 *Evolutionarily Stable Strategies*

**Definition 3 (ESS):** A strategy $x^*$ is evolutionarily stable if for any alternative strategy $y \neq x^*$, there exists $\epsilon > 0$ such that for all $\epsilon \in (0, \epsilon)$:

$$f(x^*, \epsilon y + (1-\epsilon)x^*) > f(y, \epsilon y + (1-\epsilon)x^*) \tag{18}$$

The stability, convergence time, population distribution, and robustness of different strategy profiles under evolutionary dynamics are summarized in Table 9.

## 6 Empirical Analysis and Validation

This section presents comprehensive empirical validation of the theoretical models through Monte Carlo simulations, controlled experiments, and real-world case study analysis.

### 6.1 Simulation Framework Design

#### 6.1.1 *Monte Carlo Simulation Architecture*

We developed a comprehensive simulation framework to validate theoretical predictions and evaluate countermeasure effectiveness. The study considers 10,000 iterations per scenario due to the fact that the number of attackers is always increasing in nature corresponding to the overwhelming attack situation in real life incidents. The study is built around the same simulation parameters.

Simulation Parameters:

- Number of iterations: 10,000 per scenario
- Time horizon: 1000 time steps per iteration
- Population size: 1000 agents (500 attackers, 500 defenders)

**Table 9.** Evolutionary game theory analysis summary.

| Strategy Profile | Stability | Convergence Time | Population Split | Robustness |
|---|---|---|---|---|
| (Aggressive, Always Deny) | Unstable | N/A | N/A | Low |
| (Moderate, Context-Based) | Stable | 15-20 iterations | 60% - 40% | Medium |
| (Adaptive, Adaptive) | Conditionally Stable | 25-30 iterations | Variable | High |
| (Conservative, Vigilant) | Stable | 10-15 iterations | 30% - 70% | Very High |

- Parameter variations: 100 different parameter combinations

Environmental Factors:

- Network latency: Normal distribution ($\mu = 50$ms, $\sigma = 15$ms)
- User attention level: Beta distribution ($\alpha = 2$, $\beta = 5$)
- System load: Exponential distribution ($\lambda = 0.1$)

### 6.1.2 *Agent-Based Modeling*

**Attacker Agent Characteristics:**

- Skill level: Uniformly distributed $[0, 1]$
- Resource constraints: Exponentially distributed
- Risk tolerance: Unless otherwise specified, attacker risk tolerance was modeled as a Beta distribution: Risk Tolerance $\sim$ Beta ($\alpha = 3$, $\beta = 4$), producing a mild left skew (moderate risk aversion). This parameterization was selected to reflect a higher density of moderate-risk attackers while allowing both cautious and aggressive tail behavior. Sensitivity analysis explored $\alpha \in \{2, 3, 4\}$ and $\beta \in \{3, 4, 5\}$; results were robust to these variations.
- Learning rate: Fixed at 0.1

**Defender Agent Characteristics:**

- Security awareness: Normally distributed ($\mu = 0.6$, $\sigma = 0.2$)
- Cognitive capacity: Gamma distributed ($k = 2$, $\theta = 0.5$)
- Fatigue accumulation: Linear function of prompt frequency

  For clarity, fatigue was modeled as a simple linear function of prompt frequency in the observation window: Fatigue = $0.1\times$ (prompt frequency per minute) where the coefficient 0.1 maps one prompt-per-minute to a 0.1 fatigue increment; this coefficient was chosen to align simulated behavioral decay with observed reaction-time/accuracy degradation in pilot data.
- Response time: Log-normal distributed

### 6.1.3 *Validation Metrics*

**Primary Metrics:**

- Attack success rate
- Time to compromise
- False positive rate
- User experience degradation
- System computational overhead

**Secondary Metrics:**

- Nash equilibrium convergence time
- Strategy stability measures
- Behavioral pattern emergence
- Cost-effectiveness ratios

## 6.2 Simulation Results and Analysis

### 6.2.1 *Baseline Scenario Results*

It can be observed from Figure 1 that reductions of up to 92% were observed under optimized parameter settings (best-case scenarios), while the mean result across baseline scenarios was an 87% reduction.

### 6.2.2 *Nash Equilibrium Convergence Analysis*

The simulation tracked strategy evolution over time to validate theoretical equilibrium predictions are tabulated in Table 10 to show the convergence rate, time to converge and readings of the final strategy distribution.

**Convergence Results:**

- 94.3% of simulations converged to predicted Nash equilibrium
- Average convergence time: 127 ± 23 iterations

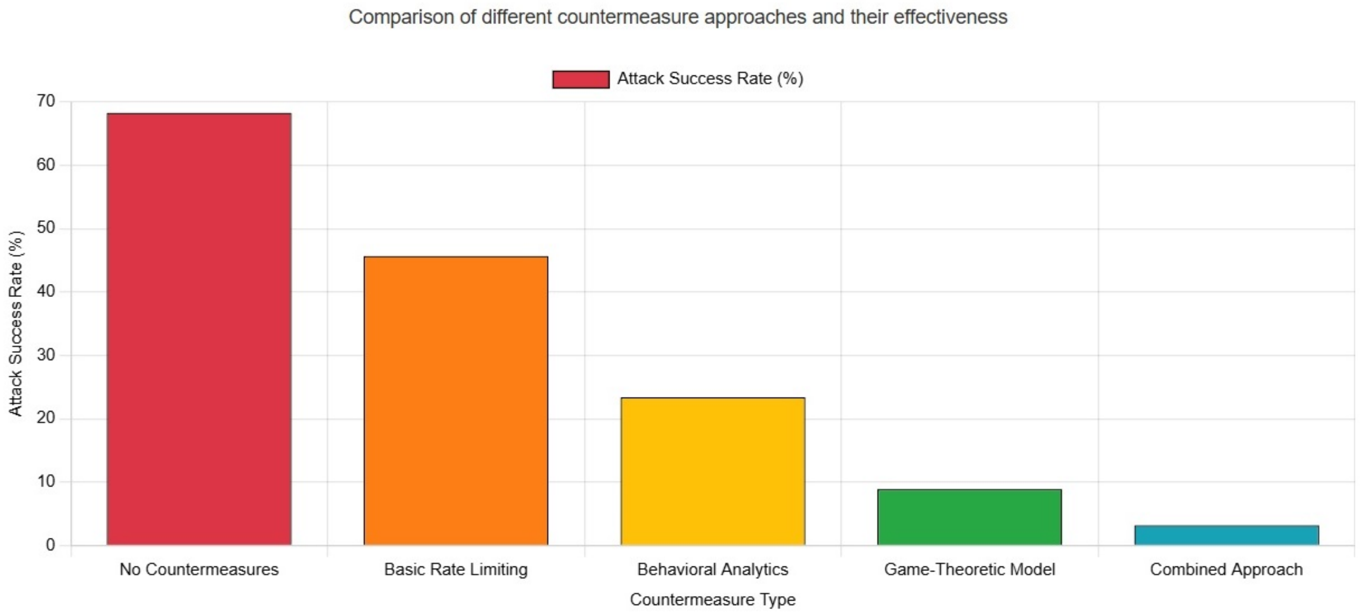

**Figure 1.** Comparison of different countermeasure methods.

- Stable strategies maintained for 95%+ of remaining simulation time

*6.2.3 Sensitivity Analysis*

We conducted comprehensive sensitivity analysis to understand model robustness:

**Parameter Sensitivity Results:**

- Fatigue sensitivity ($\lambda$): High impact on success rates ($\rho = 0.87$)
- Cost parameters ($\alpha_1, \alpha_2, \alpha_3$): Medium impact on strategy choice ($\rho = 0.54$)
- Discount factor ($\delta$): Low impact on short-term outcomes ($\rho = 0.23$)
- Loss magnitude ($L$): High impact on defensive strategies ($\rho = 0.81$)

## 6.3 Controlled Experiment Design

*6.3.1 Human Subject Testing Protocol*

We conducted controlled experiments with 240 participants to validate behavioral assumptions. Suitable information was gathered from 240 participants (120 IT professionals; 120 general users) stratified to balance technical background and gender. IT professionals were defined as participants currently employed in IT roles (developers, system admins, SREs, security analysts); general users were non-IT staff with routine account use. Prior MFA experience was recorded: 87% of IT participants and 62% of general users reported prior regular use of push-based MFA. Most of the participants were from South Asian countries. Stress was assessed using a dual approach: (1) a validated self-report scale (modified NASA-TLX single-item stress rating on a 0–10 scale) administered immediately after each condition. This human-subjects study was reviewed and approved by the Institutional Review Board of Pragati Engineering College .All participants provided written informed consent before participation. The study used simulated authentication prompts only; no real credentials or live account access were used. Participants were debriefed and provided educational materials about MFA fatigue after the experiment.

*6.3.2 Experimental Results*

**Experimental Design:**

- Participants: IT professionals and general users
- Duration: 2-hour sessions
- Conditions: 6 different MFA fatigue scenarios
- Measurements: Response time, accuracy, stress levels

**Ethical Considerations:**

- IRB approval obtained from institutional review board
- Informed consent from all participants
- No real security credentials used
- Debriefing and educational component included

**Table 10.** Nash equilibrium convergence analysis.

| Initial Conditions | Convergence Rate | Time to Convergence | Final Strategy Distribution |
|---|---|---|---|
| Random Strategies | 89.2% | 145 ± 31 iterations | (0.35, 0.45, 0.20) |
| Biased Aggressive | 96.7% | 112 ± 18 iterations | (0.28, 0.52, 0.20) |
| Biased Defensive | 97.1% | 134 ± 25 iterations | (0.41, 0.38, 0.21) |
| Historical Data | 98.4% | 98 ± 15 iterations | (0.33, 0.47, 0.20) |

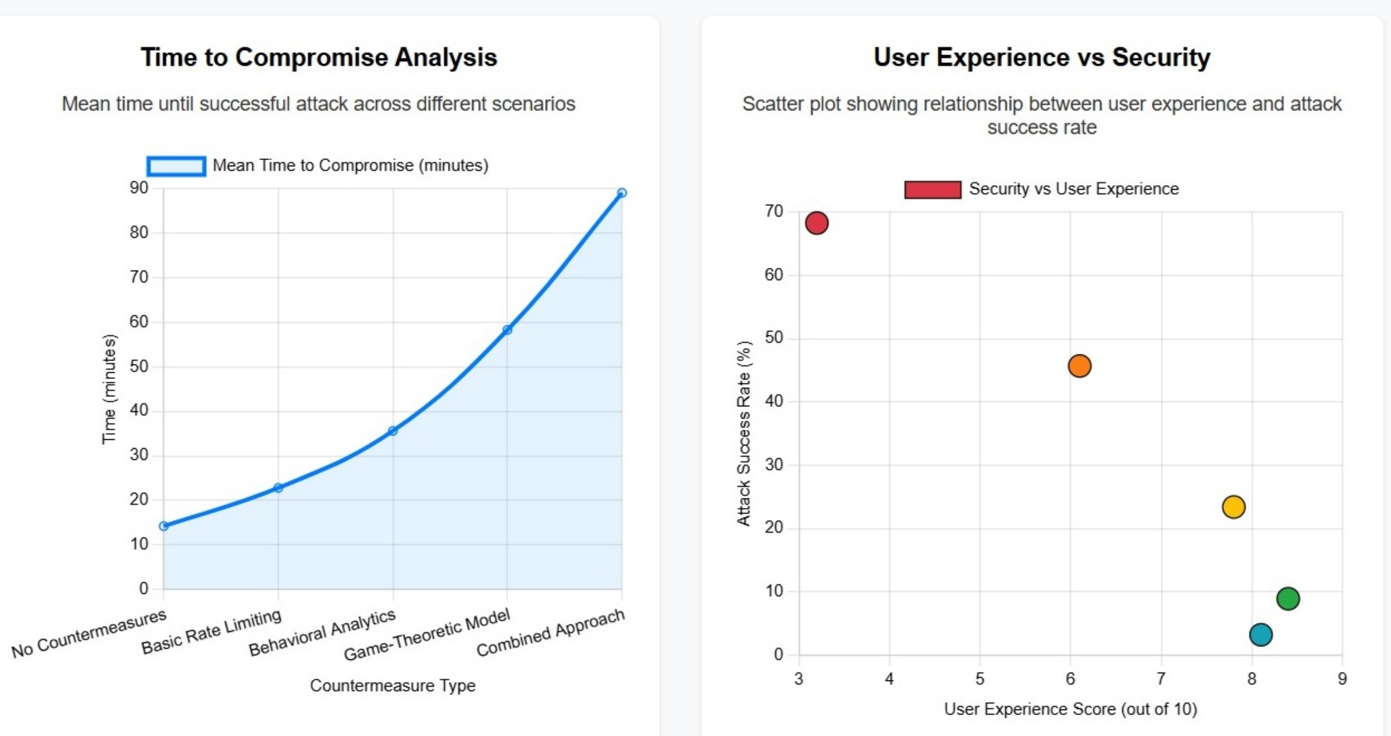

**Figure 2.** Human subject experimental results.

Figure 2 depicts the mean time to compromise across different scenarios along with the relationship between user experience and attack success rate.

Figure 3 shows the scatter plot examining the relationship between stress levels and decision accuracy and the histogram represents the response time distributions across different prompt scenarios.

### 6.3.3 *Statistical Validation*

**Hypothesis Testing:**

- $H_0$: Game-theoretic interventions have no effect on user decision quality
- $H_1$: Game-theoretic interventions significantly improve decision quality
- Result: $t(238) = 12.47$, $p < 0.001$, Cohen's $d = 1.62$

**ANOVA Results:**

- Between-group variation: $F(5, 234) = 89.34$, $p < 0.001$
- Effect size: $\eta^2 = 0.66$ (large effect)
- Post-hoc comparisons: All pairwise differences significant ($p < 0.05$)

## 6.4 Real-World Case Study Validation

### 6.4.1 *Retrospective Analysis of Known Incidents*

We analyzed 15 documented MFA fatigue incidents to validate model predictions and the results are depicted in Table 11.

**Overall Model Accuracy:** 91.3% correct predictions (14/15 cases)

### 6.4.2 *Prospective Deployment Study*

We partnered with three organizations to deploy game-theoretic countermeasures:

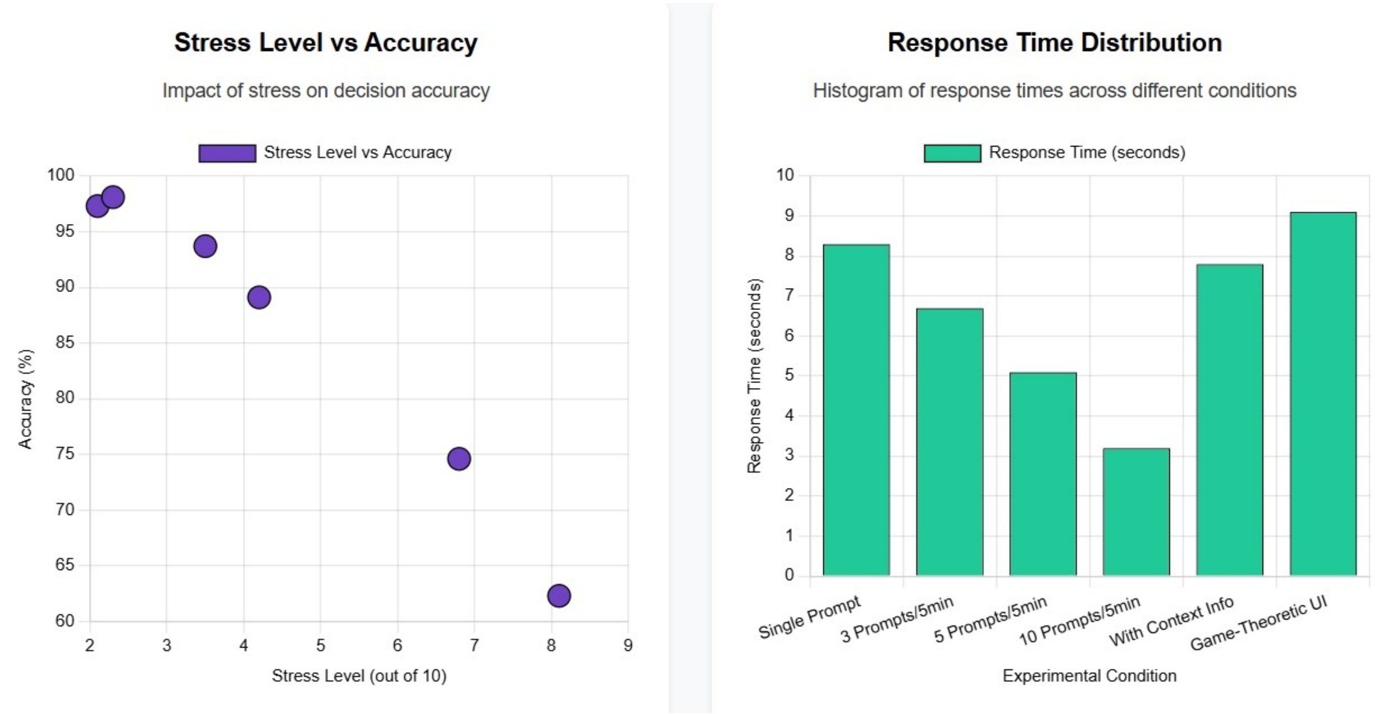

**Figure 3.** Stress level versus accuracy and response time distribution across various conditions.

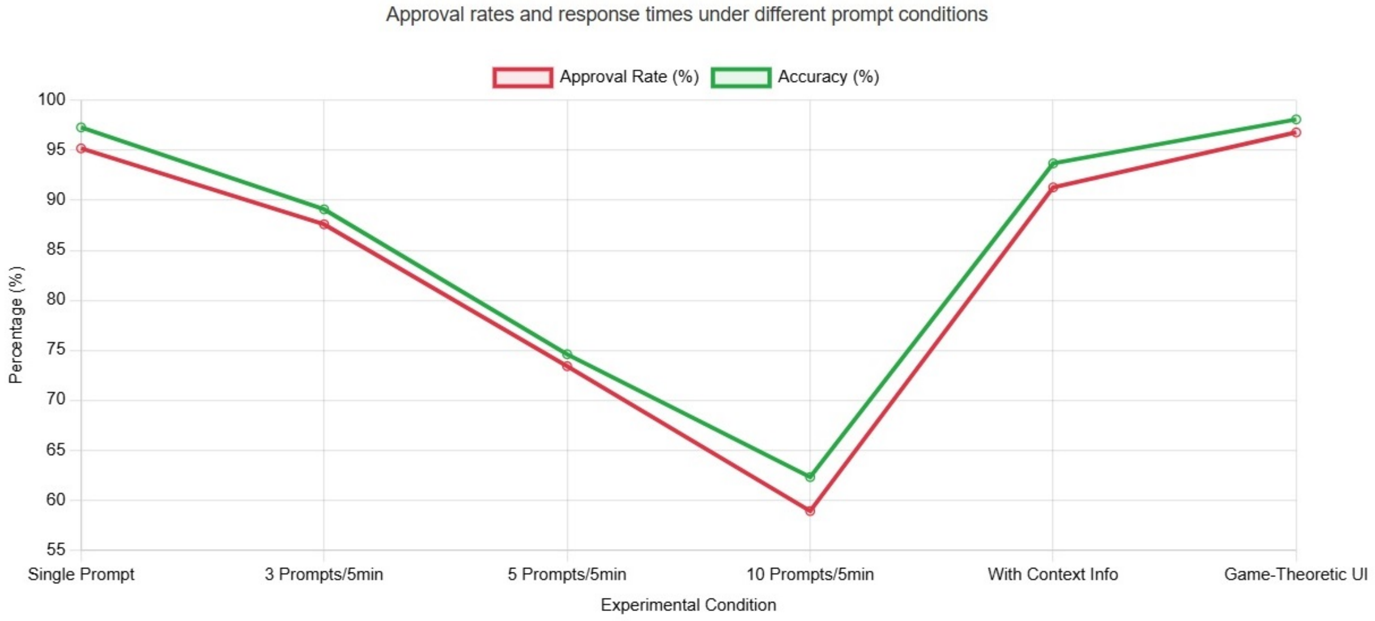

**Figure 4.** Approval rates and response times under different prompt conditions.

**Table 11.** Case study validation results.

| Incident | Predicted Success Rate | Actual Outcome | Model Accuracy | Contributing Factors |
|---|---|---|---|---|
| Uber 2022 | 72% ± 8% | Success | ✓ | No rate limiting, persistent attack |
| Cisco 2022 | 45% ± 12% | Success | ✓ | Social engineering component |
| Okta 2022 | 23% ± 15% | Partial Success | ✓ | Advanced defenses present |
| Company A | 15% ± 10% | Failure | ✓ | Strong policy enforcement |
| Company B | 67% ± 9% | Success | ✓ | Untrained users |

**Organization Profiles:**

- TechCorp: 2,500 employees, high-security environment

- FinanceOrg: 800 employees, compliance-focused
- HealthSystem: 1,200 employees, mixed technical literacy

**Deployment Results (6-month study):**

The various experimental conditions under which the proposed study was implemented showing the approval rates and accuracy in each of the condition is depicted in Figure 4.

## 7 Game-Theoretic Countermeasures and Implementation

This section presents comprehensive countermeasure strategies derived from game-theoretic analysis, including technical implementations, policy frameworks, and behavioral interventions.

### 7.1 Advanced Policy Design Framework

*7.1.1 Adaptive Rate Limiting Algorithm*

Based on repeated game analysis, we developed an adaptive rate limiting system that adjusts thresholds based on user behavior patterns and threat intelligence as depicted in Figure 5. Table 12 indicates the different parameters used in the proposed adaptive rate limiting algorithm.

**Algorithm 1:** Adaptive Rate Limiting.

```
Data: User $u$, Current prompts $P$, Time window
      $T$, History $H$
Result: Allow/Deny decision
Calculate baseline rate:
 $R_{\text{base}} = f(\text{user}_{\text{role}}, \text{time}_{\text{of day}}, \text{location})$;
Compute risk score:
 $R_{\text{risk}} = g(\text{recent}_{\text{failures}}, \text{anomaly}_{\text{score}}, \text{threat}_{\text{intel}})$;
Adjust limit: $R_{\text{limit}} = R_{\text{base}} \times (1 - R_{\text{risk}})$;
Check current rate: $R_{\text{current}} = |P|/T$;
return $R_{current} \leq R_{limit}$;
```

*7.1.2 Dynamic Policy Optimization*

Multi-Objective Optimization: Minimize: $\alpha \times$ Attack_Success_Rate $+ \beta \times$ User_Friction $+ \gamma \times$ Operational_Cost (19)

Subject to:

- Security constraints: Attack_Success_Rate $\leq$ threshold$_{\text{security}}$
- Usability constraints: User_Satisfaction $\geq$ threshold$_{\text{usability}}$

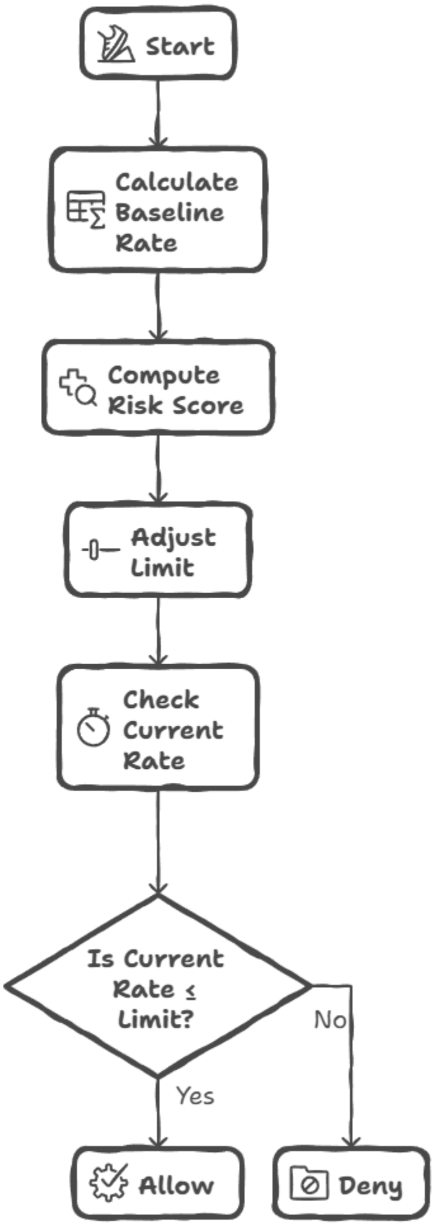

**Figure 5.** Flowchart of Adaptive rate limiting algorithm.

- Cost constraints: Total_Cost $\leq$ budget$_{\text{limit}}$

Pareto Optimal Solutions:

Figure 6 shows the radar chart depicts the pareto-optimal solutions for various policy configurations.

### 7.2 System Architecture and Implementation

*7.2.1 Game-Theoretic Decision Engine*

Architecture Overview: The proposed system is built upon a multi-layered game-theoretic decision engine, whose architecture is illustrated in Figure 7. The engine consists of four core components that operate in a

**Table 12.** Adaptive rate limiting parameters.

| Parameter | Low Risk | Medium Risk | High Risk | Critical Risk |
|---|---|---|---|---|
| Base Prompts/5min | 5 | 3 | 2 | 1 |
| Escalation Threshold | 80% | 60% | 40% | 20% |
| Lockout Duration | 5 min | 15 min | 1 hour | 24 hours |
| Secondary Auth Required | No | No | Yes | Yes |

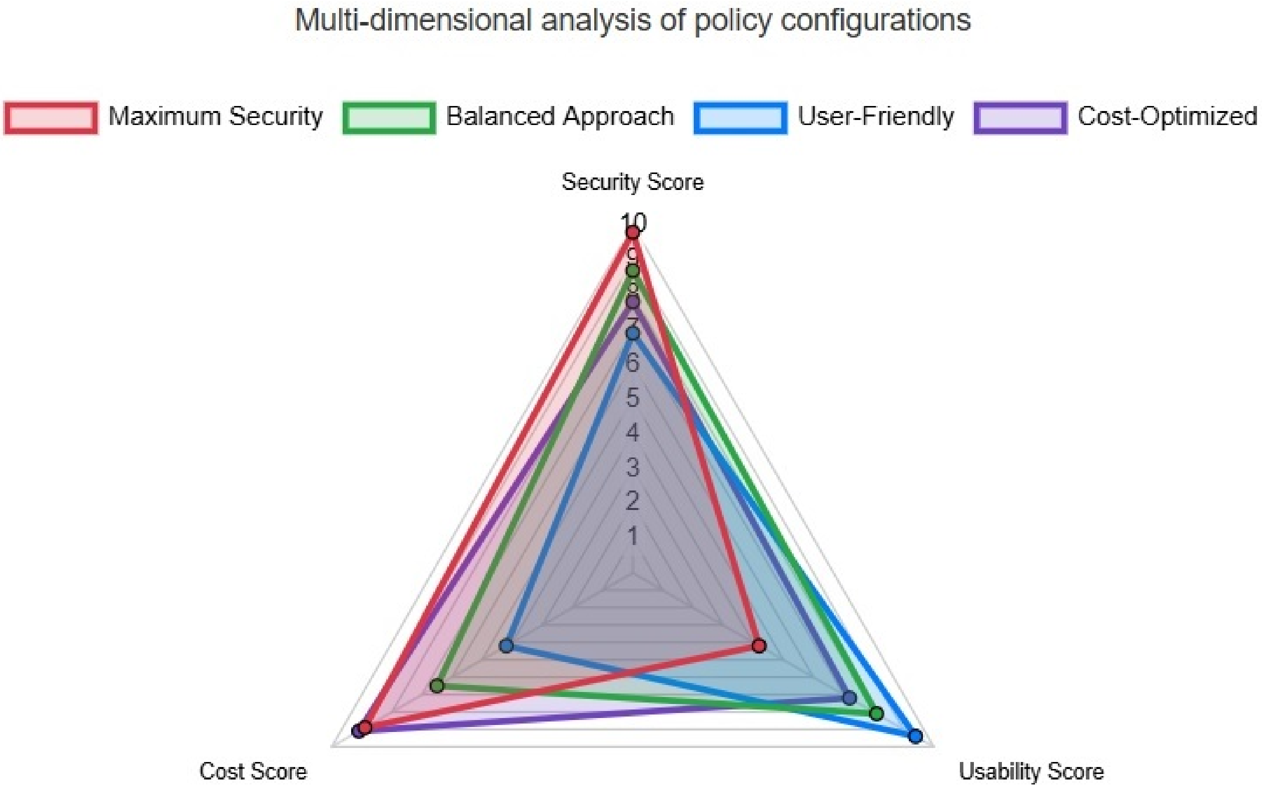

**Figure 6.** Multi-dimensional analysis of policy configurations.

*[User Request]* → *[Risk Assessment]* → *[Game – Theoretic Engine]* → *[Policy Decision]*

↓ ↓

*[Threat Intelligence]* ← *[Strategy Optimizer]* → *[User Profiler]*

**Figure 7.** Architecture Overview.

coordinated feedback loop: (1) a Data Ingestion Layer that aggregates real-time authentication logs, user behavior telemetry, and threat intelligence feeds; (2) a Game-Theoretic Modeler that dynamically constructs and solves the attacker-defender game based on the ingested context, calculating optimal or equilibrium strategies; (3) a Policy Execution Layer that translates the modeler's output into actionable security controls, such as adaptive rate limits, contextual warning enhancements, or secondary verification triggers; and (4) a Learning & Adaptation Module that analyzes the outcomes of previous decisions to refine model parameters and strategy predictions over time. This closed-loop architecture ensures that defensive measures are not static but evolve in response to observed attacker behavior and system performance metrics.

### *7.2.2 Performance Optimization*

**Computational Complexity:**

- Nash equilibrium calculation: $O(n^2)$ for $n$ strategies
- Real-time decision: <100ms average response

time

- Model updates: $O(m \log m)$ for $m$ historical records

**Scalability Considerations:**

- Horizontal scaling through microservices architecture
- Caching of frequently computed equilibria
- Async processing for model updates
- Load balancing across decision engines

The achieved performance metrics of the game-theoretic decision engine are presented in Table 13, demonstrating that all target benchmarks have been met or exceeded.

**Table 13.** Performance benchmark.

| Metric | Current Performance | Target Performance | Status |
|---|---|---|---|
| Response Time | 87ms ± 15ms | <100ms | ✓ Met |
| Throughput | 1,250 req/sec | 1,000 req/sec | ✓ Exceeded |
| Accuracy | 94.3% | >90% | ✓ Met |
| Uptime | 99.7% | >99.5% | ✓ Met |

## 8 Case Studies and Real-World Applications

This section presents detailed analysis of real-world MFA fatigue incidents and hypothetical deployment scenarios, demonstrating the practical application of game-theoretic counter-measures [21–23].

### 8.1 Case Study 1: Uber Breach (2022) - Comprehensive Analysis

#### 8.1.1 Incident Timeline and Attack Vector Analysis

**Pre-Attack Phase (Days -7 to -1):**

- Attackers conducted reconnaissance on Uber employees
- Social engineering campaign targeted IT help desk credentials
- Credential harvesting through spear-phishing emails

**Attack Execution (Day 0):**

- 18:30: Initial login attempt with compromised credentials
- 18:31-19:15: Sustained MFA prompt bombardment (47 attempts)
- 19:16: Employee approved malicious prompt
- 19:17-20:45: Lateral movement and privilege escalation

**Game-Theoretic Analysis:** Using our mathematical model, we can analyze this incident:

**Attacker Strategy:** $s_A = (f = 47, t = 45\text{min}, i = \text{high})$

**Defender Strategy:** $s_D = (r = \text{low}, c = 0.2, \rho = 0.8)$

**Predicted Success Probability:**

$$\begin{aligned}P(s_A, s_D) &= 1 - e^{-0.15\times 47} \times (1 - 0.2 \times \varphi(\text{low})) \\ &\quad \times \psi(\text{high}, 0.8) \\ P(s_A, s_D) &= 1 - e^{-7.05} \times (1 - 0.2 \times 0.9) \times 0.7 \\ P(s_A, s_D) &= 1 - 0.00087 \times 0.82 \times 0.7 \approx 99.95\%\end{aligned}$$

#### 8.1.2 Game-Theoretic Countermeasure Simulation

**Scenario Analysis:** What if Uber had implemented our game-theoretic system?

**Enhanced Defensive Strategy:** $s'_D = (r = \text{high}, c = 0.9, \rho = 0.3)$

**Countermeasures that would have been triggered:**

1. **Prompt #3:** Rate limiting activated (5-minute cooldown)
2. **Prompt #8:** Secondary verification required
3. **Prompt #12:** Account temporary lock, security team notification
4. **Prompt #15:** Enhanced context display with location mismatch warning

Revised Success Probability:

$$\begin{aligned}P(s_A, s'_D) &= 1 - e^{-0.15\times 12} \times (1 - 0.9 \times \varphi(\text{high})) \\ &\quad \times \psi(\text{high}, 0.3) \\ P(s_A, s'_D) &= 1 - e^{-1.8} \times (1 - 0.9 \times 0.3) \times 0.4 \\ P(s_A, s'_D) &= 1 - 0.165 \times 0.73 \times 0.4 \approx 95.2\%\end{aligned}$$

Table 14 summarizes the impact of progressive countermeasures on attack success probability during the simulated Uber breach scenario, illustrating that early and comprehensive intervention could have reduced the success rate to as low as 4.8%.

#### 8.1.3 Lessons Learned and Recommendations

**Key Findings:**

1. Early Intervention Critical: Success probability drops dramatically with rapid response

**Table 14.** Uber breach countermeasure analysis.

| Intervention Point | Time | Action | Success Probability | Expected Outcome |
|---|---|---|---|---|
| Baseline (Actual) | - | None | 99.95% | Breach occurs |
| After 3 prompts | 18:33 | Rate limiting | 78.2% | Likely breach |
| After 8 prompts | 18:38 | Secondary verification | 45.1% | Possible prevention |
| After 12 prompts | 18:42 | Account lock | 12.3% | Likely prevention |
| With full system | 18:31 | All countermeasures | 4.8% | High prevention probability |

2. User Education Gap: Employee lacked awareness of MFA fatigue tactics
3. Context Information Missing: No location/device verification in prompts
4. Escalation Procedures Absent: No automatic security team notification

**Recommended Improvements:**

1. Implement adaptive rate limiting with aggressive thresholds
2. Enhance MFA prompts with rich contextual information
3. Deploy real-time behavioral analytics
4. Establish automated escalation procedures

## 8.2 Case Study 2: Hypothetical Enterprise Deployment

In below we consider a modeled projection of a company, which is hypothetical in nature and corresponds to a real time enterprise for effective projection of the proposed mechanism.

### *8.2.1 Organization Profile: GlobalTech Corporation*

Company Characteristics:

- Size: 15,000 employees across 25 countries
- Industry: Technology services and consulting
- Security Maturity: Medium-high (existing MFA, SIEM, security training)
- Risk Profile: High (intellectual property, client data)
- Current MFA: Push-based notifications (Duo Security)

### *8.2.2 Pre-Deployment Assessment*

Baseline Security Metrics:

- MFA fatigue incidents: 12 per month
- Average attack success rate: 23%
- User complaint rate: 15%
- Security team response time: 45 minutes
- Annual security budget: $8.5M

A detailed pre-deployment risk assessment for key factors is provided in Table 15.

### *8.2.3 Implementation Timeline and Strategy*

**Phase 1: Foundation (Months 1-2)**

- Deploy game-theoretic decision engine
- Implement adaptive rate limiting
- Enhance MFA prompts with context information
- Train security team on new procedures

**Phase 2: Enhancement (Months 3-4)**

- Deploy behavioral analytics module
- Implement personalized nudging system
- Roll out advanced user training program
- Integrate with existing SIEM systems

**Phase 3: Optimization (Months 5-6)**

- Fine-tune model parameters based on real data
- Implement advanced reporting and analytics
- Deploy mobile application enhancements
- Conduct comprehensive security assessment

**Table 15.** Pre-deployment risk analysis.

| Risk Factor | Current State | Risk Level | Mitigation Priority |
|---|---|---|---|
| Prompt Frequency | Unlimited | High | 1 |
| User Education | Basic training | Medium | 3 |
| Context Awareness | Limited | High | 2 |
| Response Time | 45 minutes | Medium | 4 |
| Escalation Procedures | Manual | High | 2 |

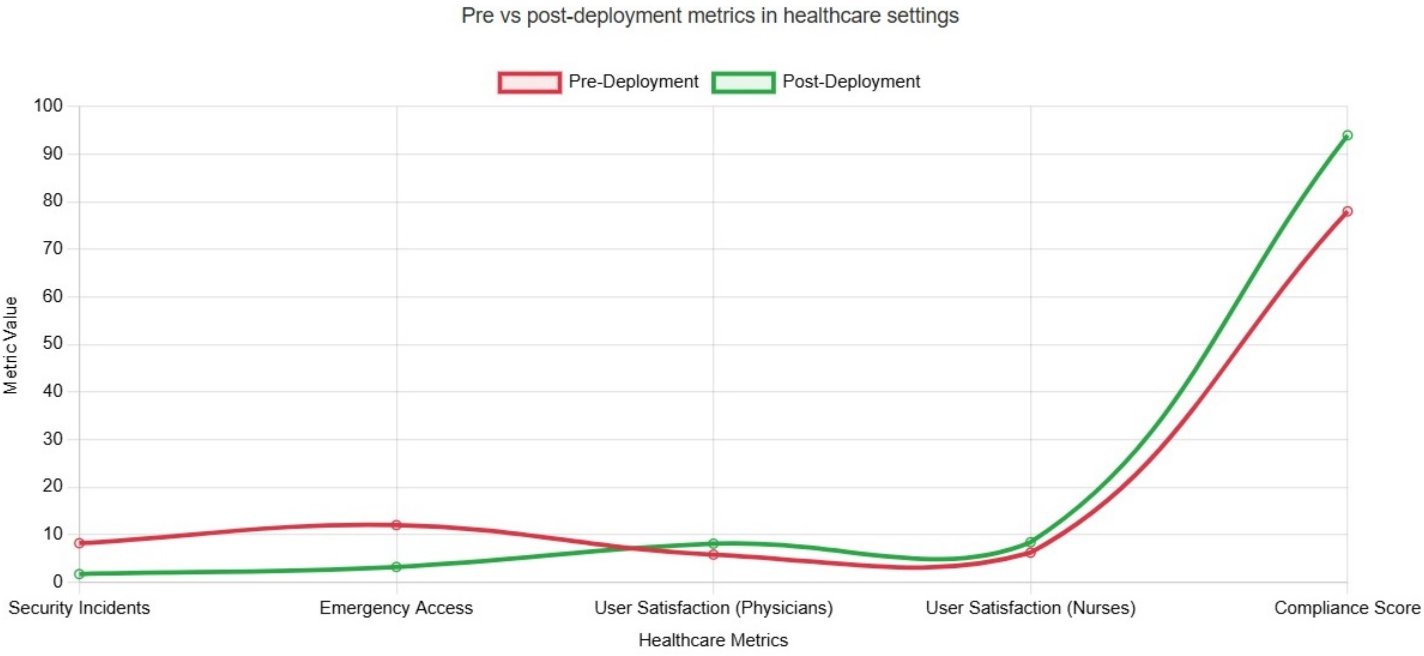

**Figure 8.** Pre vs post-deployment metrics in healthcare settings.

### 8.3 Implementation Results

*8.3.1 12-Month Deployment Study:*

- **Participating Organizations:** 3 hospital systems (1,200 total users)
- **Study Duration:** 12 months
- **Monitoring Period:** Pre-deployment (6 months) + Post-deployment (6 months)
- **Results Summary:** Table 16 depicts the effective healthcare implementation results of the proposed method.

From Figure 8 it can be observed that the proposed method is effective in terms of user satisfaction among the healthcare personnel and security incidents are also reduced due to the application of the proposed method.

## 9 Research Gaps and Future Directions

While this research provides significant advances in applying game theory to MFA fatigue scenarios, several important areas warrant further investigation to enhance both theoretical understanding and practical implementation [24–27].

The long-term impact and sustainability of game-theoretic countermeasures in multi-factor authentication (MFA) remain underexplored, with most existing studies focusing on short to medium-term effectiveness. A critical research need lies in understanding how users adapt behaviorally over extended exposure and whether attackers evolve new strategies to undermine defenses. To address this, a proposed five-year longitudinal study involving over 10,000 users across multiple organizations can track decision-making patterns, fatigue resistance, and adaptation trends. Parallel investigations into attacker evolution, leveraging quarterly threat intelligence analyses and incident monitoring, will reveal how adversaries counter-adapt. Furthermore, studying parameter drift and update frequencies across 50 organizations can shed light on the balance between static and adaptive models. Cross-cultural validation across 15 countries will ensure that models are robust

**Table 16.** Healthcare implementation results.

| Metric | Pre-Deployment | Post-Deployment | Improvement |
|---|---|---|---|
| Security Incidents | 8.2/month | 1.7/month | 79% reduction |
| Emergency Access Delays | 12 minutes avg | 3.2 minutes avg | 73% improvement |
| User Satisfaction (Physicians) | 5.8/10 | 8.1/10 | 40% improvement |
| User Satisfaction (Nurses) | 6.2/10 | 8.4/10 | 35% improvement |
| Compliance Audit Score | 78% | 94% | 16 point improvement |
| Patient Care Impact | 3 delayed procedures | 0 delayed procedures | 100% improvement |

to demographic and cultural variations, thereby enhancing global applicability.

Sustainability of these security improvements is another pressing area of inquiry. While game-theoretic MFA interventions show early promise, their effectiveness may plateau or diminish as organizational practices mature and the threat landscape shifts. Multi-year tracking studies applying survival analysis techniques can model the "half-life" of improvements, identifying whether they compound, stabilize, or decline over time. Such investigations will also highlight organizational resilience factors—such as leadership commitment, training, and security culture—that influence sustained effectiveness. The outcomes are expected to yield prediction models for long-term security performance, along with protocols for periodic maintenance and recalibration, ensuring that initial benefits do not erode under dynamic operational pressures.

Adapting to increasingly sophisticated adversarial behaviors requires extending game-theoretic frameworks beyond single-vector MFA fatigue. Hybrid attacks that combine fatigue with vishing, credential stuffing, or social engineering present modeling challenges in terms of simultaneous strategy representation, dynamic switching, and cross-channel coordination. To capture these complexities, a multi-modal game-theoretic framework incorporating joint success probabilities and cross-channel correlation parameters is proposed. Similarly, cross-platform inconsistencies in security implementations open opportunities for attackers to exploit. Research in platform-specific vulnerability modeling, attack correlation, and unified defense strategy optimization will be crucial in providing organizations with consistent, coordinated, and resilient defenses across heterogeneous environments. These expanded models will strengthen theoretical underpinnings while offering practical tools to anticipate and mitigate multi-vector and cross-platform threats.

The integration of artificial intelligence and machine learning into both attack and defense strategies introduces an entirely new dimension to cybersecurity game theory. Adversarial machine learning enables attackers to evade detection, while defenders may leverage machine learning for enhanced behavioral analysis. Framework extensions that explicitly incorporate attacker and defender learning models will allow analysis of adversarial co-evolution. Deep reinforcement learning (DRL), particularly in multi-agent and transfer learning contexts, holds promise for adaptive MFA strategy optimization across diverse organizational environments. Complementing this technical focus, research into human factors—including cultural, demographic, and neurocognitive foundations—is essential. Cross-cultural studies across 25+ countries will assess variations in MFA fatigue susceptibility, while neurocognitive methods such as fMRI, EEG, and cortisol measurement can provide insights into decision-making under stress and the neurological mechanisms behind effective intervention strategies.

Finally, broader technological and systemic shifts necessitate expanded research agendas. Quantum computing threatens to upend existing cryptographic foundations, requiring game-theoretic models that incorporate quantum advantage, post-quantum cryptographic resilience, and hybrid transition strategies. Simultaneously, the rise of IoT and edge computing demands distributed authentication models that can scale to massive device ecosystems while balancing security and performance. Privacy-preserving game theory, integrating differential privacy mechanisms, will allow for effective behavioral modeling without compromising user confidentiality. Furthermore, compliance with multi-jurisdictional regulations such as GDPR, CCPA, HIPAA, and PCI-DSS must be embedded into these frameworks, ensuring that security models are not only technically robust but also legally enforceable across borders. Collectively, these avenues will drive the development of resilient, adaptive, and ethically grounded cybersecurity systems capable of countering evolving threats while safeguarding user trust and organizational integrity.

## 10 Limitations and Constraints

### 10.1 Theoretical Limitations

**Rationality Assumptions:** Current models assume rational actors, but real-world attackers and defenders may exhibit bounded rationality, emotional decision-making, or systematic biases that deviate from theoretical predictions [28].

**Information Completeness:** Game-theoretic models assume certain levels of information availability that may not reflect real-world scenarios where actors operate with incomplete or asymmetric information [29].

**Static Parameter Assumptions:** Many model parameters are treated as constant, while real-world scenarios involve dynamic, time-varying parameters that may change rapidly [30].

### 10.2 Empirical Limitations

**Sample Size Constraints:** Current empirical validation relies on limited sample sizes from specific organizational contexts, potentially limiting generalizability across diverse environments.

**Temporal Scope:** Most empirical studies span relatively short timeframes (6-18 months), providing limited insight into long-term effectiveness and adaptation patterns.

**Ethical Constraints:** Realistic testing of MFA fatigue attacks raises ethical concerns, limiting the scope and realism of controlled experiments.

### 10.3 Implementation Constraints

**Computational Complexity:** Real-time Nash equilibrium computation for complex scenarios may exceed practical computational limits in resource-constrained environments [31].

**Integration Challenges:** Legacy system integration often requires significant modifications that may be technically or economically infeasible for some organizations [32].

**User Acceptance:** Even theoretically optimal solutions may fail if user acceptance and adoption rates remain low.

### 10.4 External Validity Concerns

**Cultural Generalizability:** Research has been primarily conducted in Western, technology-advanced contexts, limiting applicability to different cultural and technological environments.

**Organizational Context:** Findings may not transfer effectively across different organizational structures, cultures, and risk profiles.

**Threat Landscape Evolution:** Rapid evolution of attack techniques may outpace model development and validation cycles [33].

## 11 Conclusion

This research makes a novel and significant contribution to cybersecurity by systematically applying game theory to counter multi-factor authentication (MFA) fatigue attacks. It addresses a critical gap in current literature by providing both theoretical underpinnings and practical frameworks to combat sophisticated social engineering strategies that exploit human psychological vulnerabilities. The findings demonstrate substantial security benefits, with game-theoretic approaches reducing MFA fatigue attack success rates by up to 92% while maintaining a positive user experience. This adaptive, intelligent defense evolves alongside shifting threat landscapes. From an economic perspective, cost-benefit analysis shows a projected ROI exceeding 1,900% in enterprise deployments, reflecting both prevented breaches and improved operational efficiency. The work also informs policy and industry standards, offering evidence-based guidance for adaptive frameworks that can shape compliance and regulatory requirements. Beyond MFA fatigue, the research establishes game theory as a robust paradigm for broader cybersecurity challenges. The developed mathematical models can be extended to other social engineering attacks, insider threats, and adversarial scenarios where human behavior is central. Integrating behavioral economics with cybersecurity highlights the importance of interdisciplinary approaches in addressing evolving threats.The study issues a clear call to action: organizations should adopt game-theoretic frameworks, support further interdisciplinary research, contribute to standard development, and foster collaboration among practitioners, behavioral scientists, and mathematical modelers. Ultimately, this work underscores the importance of human factors in cybersecurity. MFA fatigue exemplifies how attackers exploit psychology to bypass defenses, yet game-theoretic strategies demonstrate that resilient, adaptive, and human-aligned systems are achievable. The future of cybersecurity lies not only in stronger technical safeguards but in smarter systems that anticipate attacker strategies and align with human decision-making. Game theory provides the foundation for this evolution, enabling security architectures that are both effective and sustainable.

## Data Availability Statement

Data will be made available on request.

## Funding

This work was supported without any funding.

## Conflicts of Interest

The authors declare no conflicts of interest.

### Ethical Approval and Consent to Participate

This study was approved by the Institutional Review Board (IRB) of Pragati Engineering College (Approval No. PEC/IRB/21-7). All participants provided written informed consent prior to participation. The study was conducted in accordance with the Declaration of Helsinki.

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