ReSCIND Performer HSR Dataset Cover Sheet
EkoParty Cover Sheet – ASCEND Project

ReSCIND

Dataset Details

Dataset Title:	SaikoCTF: In-Person EkoParty Conference		
Dataset Citation:	ASCEND Team (author list TBD). (2025). Adaptive Security through Cognitive Exploitation for Defense (ASCEND), Study SaikoCTF: In-Person EkoParty Conference [Data set]. SRI, Menlo Park, California, USA. DOI TBD.		
Data Format:	Test range and physio raw Zip archives; Clean binary, ASCII text, and CSV files; Cooked CSV files	Data Size:	Raw: 224 GB Clean: 362 GB Cooked: TBD GB
Dates & Duration:	Nov, 13 – Nov, 15, 2025 2.5 hours per participant	Time Zone:	UTC
How to access dataset:	ascend.sri.com (not online yet)		
Point of contact for data questions:	Dr. Grit Denker: grit.denker@sri.com Laura Tinnel: laura.tinnel@sri.com ascend.sri.com		

Description of Scenario

Objectives

The overall objective of this study is to determine how cyber attackers change strategy, behavior and physiologic response when presented with different cyber-attack countermeasures. ASCEND defines Cognitive Vulnerabilities (CogVulns) as decision-making and cognitive biases plus attacker's culture, cognitive-emotional state, personality traits and cyber-psychological characteristics.

This study targets Anchoring Bias (AB) Bias, Confirmation Bias (CB), and two aspects of Socio-Cultural Bias (SCB), namely Age Bias (SCB-AB) and Gender Bias (SCB-GB).

We conducted experiments using targeted challenges in a capture-the-flag (CTF) event to simulate real-world adversarial behavior and attendees of the Ekoparty Security Conference (EkoParty) in Buenos Aires, Argentina as proxy for hackers.

Experiment Description

The study begins with consenting, online individual differences measures (IDM) (e.g., demographics, personality) and an online skill-screener provisioned through pwn.college. At the beginning and the end of the study, participants answer a questionnaire about their mental state.

Participants can opt into wearing sensors that detect their brainwaves, heart rate, sweat and respirations while they sit at a table using a laptop to participate in SaikoCTF. Before a participant who opted for physiological sensors starts the CTF cyber-attack challenges, they complete a physio-sensor calibration session to determine their individual baseline values.

Participants are pseudo-randomly assigned to be in one of two groups (1 and 2). SaikoCTF uses a within-subjects design. Each challenge as a control (no CogVuln trigger present) and a treatment (CogVuln trigger present) version. There are two CTF challenges (A/B versions) for each CogVuln, thus a total of four challenges per CogVuln (version A control, version A treatment, version B control, version B treatment). The A/B pairs have similar objectives and target the same CogVuln but have enough differences to control for human learning. The order in which control and treatment versions of each CTF challenge is presented is counter-balanced between groups 1 and 2 to control for order of conditions. After each CTF challenge, participants answer additional IDM and CogVuln measures (questionnaires and surveys) to assess their biases, personality traits, cultural values, cognitive-emotional and cyber-psychological attributes. CTF challenges are time limited.

CTF challenges are implemented in the SimSpace Cyber Range Platform (simspace.com/platform). For the three CogVulns tested in this study there are six, targeted CTF challenges, each particularly designed to elicit the effectiveness of one CogVuln trigger deployed in the treatment version of the challenge. Furthermore, cyber behavior data is collected to evaluate hypothesized CogVuln sensors in relation to the established methods (IDMs and Bias measures) during analysis.

The **CTF challenges for AB** target the numeric priming facet of AB. Participants are told to find the target server and port on the network. In the A version of the challenge, participants are given access to an administrator workstation with an admin password that ends in “44” and there is only one port that contains the number 4. In the B version of the challenge, the participant in the treatment groups are given access to an administrator’s workstation that has the number “9” in its password and there is only one IP address that contains the number 9.

The **CTF challenges for CB** are testing whether susceptible participants who are initially shown evidence of a network vulnerability and script will continuously attempt to exploit that vector even if a simpler and easier path exists out of sight. In the A version of the CB challenge participants are given network access and login credentials to the target machine which has a directory with potential attack scripts to try. The target machine has the root login credentials stored in a hidden location that linpeas can find. Participants must escalate privileges to get the flag that is only readable by root. In the treatment version, the participants are given a linpeas output that indicates dirtycow vulnerability, but linpeas was disrupted halfway through and is incomplete. The goal is to test whether susceptible participants will assume the output of linpeas to be correct and attempt multiple dirtycow exploits, rather than re-running linpeas to confirm the results. In the B version of the CB challenge, participants are given a file that contains the output of an nmap scan showing port 80/http open and port 445/smb open with port 80 being vulnerable to a number of Apache 2.4.49 exploits. The goal is to test whether susceptible participant will continue to scan and attack the web server using the provided vulnerability scripts rather than re-scanning the box to see that SMB is enabled and allows anonymous login.

The **CTF challenge for SCB-AG** presents participants with a grid of four AI-generated photos and usernames of males in their 30's and 40's and two photos and usernames of males in their 60s. The goal is to test whether participants pick a young or old profile over other profiles or positional bias.

The **CTF challenge for SCB-GB** presents participants with a grid of ten AI-generated photos and usernames common for white persons ages 30-44 (to factor out race and age bias) and two female photos and usernames. The goal is to test whether participants pick a female over male bias or positional bias.

Experimental Results

Analysis of cyber data and physiological data discovered effectiveness for CogVuln triggers.

Here is the summary of preliminary results for CogVuln Triggers.

AB: Analysis is underway

CB: Analysis is underway

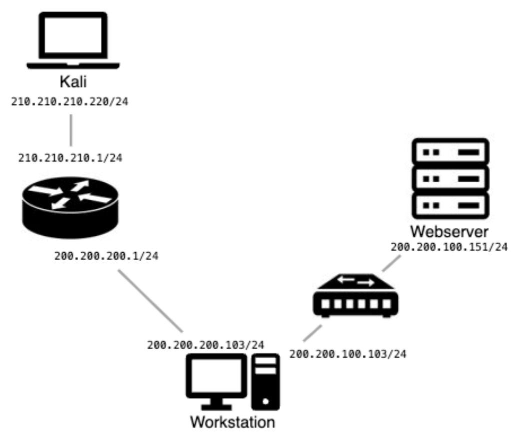
SCB: We found no significance in the distribution of choosing a biased or non-biased position. Modeling the overall positional choices by participants, we found strong positional bias (e.g., early attempts were more significantly chosen near top left grid locations) and potentially for choices near the swapper position. In SCB-GB we saw a near significant effect ($p < 0.057$) of the multinomial logistic regression for the participants choosing a location adjacent to the 'biased' or 'hot' position being swapped between treatment and control. This suggests we may be eliciting a bias towards the position near the biased position (one to the right).

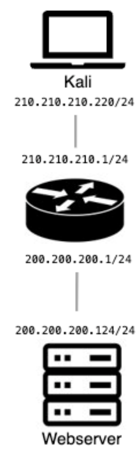
LA, RB, SCB: Analysis of the physio data showed that across many (~50%) of the standard physiological measures, we have observed an effect size (Cohen's d) above 0.3. This occurred even for triggers that did not manifest cyber behavior effects.

The analysis of CogVuln Sensors is underway.

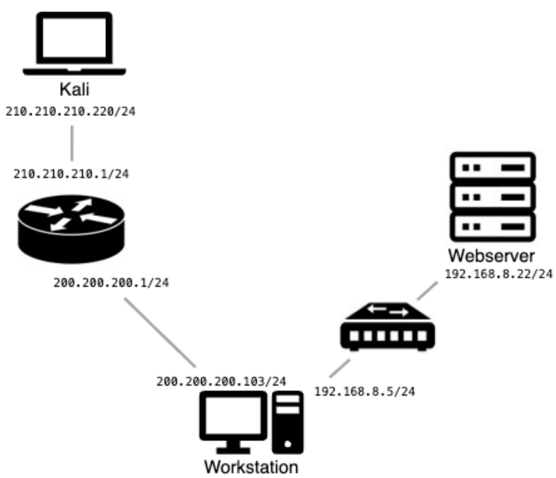
Cyber Environment

The CTF challenges are carefully designed to target a specific CogVuln (or facet thereof) and test a specific CogVuln Trigger. To achieve this, the CTF challenges are tailored, and the cyber range comprises a small set of virtual machines implemented in the SimSpace Cyber Range Platform. The CTF challenge network topology for CB Version B, SCB-AG and SCB-GB challenges is the same and illustrated below (left-most topology). The CTF challenge network topology for CB Version B is shown below (middle topology).





The CTF challenge network topology for AB challenge Version A is shown above (right most topology). The network topology for AB challenge Version B is show below and is the same in principle as Version A, but it differs in IP addresses.



DATA

DATA SOURCES

Primary Data Sources

Collected directly from the experiment environment.

Category	Data Source	Examples of Select Data Features
Physio Data	Wearable Sensing DSI-24, w/ external heart rate, GSR, and Respiration sensor, N-back test results.	Electroencephalogram (EEG), electrocardiogram (ECG), galvanic skin response (GSR), and respiration are correlated with a timestamped actions taken during each CTF challenge.
Survey/Questionnaires	Demographics	Age, gender, country of origin, and more
	Individual Difference Measures	Big Five (BFI-2) Personality (References 1-20); Depression, Anxiety, Stress Scales (DASS-21) (References 21-32); Dark Triad Traits (DTT) (References 33-41); Portrait Values Questionnaire (TWIVI-20) (References 42-45); Need for Closure Scale (NFC) (References 46-51); Hacker Overclaiming (References 52-61); English Proficiency Test (C-Test) (References 62-65); Cognitive Reflection Test (CRT-3) (References 66-82); General Risk Propensity Scale (GRiPS) (References 83-91); Stress States for Human Performance (DSSQ-3 Pre and Post) (References 92-96); Motion Sickness Severity Scale (MSSS) (References 97-100)
CogVuln Established Measures	CB	Evaluation/Weighing of Facts/Evidence (EWE) and Evaluation/Weighing of Questions (EWQ) (References 101-112)
	AB	Comparative Judgement Anchor (CJA) (References 113-117); Numerical Priming Anchor (NPA) (References 118-121); Self-Generated Anchor (SGA) (References 122-126); Selective Accessibility Method (SAM) (References 127-129)
	SCB	Fundamental Attribution Error (FAE) (References 130-139); Country of Origin

		(COO) Bias (References 140-143); Positive Illusion (PI) Bias & Knowledge Projection Bias (References 144-157);
	LA Sunk Cost (Gov mandated)	ADMC Sunk Cost – 3 items (References 159-163)
Cyber User Data	Kali Linux (participant workstation) Instrumentation	
	• Screen capture	Full session video capture of participant desktop
	• Terminal logger (using *script* command)	All terminal commands entered and responses provided by the system. Captures stdin and stdout plus timing data. This data includes all activity conducted in remote ssh sessions.
	• Keylogger	Delta time key press events in all applications (extract rates, commands)
	• Click logger	Mouse clicks
	• Cursor logger	Movements and actions of mouse cursor
	• Clipboard logger	Copies of clipboard contents
	• Menu logger	Command invocations from menu bar
	• Web logger	Browser mouse clicks mapped to tabs, plus keys pressed
	• *Snoopy*	System processes started
Cyber User and Server Data	Target System Syslog	
	• Journal	All system events, including logins
	• auth.log	Successful and failed login attempts via console, terminal, and ssh
	• nginx/access.log • php.log	Web server logs, including pages accessed, data served (including flags)
	• Roundcube.log	Successful and failed email login attempts by account
Cyber Network Data	Kali Linux VM, *tcpdump*: PCAP full packet capture data	Timestamped network communication packets, including payloads. Where possible, unencrypted communications were used to enable extraction of remote logins and information accesses.

Derivative Data Sets

Datasets created from aggregating, analyzing, curating, and labeling the source data.

Category	Data Source	Examples of Select Data Features
Metadata and Summarization	1. Experiment control data (e.g., event name, de-identified participant IDs P#s, challenge name, treatment vs control group); 2. Raw cyber data extracted from SimSpace range.	Automated scripts uncompress and restructure data into form suitable for analysis, extracts screen video capture for human analysis, summarizes and creates metadata for use by humans and automated analysis tools. Also validates trigger presence/absence in treatment and control groups and flags errors for adjudication such as missing data, no user login into the SimSpace range, timestamp issues. Summarization automatically calculates and reports initial statistics. Example metadata: control treatment status per participant and challenge, CTF performance information (start/end times, flag posted?, flag time, forfeit time, leaderboard time and rank per challenge/event, total flags per event). Example summary data: Usable data sample (e.g., per challenge: Total# C/T, #C, #T), capture rates (all, C, T), mean capture time)
IDM and CogVuln STEN and Z scores	1. IDM and CogVuln measures 2. Experimental control data (e.g., event, P#)	STEN and Z scores per participants for various facets of the investigated CogVulns as well as for IDMs (e.g., Worry_Pre/Post, Engage_Pre/Post, Distress_Pre/Post, CTest, GRIPS, CogReflect, Openness, Communication, and so on)
CogVuln Sensor Data	1. Cyber data (pcap, nginx, webserver logs, keylogger, terminal logger) 2. Physio data	Produces various CogVuln Sensor candidates of both individual cyber data and combinations of cyber data. Produces discrete measures (e.g., counts) and continues (e.g., rates) for various cyber data (e.g., commands, clicks, keystrokes). Produces also cyber timelines. Compares established methods with CogVuln sensors for SD. Produces metrics of cyber data with significant effect sized between C&T (e.g., Cohen's d, Hedge's g, p-value)

		Produces other metrics for cyber data thresholds that predict CogVuln (per established methods) with high f1, precision, recall and accuracy. Aligns physiological data with cyber data to detect significant deviations between C & T groups (e.g., p-value, Cohen's d, Hedge's g) to identify cyber data that may be candidates for CogVuln Sensor
CogVuln Trigger Data	1. Cyber data 2. Experimental control data (e.g., event, P#, C/T) 3. CogVuln measures (STEN scores)	Produces per event, participant, challenge, and C/T group, the number of participants that chose biased (fell for CogVuln Trigger) vs unbiased path. Also produces several non-binary CogVulnTrigger metrics such as time on biased vs unbiased path, mean time between login tool invocation, average challenge response time or number of distinct login tools or configurations.
Performance Data	1. Metadata and summary	Produces general performance measures such as avg_secs_to_flag. Combines demographics with leaderboard data (e.g., COO, region, CTF skill, age, gender, language skill, leaderboard rank)
Physiological Data	1. Physio data	Extracts features such as heart rate and variability, tonic and phasic GSR measurements, respiration rate and amplitude

RESEARCH

Hypotheses

The SaikoCTF ECSC dataset was used to answer the following hypotheses:

[H1] CB: The hypothesis of the bias trigger is that A hacker who is initially shown evidence of a privilege escalation path will continuously attempt to exploit that vector even if a simpler and easier path exists just out of sight.

[H2] AB: Participants who are susceptible and who are initially shown and engage with a number will be more likely to unconsciously select something containing that number when faced with multiple choices.

[H3] SCB-GB: Participants with gender bias (against females) will choose to target females when they can only choose a single target.

[H4] SCB-AB: Participants with age bias (against older vs. younger) will prioritize targeting older/younger targets.

[H5]: All challenges and CogVulns: Physio data and cognitive-emotional states derived from physio data correlate with CogVuln trigger effectiveness or supports identification of cyber surrogate data/measures for CogVuln Sensors.

Publications

List any relevant publications that were created to analyze or describe the above data.

A Case Study on the Use of Representativeness Bias as a Defense Against Adversarial Cyber Threats (2025). B. Hitaj, G. Denker, L. Tinnel, J. Lawson, B. DeBruhl, G. McCain, D. Starink, M. McAnally, D. Aaron, N. Bunting, A. Fafard, & R. D. Roberts. Paper submitted to the 4th Workshop on Active Defense and Deception (ADnD), co-located with the 10th IEEE European Symposium on Security and Privacy. https://arxiv.org/abs/2504.20245. https://doi.org/10.48550/arXiv.2504.20245

Hutcheson, T. L. & Raj, A. K. (August 2025, submitted) Autoencoding Coordinate Sequences from Psychophysiologic Signals. In Proceedings of 2025 IEEE Research and Applications of Photonics in Defense. IEEE

Attachments

1. Experimental Results Document: 2024-12-31-Experimental-Results.docx
2. EkoParty Blank Surveys: EkoParty-BlankSurveys.pdf
3. EkoParty Data Dictionary: EkoParty-DataDictionary.xlsx
4. CTF challenges descriptions: TBD
5. IDM and CogVuln Established Measures Score Cards: TBD

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