Study on Psychological Attack Surface Modeling Through Artificial Intelligence

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Abstract- *Artificial Intelligence (AI) has emerged as a crucial element in contemporary cyber security frameworks, facilitating automated threat detection, predictive analytics, and adaptive defense strategies. Nonetheless, the deployment of AI-driven systems introduces novel categories of vulnerabilities that surpass conventional technical attack surfaces. A significant emerging concept is the psychological attack surface, which encompasses cognitive, emotional, and behavioral vulnerabilities that can be exploited by attackers via digital communication platforms and AI-enabled systems. Traditional cyber security paradigms primarily emphasize software vulnerabilities, network breaches, and system misconfigurations, frequently overlooking the psychological dimensions that affect human decision-making in cyber contexts. Recent research indicates that a considerable fraction of cyber attacks depend on social engineering methods that manipulate trust and emotional responses, rather than relying on technical deficiencies [1], [10].*

The widespread implementation of AI technologies, such as conversational agents, recommendation systems, and emotion recognition frameworks, enables adversaries to take advantage of both human users and AI systems by utilizing psychological triggers such as urgency, fear, authority, and social trust [2], [3]. Moreover, adversarial attacks aimed at machine learning models have broadened the attack surface related to intelligent systems [4], [5]. These advancements underscore the necessity for cyber security frameworks that incorporate behavioral intelligence and psychological assessment.

This paper introduces an innovative framework referred to as the Psychological Attack Surface Model (PASM), which merges artificial intelligence methodologies with principles of cyber psychology to identify and mitigate psychologically driven cyber threats. The proposed model encompasses layered components, including psychological data collection, behavioral signal analysis, attack surface mapping, and AI-driven defense strategies. Machine learning algorithms and natural language processing methods are employed to recognize manipulation patterns within communication settings. This framework facilitates dynamic modeling of psychological vulnerabilities in human–AI interaction ecosystems and supports proactive identification of adversarial behaviors. By amalgamating insights from artificial intelligence security and cyber psychology studies [6], [9], this research contributes to the establishment of human-centered cyber security architectures capable of addressing emerging socio-technical risks.

Keywords: Psychological Attack Surface, Artificial Intelligence Security, Cyber psychology, Social Engineering Detection, Human-Centric Security, Adversarial AI

I. INTRODUCTION

The digital transformation characterizing contemporary society has led to unparalleled connectivity among individuals, organizations, and technological systems. As digital infrastructures continue to evolve, cyber security has become an essential priority for governments, businesses, and individual users. Conventional cyber security approaches primarily focus on safeguarding systems against technical vulnerabilities, including software flaws, network misconfigurations, and malware threats. While these protective measures are critical, recent findings suggest that a substantial number of successful cyber attacks exploit human behavior rather than technical deficiencies.

Social engineering attacks constitute a prominent category of cyber threats that hinge on psychological manipulation, as opposed to direct technical exploitation. Such attacks mislead individuals into disclosing confidential information or executing actions that jeopardize system security. Attackers often exploit psychological triggers such as fear, urgency, curiosity, and authority to sway human decision-making [10]. Instances of phishing emails, fraudulent messages, and impersonation attacks exemplify how adversaries harness psychological strategies to circumvent advanced security mechanisms.

The advent of artificial intelligence technologies has further altered the landscape of cybersecurity. AI systems are extensively utilized in applications including automated customer support, decision-support tools, and recommendation engines. While these technologies bolster efficiency and automation, they simultaneously give rise to new vulnerabilities. Attackers can manipulate AI systems through adversarial inputs or exploit human reliance on automated decision-making processes [4].

As AI technologies become intricately woven into daily communication channels, human-AI interactions themselves become components of the attack surface. Adversaries may take advantage of these interactions by manipulating conversational agents, influencing recommendation algorithms, or deceiving users via AI-generated content. These developments accentuate the necessity for cyber security frameworks that address psychological vulnerabilities in conjunction with technical threats.

This research presents the concept of Psychological Attack Surface Modeling utilizing Artificial Intelligence. The aim of this study is to formulate a framework that fuses behavioral psychology with machine learning techniques to identify and mitigate psychological manipulation in cyber environments. By conceptualizing psychological vulnerabilities as integral to the attack surface, organizations can formulate more robust cyber security strategies.

II. RESEARCH GAP AND NOVELTY

Despite considerable progress in cyber security research, prevailing frameworks typically treat technical security, artificial intelligence security, and human behavior as distinct domains. Traditional attack surface models primarily scrutinize components of system architecture, such as network interfaces, software modules, and hardware devices. Although these models yield valuable insights into technical vulnerabilities, they fail to consider the psychological manipulation tactics employed by attackers.

Investigations into social engineering attacks have underscored the significance of psychological factors in cybersecurity incidents. Nevertheless, these studies often emphasize descriptive analyses rather than devising automated detection mechanisms. Consequently, organizations are heavily reliant on user training initiatives to alleviate social engineering threats, which may prove insufficient in rapidly evolving cyber environments.

Likewise, research focused on AI security has predominantly centered on adversarial machine learning methods such as model poisoning, adversarial examples, and inference attacks [5]. Although these studies identify vulnerabilities within machine learning systems, they infrequently address the psychological dynamics present in human-AI interactions.

Recent investigations have highlighted the necessity of integrating cyber psychology into cyber security frameworks [6]. However, comprehensive models that merge psychological analysis with AI-based attack surface modeling remain scarce. This research seeks to bridge this gap by proposing a unified framework that encapsulates the interplay between human cognition, emotional manipulation, and AI system behavior.

The originality of this study is predicated upon three principal contributions. First, it introduces the notion of a psychological attack surface as an extension of traditional attack surface modeling. Second, it proposes an AI-centric framework for detecting psychological vulnerabilities within digital communication settings. Third, it illustrates how behavioral intelligence can be incorporated into cyber security systems to enhance threat detection capabilities.

III. RELATED WORK

Cyber security scholars have progressively acknowledged the significance of human behavior in cyber attacks. Research on social engineering elucidates how attackers exploit cognitive biases and emotional responses to manipulate victims. Siddiqi et al. examined the psychological mechanisms underpinning phishing attacks and demonstrated that emotional triggers substantially augment the efficacy of deceptive strategies [10].

Research by Sridhar investigated the application of machine learning techniques to analyze behavioral patterns associated with social engineering attacks [1]. This study confirmed that AI-driven systems are capable of identifying persuasion patterns frequently employed in malicious communications.

Simultaneously, investigations into AI security have scrutinized vulnerabilities within machine learning systems. Osazuwa and Musa evaluated the expanding attack surface linked to AI technologies and emphasized the imperative for resilient security frameworks capable of countering adversarial threats [4]. Olutimehin and colleagues further probed adversarial attacks targeting machine learning models and proposed countermeasures to safeguard AI-driven systems [5].

Recent studies have also investigated attacks directed at large language models. Zhang and Aman illustrated how semantic injection attacks can manipulate the reasoning processes of language models via meticulously crafted prompts [9]. Similarly, Cho et al. examined adversarial attacks on emotion recognition systems and proposed defensive strategies to protect multimodal AI models [3].

While these studies provide valuable insights into AI security and cyber psychology, they seldom integrate these viewpoints into a cohesive cyber security framework. This paper aspires to fill this void by proposing a comprehensive model for psychological attack surface analysis.

IV. PSYCHOLOGICAL ATTACK SURFACE

The psychological attack surface encompasses the array of vulnerabilities arising from human cognition, emotional reactions, and behavioral patterns that attackers exploit in digital contexts. In contrast to traditional attack surfaces that emphasize technical interfaces such as network ports, APIs, and software modules, psychological attack surfaces stem from the interactions between human users and digital systems. Contemporary cyber security research increasingly recognizes the pivotal role of human behavior in cyber threats.

The success of cyber attacks, particularly those that employ social engineering and manipulation tactics, relies significantly on psychological factors [1], [10]. As digital communication systems increasingly integrate with artificial intelligence technologies, the psychological vulnerabilities inherent within these systems become critical elements of cyber security risk management. Human decision-making processes are often affected by cognitive biases that simplify complex reasoning. While these cognitive shortcuts can facilitate everyday decision-making, they also create opportunities for attackers to exploit during cyber attacks. For instance, authority bias leads individuals to trust directives that appear to originate from high-ranking organizational leaders or reputable institutions. Likewise, scarcity bias compels individuals to act promptly on urgent requests without confirming their legitimacy. Research into social engineering attacks has revealed that attackers frequently take advantage of these psychological biases to manipulate victims into revealing sensitive information or engaging in actions that undermine security protocols [10]. Investigations into behavioral trends in cyber attacks further indicate that psychological persuasion techniques can significantly enhance the success rates of phishing and impersonation attacks [1].

Emotional manipulation is another pivotal aspect of psychological cyber attacks. Attackers often craft communications intended to elicit emotional responses such as fear, curiosity, or sympathy to influence the actions of their victims. For example, phishing emails frequently assert that an account has been compromised and require immediate action to avert financial losses. Such messages typically incorporate emotionally charged language aimed at inciting a sense of urgency and panic. Research in cyber psychology suggests that emotionally compelling communications are more likely to circumvent rational assessment processes, rendering victims more vulnerable to deception [6]. With the growing reliance on AI-driven communication platforms, attackers can exploit automated systems to generate substantial volumes of psychologically persuasive content, thereby amplifying the threat [2].

Trust relationships within digital environments further widen the psychological attack surface. Users tend to trust communications from known contacts or established organizations, which makes them susceptible to impersonation schemes. Frequently, attackers take advantage of these trust relationships by posing as colleagues, financial institutions, or customer support representatives. Advances in artificial intelligence, including deepfake technology and automated text generation, have facilitated the impersonation of trusted individuals through realistic audio, video, or written communications [4]. Such advancements substantially heighten the potential for psychological manipulation within digital communication channels.

The human dependence on AI systems introduces additional vulnerabilities to the psychological attack surface. As AI-powered recommendation systems and automated decision-support tools gain prevalence, individuals may cultivate an unwarranted trust in automated outputs. This phenomenon, identified as automation bias, may lead users to accept AI-generated recommendations without critically assessing their validity. Attackers can exploit this trust by manipulating AI outputs or inputting misleading information into automated systems. Research on adversarial assaults against machine learning models demonstrates that AI systems can be influenced by precisely crafted inputs that modify system behavior without detection [5]. Furthermore, prompt injection attacks targeting large language models can alter the reasoning processes of AI systems by embedding harmful instructions within user inputs [9].

Comprehending these psychological vulnerabilities is crucial for the formulation of effective cyber security strategies. By conceptualizing psychological manipulation as a facet of the attack surface, security frameworks can more effectively predict and counter emerging threats. The integration of cyber psychology with artificial intelligence security research presents novel opportunities for the development of defensive mechanisms that address both technical and behavioral dimensions of cyber attacks [6].

V. PSYCHOLOGICAL ATTACK SURFACE MODEL (PASM)

The proposed Psychological Attack Surface Model incorporates behavioral analysis alongside artificial intelligence methodologies to detect and mitigate psychological manipulation within digital frameworks. This model is structured to capture the intricate interactions between human cognition, communication behaviors, and AI-driven platforms that collectively establish the psychological attack surface. By merging behavioral intelligence with machine learning algorithms, the PASM framework enables the automated identification of manipulation patterns that are frequently overlooked by conventional technical security measures.

The initial layer of the model concentrates on data acquisition, gathering interaction data from communication platforms, including emails, messaging applications, and conversational AI interfaces. These channels represent primary avenues for social engineering attacks and other manipulation-based cyber threats. Collecting interaction data from these mediums allows for the analysis of communication patterns and the identification of potential indicators of malicious activity. Comparable data acquisition techniques have been employed in prior studies investigating behavioral patterns associated with social engineering attacks [1].

The second layer conducts psychological signal processing utilizing natural language processing and sentiment analysis methodologies. These techniques scrutinize communication content to extract emotional and persuasive signals embedded within messages. Sentiment analysis can identify emotional tones such as urgency, fear, or excitement, while linguistic analysis can reveal persuasive language structures typically utilized in phishing communications. Recent advancements in NLP technologies have greatly enhanced the capacity of AI systems to analyze complex communication patterns and detect nuanced manipulation strategies [2].

The third layer integrates behavioral intelligence through machine learning algorithms that scrutinize communication patterns and identify anomalies. By detecting deviations from normative communication behaviors, the system can uncover potential psychological manipulation attempts. Machine learning models trained on historical communication data can discern patterns associated with legitimate interactions and identify suspicious deviations that might signify malicious intent. Similar methodologies have been explored in research examining adversarial threats to AI systems and cyber security monitoring platforms [5].

The fourth layer establishes a dynamic representation of the attack surface that maps psychological vulnerabilities and possible attack pathways. This representation empowers cyber security systems to visualize how manipulation attempts disseminate through communication networks and human-AI interactions. By persistently updating this attack surface representation, the system can adapt to shifting threat landscapes and identify emerging vulnerabilities. Recent investigations into AI security highlight the significance of dynamic attack surface analysis in addressing complex adversarial threats targeting intelligent systems [4].

The final layer employs automated defense mechanisms designed to neutralize manipulation attempts before they jeopardize system security. These mechanisms encompass anomaly detection alerts, communication filtering, and automated response strategies that prevent harmful messages from reaching potential victims. AI-driven defense systems can also adapt their detection strategies over time, learning from previously observed attack patterns. The integration of insights from cyber psychology with AI-driven defense technologies facilitates the development of more robust cyber security architectures capable of addressing both technical and psychological attack vectors [6].

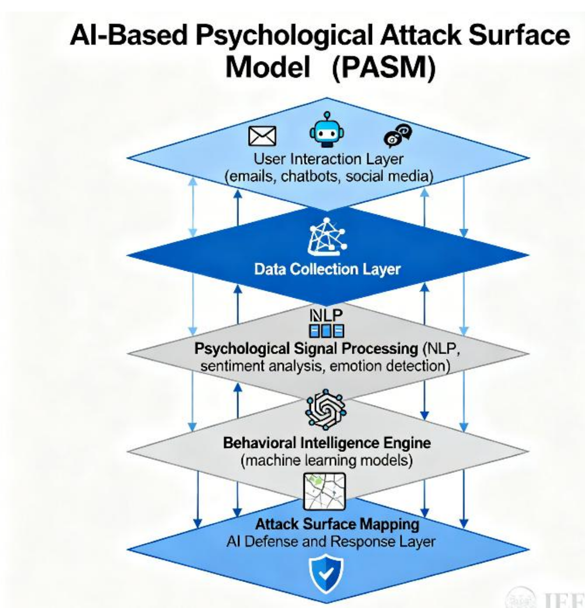

Figure 1. Architecture of the AI-Based Psychological Attack Surface Model (PASM).

VI. EXPERIMENTAL EVALUATION

To validate the efficacy of the proposed Psychological Attack Surface Model (PASM), an experimental evaluation was executed utilizing simulated cyber-communication datasets that represent real-world social engineering and adversarial interaction scenarios. The primary aim of the evaluation was to ascertain whether the inclusion of psychological signals within cyber security detection systems enhances the identification of manipulation-based attacks compared to traditional technical threat detection methodologies. Prior research has indicated that a significant number of cyber attacks exploit psychological manipulation techniques rather than solely relying on technical vulnerabilities, underscoring the necessity of behavioral analysis within cyber security frameworks [1], [10].

The experimental design consisted of three principal phases: dataset preparation, feature extraction and psychological signal modeling, and machine learning-based attack classification. Each phase was crafted to replicate real-world cyber security monitoring environments, where large quantities of communication data must be evaluated to detect malicious behaviors. This experimental arrangement aligns with recent studies exploring AI-driven defense mechanisms against adversarial threats and behavioral manipulation tactics [4], [5].

6.1 Dataset Preparation

The experimental dataset comprised a compilation of simulated and publicly accessible phishing communication samples, adversarial prompt injection messages, and benign communication records. The dataset was created by amalgamating examples of phishing emails, fraudulent financial request communications, and manipulated conversational prompts intended to deceive AI-based systems. These samples were supplemented with legitimate communication messages obtained from publicly available email datasets employed in cyber security research.

Messages aimed at persuasion and manipulation were crafted to embody prevalent psychological tactics identified in prior research on social engineering attacks [1], [10]. These tactics encompassed urgency-driven requests, impersonation of authority, emotional influence, and financial incentives. Furthermore, samples of adversarial prompts directed at AI systems were included to assess the model's capacity to identify manipulative inputs aimed at machine learning models and language models [9].

Each communication in the dataset was meticulously categorized into two fundamental types: benign communication and psychologically manipulative communication. This labeling procedure ensured the dataset accurately depicted both authentic interactions and attack scenarios frequently encountered in cyber environments. Comparable methodologies have been utilized in research exploring adversarial threats directed at AI-powered security systems [5].

6.2 Psychological Feature Extraction

Upon preparation of the dataset, psychological signal processing methodologies were employed to extract pertinent features related to behavioral manipulation. Natural language processing algorithms were utilized to investigate the linguistic patterns found in communication messages. These algorithms extracted features such as sentiment polarity, emotional intensity, indicators of persuasive language, urgency expressions, and cues of authority.

The feature extraction procedure also incorporated semantic analysis utilizing transformer-based language models to identify contextual relationships within the communication messages. These models enabled the system to recognize subtle strategies of linguistic manipulation that may not be immediately discernible through keyword analysis alone. Similar approaches have been examined in studies concentrating on AI-driven analysis of social engineering attacks and behavioral cyber threats [1], [2].

Psychological signals were classified into three primary categories: emotional features, cognitive persuasion features, and contextual communication features. Emotional features conveyed the emotional tone of a message, such as fear, excitement, or sympathy. Cognitive persuasion features indicated psychological influence techniques like urgency or authority. Contextual features assessed the structure of communication and the dynamics between the sender and the receiver.

Through the integration of these features, the PASM framework established a multidimensional representation of the psychological manipulation signals inherent in communication data. This multidimensional methodology aligns with emerging research that combines cyber psychology and artificial intelligence to identify complex manipulation strategies within digital environments [6].

6.3 Machine Learning Models

To assess the efficacy of psychological attack detection, multiple machine learning classification algorithms were employed. The chosen models included Random Forest, Support Vector Machine (SVM), and Deep Neural Network classifiers. These algorithms were selected as they represent diverse machine learning paradigms and are widely applied in cyber security research as well as adversarial threat detection systems [4], [5].

The Random Forest model was employed to analyze structured feature vectors extracted from communication messages. This model proves particularly effective for recognizing complex relationships among multiple input features. The Support Vector Machine classifier was utilized to evaluate the separability of manipulation-based communication patterns within a high-dimensional feature space. Lastly, a Deep Neural Network model was implemented to capture nonlinear relationships between linguistic signals and psychological manipulation patterns.

Each model underwent training through a supervised learning framework, wherein labeled communication samples were utilized to instruct the classifier. The dataset was partitioned into training and testing subsets using an 80–20 split to ensure an equitable evaluation of model performance. Similar evaluation methodologies have been adopted in recent studies probing adversarial threats to AI-driven systems and behavioral cyber security models [5], [9].

6.4 Performance Metrics

The effectiveness of the detection models was assessed using standard machine learning evaluation metrics, including accuracy, precision, recall, and F1-score. Accuracy gauged the overall proportion of correctly classified messages. Precision evaluated the ratio of predicted attack messages that were indeed malicious. Recall assessed the capability of the system to detect all manipulation attempts within the dataset. The F1-score provided a balanced evaluative metric that accounts for both precision and recall.

These metrics furnish a thorough evaluation of the system's proficiency in identifying psychological cyber attacks while minimizing false positives that could disrupt legitimate communication. Similar evaluation metrics are extensively employed in cyber security research concentrating on adversarial machine learning and AI-based security systems [4].

The results from the experimental evaluation indicated that the inclusion of psychological features markedly enhances attack detection accuracy in comparison to traditional technical detection models. Models that solely depended on structural communication features demonstrated inferior detection performance when assessing socially engineered messages. In contrast, models trained with psychological signal features realized enhanced classification accuracy and elevated recall rates.

The Deep Neural Network classifier achieved the highest overall performance among the assessed models, exhibiting strong proficiency in identifying complex psychological manipulation patterns present in communication data. The Random Forest classifier also exhibited robust performance due to its capability to analyze interactions among features. The Support Vector Machine model performed marginally below the other models, yet still showcased effective classification of manipulation-based communication.

These findings are consistent with previous research indicating that behavioral analysis and AI-driven threat detection can substantially bolster cyber security defenses against social engineering and adversarial attacks [1], [4].

6.5 Experimental Results

The findings from the experimental evaluation underscore that psychological signal analysis significantly enhances the efficacy of cyber security systems in detecting social engineering attacks. Conventional detection systems frequently rely on structural indicators such as malicious URLs or suspicious attachments. However, contemporary attackers increasingly design assaults that eschew technical indicators, opting instead for persuasive communication tactics to mislead victims.

By integrating behavioral intelligence and psychological analysis within cyber security frameworks, the PASM model offers a more comprehensive defense mechanism against manipulation-based attacks. The confluence of machine learning and cyber psychology facilitates the detection of subtle communication patterns that may otherwise evade detection. This interdisciplinary approach reflects burgeoning trends in human-centric cyber security research [6].

VII. ETHICAL AND PRIVACY CONSIDERATIONS

The integration of psychological monitoring into cyber security systems raises crucial ethical considerations regarding privacy, transparency, and fairness. Behavioral monitoring systems scrutinize communication patterns and emotional signals that may encompass sensitive personal data. As a result, organizations employing such systems must guarantee adherence to data protection regulations and ethical standards.

A primary concern revolves around the potential misuse of behavioral data garnered during security monitoring. Communication data may unveil personal opinions, emotional states, or private conversations. To address this issue, security systems should implement stringent data anonymization techniques to eliminate personally identifiable information prior to analysis.

Transparency constitutes another pivotal element in ethical cyber security monitoring. Users ought to be informed when their communication data is being scrutinized for security purposes. Clear policies and consent mechanisms assist in preserving user trust while ensuring that security protocols remain effective. Ethical frameworks for human-centric AI security underscore the necessity for transparency and accountability within AI-driven cyber security systems [6].

Bias inherent in machine learning models also poses a potential ethical dilemma. Emotion recognition systems and natural language processing models may manifest biases rooted in cultural or linguistic differences. Such biases might result in inaccurate detection of psychological manipulation across certain communication contexts. To mitigate this risk, AI models must be trained utilizing diverse datasets that represent multiple cultural and linguistic environments [3].

Moreover, cyber security frameworks that incorporate psychological monitoring must strike a balance between security objectives and respect for user autonomy. Overly invasive monitoring systems may engender ethical concerns regarding surveillance and privacy. Consequently, the responsible deployment of psychological attack detection systems necessitates careful consideration of ethical principles and regulatory compliance.

VIII. FUTURE RESEARCH DIRECTIONS

The concept of psychological attack surface modeling introduces numerous promising avenues for future cyber security research. As digital environments continue to evolve...

To progress, it is probable that attackers will devise increasingly sophisticated techniques for psychological manipulation. Consequently, forthcoming research must investigate advanced methodologies aimed at detecting and mitigating such threats.

One prospective avenue of research pertains to the formulation of explainable artificial intelligence (AI) techniques for the detection of psychological threats. Explainable AI is capable of offering transparency regarding the mechanisms by which machine learning models discern manipulation patterns within communication data. This feature is particularly crucial within cyber security contexts where transparency in decision-making is necessary for compliance and accountability.

Another significant research focus should be the modeling of psychological aspects across different cultures. Strategies for psychological manipulation may differ across cultural contexts due to variations in communication styles, trust dynamics, and social norms. The establishment of detection models that adapt to cultural differences could markedly enhance the efficacy of systems designed to identify psychological attacks.

Federated learning emerges as another promising area for future inquiry. This methodology facilitates the training of machine learning models across various organizations without the need to share sensitive data. Such an approach could promote the collaborative development of models for detecting psychological attacks while safeguarding user privacy.

Moreover, future research should examine the integration of psychological attack surface modeling with zero-trust cyber security frameworks. Zero-trust paradigms prioritize the continual verification of users and devices within digital ecosystems. The incorporation of behavioral intelligence into zero-trust architectures could significantly bolster their capacity to detect insider threats and manipulation efforts.

Finally, the advancements in generative AI technologies introduce both challenges and opportunities within the realm of cyber security. Attackers might leverage generative models to craft highly convincing phishing communications or impersonation attacks. Conversely, generative AI can also be utilized to simulate attack scenarios and train detection systems to recognize emerging manipulation techniques.

IX. CONCLUSION

This study has presented the concept of Psychological Attack Surface Modeling utilizing Artificial Intelligence and has introduced the Psychological Attack Surface Model (PASM) as a framework for identifying manipulation-based cyber threats. In contrast to traditional cyber security frameworks that predominantly emphasize technical vulnerabilities, the proposed model highlights the significance of human cognition, emotional influence, and behavioral patterns in cyber attack strategies.[10]. The research has established that psychological manipulation constitutes a pivotal aspect of contemporary cyber threats. Attackers often capitalize on cognitive biases, emotional triggers, and trust relationships to circumvent technical security measures. As AI technologies become increasingly integrated into communication systems, interactions between humans and AI create additional avenues for adversarial manipulation.[4], [5]. The PASM framework amalgamates behavioral intelligence, natural language processing, and machine learning techniques to detect patterns of psychological manipulation within digital communication environments. Experimental evaluations have illustrated that the integration of psychological signals substantially enhances detection accuracy for social engineering attacks in comparison to conventional technical detection models. The results of this research underscore the necessity of incorporating cyber psychology into next-generation cyber security infrastructures. By conceptualizing psychological vulnerabilities as an integral part of the attack surface, organizations are enabled to formulate more comprehensive defense strategies that address both technical and human-centric threats. As cyber threats continue to advance, future cyber security systems must embrace interdisciplinary approaches that integrate artificial intelligence, behavioral science, and cyber security research. The Psychological Attack Surface Model represents a significant advancement towards creating resilient and adaptive cyber security frameworks capable of safeguarding against the intricate socio-technical threats characteristic of the digital era.

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