Toward Quantitative Modeling of Cybersecurity Risks Due to AI Misuse

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Abstract

Advanced AI systems offer substantial benefits but also introduce risks. In 2025, AI-enabled cyber offense has emerged as a concrete example. This technical report applies a quantitative risk modeling methodology (described in full in a companion paper) to this domain. We develop nine detailed cyber risk models that allow analyzing AI uplift as a function of AI benchmark performance. Each model decomposes attacks into steps using the MITRE ATT&CK framework and estimates how AI affects the number of attackers, attack frequency, probability of success, and resulting harm to determine different types of uplift. To produce these estimates with associated uncertainty, we employ both human experts, via a Delphi study, as well as LLM-based simulated experts, both mapping benchmark scores (from Cybench and BountyBench) to risk model factors. Individual estimates are aggregated through Monte Carlo simulation. The results indicate systematic uplift in attack efficacy, speed, and target reach, with different mechanisms of uplift across risk models. We aim for our quantitative risk modeling to fulfill several aims: to help cybersecurity teams prioritize mitigations, AI evaluators design benchmarks, AI developers make more informed deployment decisions, and policymakers obtain information to set risk thresholds. Similar goals drove the shift from qualitative to quantitative assessment over time in other high-risk industries, such as nuclear power. We propose this methodology and initial application attempt as a step in that direction for AI risk management. While our estimates carry significant uncertainty, publishing detailed quantified results can enable experts to pinpoint exactly where they disagree. This helps to collectively refine estimates, something that cannot be done with qualitative assessments alone.

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Executive Summary

Risk management for frontier AI systems is a nascent science. It has so far focused on "if-then scenarios", where an evaluation result pointing to a certain level of a dangerous capability triggers a certain set of mitigations. This approach has several limitations. First, as risk itself is not measured, we cannot know by how much the mitigations reduce risk or provide justification for whether the mitigations are sufficient. Second, it leads to the treatment of capabilities measured by standardized benchmarks in isolation, ignoring interactions between capabilities that can impact real-world risks and important factors related to the precise path to harm.

The role of risk modeling is to bridge the gap between the source of risk (e.g., dangerous capabilities or propensities, deployment conditions or affordances) and the actual harm, to enable systematically analyzing the risk. This technical report applies the methodology we have developed for quantitative modeling of AI-enabled risks to the domain of cyber offense. We provide a road map for implementing the methodology as well as tentative results from applying it to nine risk models. As a common criticism of quantitative risk assessment is its lack of scalability, we also experiment with the use of LLM-simulated experts to provide estimates, in addition to our human expert Delphi study.

Comprehensive and systematic risk modeling can provide numerous benefits to different groups of AI risk stakeholders:

- Cybersecurity defenders and vendors can leverage the insights on where AI uplift is the hightest to prioritize their mitigation efforts.
- In the AI evaluation and benchmark community, evaluators can leverage the insights to see where new benchmarks would reduce the greatest uncertainty in risk estimates and hence where they should focus their efforts.
- In AI companies, decision makers can use the more precise and forward-looking data to make more informed development and deployment decisions.
- Regulators and policymakers can gain more foresight on where AI risk is heading and start to determine expected harm to define risk thresholds.

In other high-risk industries, such as nuclear power and aviation, these types of benefits drove a shift over time from qualitative risk assessment to quantitative. In order to prompt a step in that direction for AI risk management, we present this methodology and initial attempt at applying it. While the resulting estimates necessarily carry significant uncertainty, we hope that publishing specific numbers can enable experts to pinpoint exactly where they disagree, and collectively refine estimates, something that cannot be done with qualitative assessments alone.

Methodology (Section 2)

Our risk modeling methodology consists of six, interlinked steps:

1. Selecting risk scenarios. We systematically decompose the risk universe into a set of representative scenarios.
2. Constructing risk scenarios. We build risk models for each scenario. These comprise four types of risk factors: the number of actors, the frequency with which attacks are launched, the probability of the attack succeeding, and the harm that would arise as a result. The steps in an attack are modeled using the MITRE ATT&CK framework.
3. Quantifying "baseline" risk. We establish estimates for the "baseline" risk (negligible or non-existent use of AI) case, in order to create a reference point, based on cyber threat intelligence data, historical case studies and expert review. This is captured as a Bayesian network.
4. Determining key risk indicators (KRIs) for AI "uplift". We establish which forms of KRIs, such as benchmark performance, can serve as evidence to infer values for uplifted risk factors. This technical report uses Cybench and BountyBench as examples.
5. Estimating AI uplift. We build a quantitative mapping between the KRIs and the risk factors in the risk model and use these to generate estimates for the risk factors. We conduct a Delphi study with cybersecurity experts for one risk scenario and we experiment with the use of "LLM-estimators" to generate estimates at scale. Experts provide confidence intervals around their estimates.
6. Propagating individual estimates among experts and across risk factors to aggregate estimates. We fit the estimates to the appropriate distributions and propagate the individual parameter estimates using Monte Carlo simulations to arrive at an overall risk distribution of the scenario.

Throughout this methodology, we rely extensively on cybersecurity experts. We iterate multiple times with four cybersecurity experts with complementary backgrounds to develop and refine the list of nine selected risk scenarios. Each baseline risk model is reviewed by one expert with relevant domain expertise, who validates the parameter values and suggests corrections where appropriate. Nine cybersecurity experts participated in the Delphi study for uplift estimation, and one expert reviews all of the uplift values produced by the LLM estimators to identify implausible estimates.

Results from Delphi Processes (Section 3)

In the modified Delphi study we conducted with cybersecurity experts, we had nine cyber experts provide two round of estimates of risk factors for one risk model, with a facilitated discussion in-between to discuss points of contention. We find that experts vary highly in how confident they are in assessing their uncertainty. Further, uplift estimates on risk factors associated with quantities (number of actors, number of attempts/actor/year, impact) exhibit a much greater variance than those associated with probabilities that are bounded by [0,1]. It is also noteworthy that the uplift variance increases as the corresponding benchmark task gets more difficult.

We also experiment with LLM-simulated expert estimators. Their estimates of probability risk factors closely follow those of humans. However, for quantity risk factors, there is more disagreement. LLM estimators are often more conservative, providing significantly lower predictions of uplift than human experts. LLM estimators predict a lower total risk than their human counterparts, with the deviation from human estimates increasing as task difficulty grows. LLMs also demonstrate lower uncertainty than humans, especially at higher AI capability levels.

Results from the Quantitative Evaluation (Section 4)

In Section 4, we provide the tentative quantitative results of our nine risk models in order to demonstrate the many use cases of risk modeling and create scrutiny, debate, and criticism around specific values so that we can iteratively work toward more exact estimates. Given the nascency of the science of AI risk modeling and the limitations of our methodology, we do not recommend making use of the exact numbers for decision-making at this time. We provide detailed results of our early comparative findings (intra- and inter-model) as a proof of concept for the potential value in quantitative risk modeling. Interesting results indicated by the models include:

- For seven out of nine scenarios, the models indicate that state of the art (SOTA) (at the time of conducting experiments) AI systems provide uplift relative to the baseline, i.e., the estimated total risk is higher when malicious actors' use AI at current capabilities.
- At "saturation", i.e., when AI can reliably perform all tasks in the benchmarks we use, the models indicate that the total risk estimates are again significantly higher than the SOTA-level.
- Across risk models, the models do not suggest a uniform pattern (i.e., AI is not consistently helping low-level or high-level attackers more)
- None of the four risk factors (number of actors, number of attempts, probability of success, and damage per attack) is suggested to play the key role in uplift, but rather all contribute to the increase in risk across different scenarios, i.e., AI helps with both "quantity" and "quality".
- The models suggest that AI provides more uplift for three MITRE tactics, Execution, Impact, and Initial Access, relative to the other eleven. However, there is significant variability in uplift within each factor.

Limitations and Future Work (Section 5)

This is, to our knowledge, one of the first attempts at building a systematic procedure for quantitative modeling of cybersecurity risks arising from AI misuse. Therefore, we acknowledge a number of limitations with our methodology and discuss them at length in Section 5 to guide future work.

1 Introduction

AI systems present many benefits for society, but at the same time introduce and exacerbate risks, ranging from misuse by humans to loss of control of powerful autonomous AI systems. The domain of cybersecurity serves as a potential early warning signal, with examples this year of AI systems providing meaningful assistance to malicious actors capabilities in their cyber attacks (Anthropic, 2025a; Hao et al., 2025). The combination of AI assistance and the already large economic damage inflicted by cyber crime (estimated to be in the hundreds of USD billions (Miliefsky, 2025)makes it a domain requiring urgent attention on how to best measure and mitigate these risks (AISI, 2025). New cybersecurity risks can range from relatively low-skilled individual threat actors using AI to efficiently craft more convincing phishing emails to nation-state actors using AI to develop more advanced malware (OpenAI, 2025). Nevo et al. (2024) classify these operations as ranging from OC1 (Operational Capacity 1 – amateur attempts) to OC5 (top priority operations from cyber-capable institutions). AI may be misused by threat actors to fill knowledge and skill gaps, scale operations and potentially enable attack of new types of targets, overall increasing both the efficiency and efficacy of attacks.

Although risks from AI systems have the potential to pose significant harm to society, frontier AI risk management is still an immature discipline. Typical current risk management practice for frontier AI systems is based on determining whether capability thresholds, measured through evaluations and benchmarks, are exceeded and then implementing mitigations accordingly (see Fig. 1) (METR, 2025). This is problematic for several reasons.

First, as risk itself is not measured, we cannot know by how much mitigations reduce risk or justify that they are sufficient (Campos et al., 2025). Second, the risk assessment should not end at evaluating capabilities of models, since what matters is the harm in the real world. Focusing on capabilities measured by standardized benchmarks in isolation ignores interactions between capabilities that can impact real-world risks and important factors related to threat actor behavior, the target, or the precise path to harm (Lukošiūtė and Swanda, 2025; Raman et al., 2025; Weidinger et al., 2023; Solaiman et al., 2023). Relying on capability assessments, therefore, is an imperfect proxy for the actual quantity of interest, which is risk.

In a first companion paper (Touzet et al., 2025), we investigate risk management practices across five safety-critical domains and from this, we derive a recommendation for a structured approach to AI risk

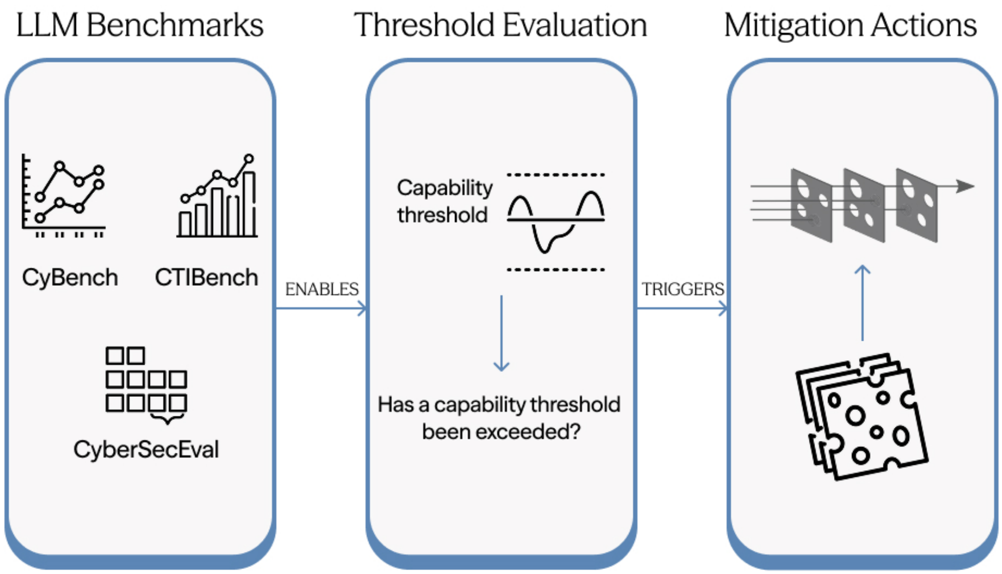


Figure 1: Typical industry practice, as described in frontier AI safety frameworks, is to rely on frameworks built around "if-then scenarios" (Karnofsky, 2024; METR, 2025).

modeling drawing on lessons from probabilistic risk assessment and causal trees in other industries. In a second companion paper (Murray et al., 2025a), we build on that work to outline a quantitative risk modeling approach for AI with methods for risk scenario building and risk quantification. This technical report is self-contained but for related work, see these two companion papers.

In this technical report, we apply our detailed quantitative AI risk modeling methodology specifically to the domain of AI-enabled cyber-offense risk. We provide a road map for implementing the methodology and provide initial results from modeling nine risk scenarios. A common criticism of quantitative risk assessment is its lack of scalability: in this work therefore, we experiment with the use of LLM-simulated experts to provide estimates for risk model parameters, alongside a more conventional human expert Delphi[3]. By linking hazards (dangerous capabilities or propensities) to specific harms and by quantifying both the probability and severity of the harm, there are a number of benefits, as shown in Fig. 2:

1. Quantification of risks enables defenders to better prioritize the development and deployment of mitigations against cyber attacks.
2. This approach can be used to shine a light on gaps where evaluations are missing and new ones might be required.
3. Access to quantified risk information, as well as a view that considers the impact of several capabilities in tandem (rather than each capability in isolation), is a powerful enabler for decision-makers to assess whether an AI is safe enough to be developed or deployed.
4. Quantified risk information can help regulators and policymakers define risk thresholds in terms of expected harm, which is a more concrete basis on which to build consensus than capability thresholds.

Our risk models take advantage of the reproducible nature of benchmark evaluations in order to construct static, forward-looking mappings from AI capabilities to real-world risks. This enables our models to adapt to a changing risk environment and provides a mechanism for forecasting of risk as AI becomes increasingly powerful.

This technical report proceeds as follows. Section 2 provides a detailed description of our risk modeling methodology. Section 3 describes our findings from the cybersecurity experts in the Delphi

[3]We will publish the code for conducting simulated Delphi studies with LLM experts, along with the associated prompts, in the near future.

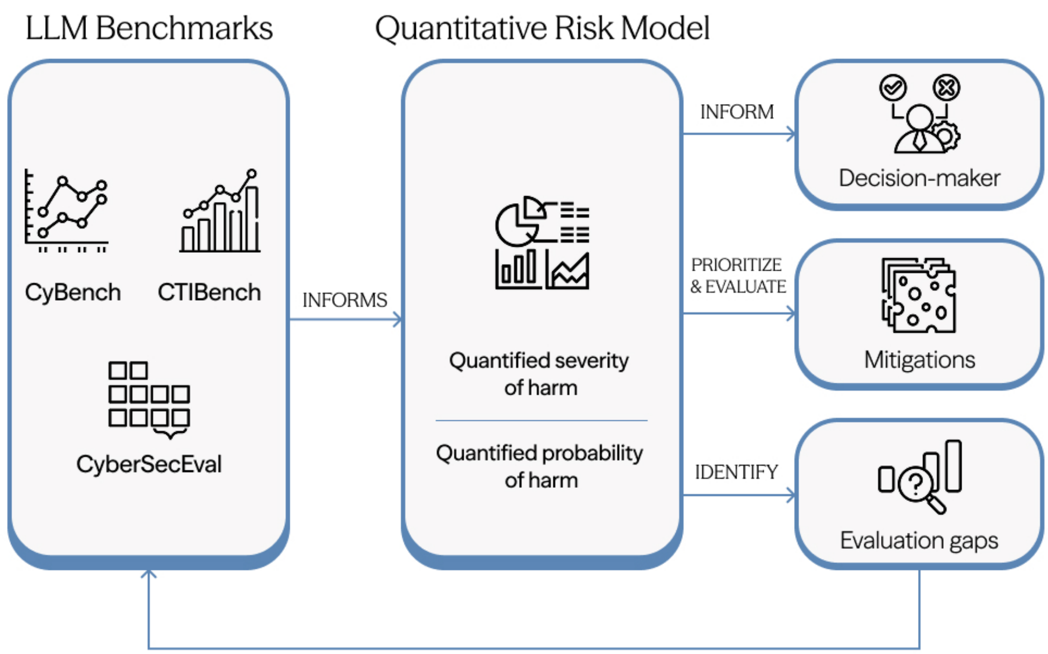


Figure 2: Benefits of quantitative risk modeling.

study and from comparing them with the "LLM estimators". Section 4 provides the quantitative results suggested by our models in terms of overall changes in risk as well as uplift of different types: "efficacy uplift" (the increase in probability of success of an attack), "volume uplift" (the increase in quantity of attacks which can be launched), and "target uplift" (the ability with which larger, more valuable, and better defended victims can be targeted). Section 5 provides limitations and future work, and Section 6 presents conclusions.

2 Methodology

A high-level summary of our risk management methodology is illustrated in Fig. 3. As is common in risk management practice (ISO, 2023; Kaplan and Garrick, 1981), first we decompose the risk universe into distinct risk scenarios, which for the case of cyber offense correspond to a variety of different cyber-attack archetypes. Risk models for each scenario comprise four risk factors: the frequency with which attacks of the specific cyber-attack archetype are launched, the probability of the set of steps in the attack succeeding, the number of actors that would attempt an attack, and the harm that would arise as a result of a successful attack. The individual factors in the risk model are then aggregated to determine an overall level of risk for that scenario expressed as the expected level of annual economic damage (Vose, 2008; de Vasconcelos et al., 2019).

Our risk modeling methodology consists of six steps, briefly described below. For a full description of the methodology, please see our companion paper (Murray et al., 2025a).

1. **Defining risk scenarios to model:** We systematically decompose the risk universe into a set of representative scenarios, and we build risk models for each representative scenario.
2. **Constructing risk models:** Risk is modeled as a combination of four factors. First, the number of threat actors conducting this type of attack. Second, the number of attack attempts per actor per year. Third, the set of tactics required in the attack and their associated probability of successful application. Fourth, the damage resulting from each successful attack.
3. **Quantifying "baseline" risk:** We establish estimates for the risk of "baseline" threat actor capabilities (with negligible or absent use of AI) as a reference point for uplift.

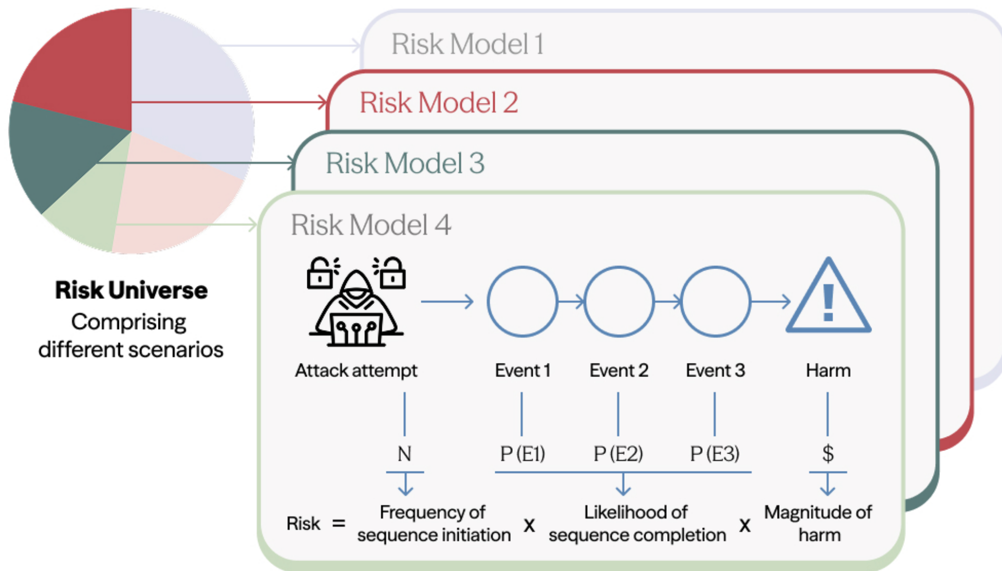


Figure 3: Our risk management methodology first decomposes the risk universe into distinct scenarios, then models each using various risk factors: the frequency with which a specific sequence of events is initiated, the probability of the sequence completing, and the harm that would arise as a result.

4. **Determining key risk indicators (KRIs) for AI "uplift":** We establish which forms of evidence (KRIs) risk factors can be conditioned on, such as benchmark performance.
5. **Estimating AI uplift:** We conduct expert elicitation to build a quantitative mapping between the KRIs and the factors in the risk model and use these to generate uplift estimates.
6. **Propagating individual estimates to aggregate estimates:** Distributions are fitted to central tendencies and confidence intervals provided by the expert for each risk factor, conditioned on benchmark scores. For each expert, we perform Monte Carlo sampling from the joint distribution across all risk factors. The result is a mixture distribution that captures expert epistemic uncertainty about overall risk.

The following sections provide additional detail on the methodology as applied to the misuse of AI for cyber offense.

2.1 Determining the Set of Risk Scenarios

The first step in our methodology is to determine which risk scenarios warrant detailed modeling. The risk space is large; therefore, not all scenarios can be modeled in detail. In the domain of AI-enabled cyber attacks, the main type of harm is economic, but other types of harm are also possible such as psychological, reputational, or physical harms. Cyber attacks may even lead to loss of life, especially in settings involving threat actors targeting critical infrastructure. For simplicity, we focus on economic harm across this set of risk models as an all-encompassing metric, using dollars (US) as a common unit of harm to maintain consistency.

In order to narrow the full risk space into a set of the most important risk scenarios, we start by determining a set of key dimensions that are common to attacks. For AI-enabled cyber attacks resulting in economic harm, such dimensions may include, e.g., the type of threat actor, the type of target, the type of attack (the vector), the intent of the attack, and the defense level of the target. Our analysis suggests that the key dimensions to focus on are actor, target and vector. The defense level can be specified as a function of the target in question, and similarly, the intent can be determined from the actor and vector. In order to make our modeling approach easily replicable, we rely as much as possible on existing taxonomies to define these aspects.

Actor: There needs to be a threat actor, who exploits a vulnerability to cause harm. A taxonomy of threat actor categorizations expressed as operational capacities (OC) can be found in Nevo et al.

(2024). Here, offensive cybersecurity operations are classified on a scale, from OC1 (amateur attempts by hobbyist hackers) to OC5 (top-priority operations by the most cyber-capable nation-states). It should be noted that their taxonomy is for operations, not actors, but it easily maps onto the type of actor. For example, we define an OC3 actor as one that would perform at most OC3 level operations.

Target: For there to be harm, there needs to be a specified entity that experiences said harm, here referred to as the target. For targets, we start with CISA's (US) and NPSA's (UK) list of critical national infrastructure sectors (CISA, 2025; NPSA, 2025). These include, e.g., Financial Services, Healthcare, Transportation Systems, and Defense. We then group these into types of targets, based on similarities in the attack surface, the intent of threat actors and the impact of disruption. This results in the following categories of targets: Financially attractive and data-rich targets (Financial Services, Healthcare & Public Health, Commercial Facilities, Information Technology); Espionage and state-interest targets (Defense Industrial Base, Government Facilities, Communications); Critical infrastructure and control-system-heavy targets (Energy, Water & Wastewater Systems, Chemical, Critical Manufacturing); and Logistics & national mobility targets (Transportation Systems, Emergency Services).

Vector: Finally, a sequence of events needs to take place for the threat actor to turn the threat into a harm, which we refer to as the vector. Here, we take as our starting point a list from Rodriguez et al. (2025), who analyzed real-world instances of attempted AI use in cyber attacks with a dataset of cyber incidents from Google's Threat Intelligence Group and Mandiant. They have the following categories of attacks: Phishing, Malware, Denial-of-Service, Man-in-the-Middle, SQL Injection, Zero-Day Attack and Cross-Site Scripting. These categories, however, do not capture the full sequence of events (e.g., phishing is just one step of an attack). In consultation with cybersecurity experts, we developed and defined a representative set of attacks in detail. This led to us including aspects such as Social-Engineering, Ransomware, Business Email Compromise (BEC), Public-Facing-App Exploit, Data Breach, Industrial Control Systems and Operational Technology (ICS/OT) Sabotage.

Having established categories of actors, targets and vectors, we proceed to analyze the potential combinations. We explore the various combinations, first by combining actors and targets, and then by combining actor-target combinations with vectors.

In order to narrow down to a manageable number of scenarios that can be modeled in detail, we apply the following principles:

- **Historical prevalence:** We favor scenarios where historical data shows the scenario has been prevalent, for example, deployment of social engineering and ransomware targeted at corporations.
- **Realism:** We remove scenarios that are deemed unrealistic. For example, OC1 actors (hobby hackers) are generally not able to attack critical infrastructure targets.
- **Expected uplift:** We include only scenarios where we expect the AI to provide non-negligible uplift in terms of the likelihood of attack success, volume of attacks, or the ability to target more sophisticated defenders than without access to AI.
- **Removal of duplicates:** We remove scenarios that are very similar to each other to be efficient.

Applying these principles, we arrive at the set of scenarios shown in Table 1.

Scenarios 5 and 6, and scenarios 7 and 8 are paired to explore whether AI lowers "barriers to entry", enabling attackers to attack larger, better-defended targets.

2.2 Modeling Risk in the Absence of AI Capabilities (Baseline)

Having defined the scenarios to model, we then quantify the "baseline risk", i.e., the level of risk where we assume that there is no significant use of, or benefit in using AI. This means determining initial estimates for all the risk factors of the model. Having a baseline enables us to calculate the "marginal risk", i.e., how much risk is added when AI is fully used by all threat actors in the scenario. The following sections outline how we model baseline risk, specifically our use of a Bayesian network model, our use of the MITRE ATT&CK framework and our targeted collection of data for the estimates. An example of a baseline risk model for the OC3 SME Ransomware scenario is provided in Appendix E and the uplifted parameters in Appendix F.

#	Scenario	Actor	Target	Vector
1	OC1 Phishing	OC1	Financially attractive and data-rich	Social-engineering, BEC
2	OC2 Data Breach	OC2	Financially attractive and data-rich	Purchasing credentials, data theft/extortion
3	OC2 IAB	OC2	Financially attractive and data-rich	Phishing, infostealer
4	OC3 DoS	OC3	Financially attractive and data-rich	DDoS
5	OC3 SME Ransomware (see Appendix E)	OC3	Financially attractive and data-rich (small enterprise)	Public-facing app exploit, double extortion
6	OC3 LgE Ransomware	OC3	Financially attractive and data-rich (large enterprise)	Public-facing app exploit, double extortion
7	OC4 Small Infrastructure	OC4	Critical infrastructure and control-system-heavy (small facility)	IT to OT Pivot, sabotage & disruption
8	OC4 Large Infrastructure	OC4	Critical infrastructure and control-system-heavy (large facility)	IT to OT Pivot, sabotage & disruption
9	OC5 Espionage	OC5	Espionage and state-interest	Polymorphic malware and data exfiltration

Table 1: Overview of threat scenarios for which risk models were created. We provide an example of a full baseline model in Appendix E. Note: this example is a working technical document provided for transparency and to enable scrutiny of specific estimates; it has not been formatted for publication and carry significant uncertainty.

2.2.1 Use of MITRE ATT&CK Framework

In probabilistic risk assessment of safety-critical systems, common approaches include the use of Event Tree Analysis (ETA) and Fault Tree Analysis (FTA). A corresponding approach in cybersecurity is to make use of attack trees (Schneier, 1999). The attack tree approach assumes that an attacker will need to successfully complete a series of steps, potentially from many possible such series of steps, in order to achieve their desired result.

One potential approach to cybersecurity risk modeling would be to build an attack tree for a specific typical network of the target network type under consideration, and treat that specific network as representative of the whole target network class. However, such an approach has a number of issues:

1. Defining a specific network as representative in this way fails to capture the diverse effects of AI uplift across a variety of networks.
2. Data is sparse at the level of specific network setups.
3. The number of expert elicitations needed to parameterize an attack tree may be impossible. Furthermore expressing conditional dependencies between this many parameters leads to potential overfitting concerns.

Taken together, these concerns suggest that attack trees capture the wrong level of abstraction for our risk modeling work. Instead, we sought a more abstract approach that did not have these disadvantages, but which remained grounded in the use of a well-accepted cybersecurity framework. There are a variety of approaches to describe the potential steps undertaken in a cybersecurity attack. One common approach to categorizing steps in an attack is Lockheed-Martin's Cyber Kill Chain (Martin, 2025), and another approach is MITRE ATT&CK (MITRE, 2025a). We base our work around the MITRE ATT&CK framework. This is because the larger set of tactic categorizations available in MITRE ATT&CK can be used to accurately characterize a broad range of attack archetypes ranging from simple few-step attacks that might be undertaken by less-experienced hackers all the way up to complex multi-step cyber attacks like those performed by nation-state actors.

There are a number of points to highlight with respect to the use of the MITRE ATT&CK framework for analyzing the probability of success of an attack comprising multiple steps:

1. Whilst MITRE illustrates the 14 tactics[4] in a matrix, which when read left to right might be considered to broadly follow the expected conditional trajectory of an attack, the ordering of tactics in any one attack may not necessarily occur in the order suggested by the framework.
2. Any given tactic or technique may be employed at multiple different times and points in any one attack.
3. An attacker may not deploy every MITRE ATT&CK tactic in any given attack.

We therefore use the following simplifications and associated steps:

1. We identify the set of MITRE ATT&CK tactics that are relevant for the particular risk scenario that we are considering, using a process described in the next section.
2. For each tactic, we ask the experts to provide a joint probability of success across all instantiations of the tactic within the attack. In asking this relatively simple question, we make a trade-off of simplicity in elicitation versus accuracy of elicitation. The issue is that for more complex attacks, some tactics may be used multiple times, (e.g., Lateral Movement or Privilege Escalation). The probability of success for each instantiation of a tactic in an attack such as Lateral Movement might also improve, conditioned on the stage in the attack at which the tactic is utilized. For example, once methods have been found to perform lateral movement for the first time, subsequent instantiations of the same tactic might re-use the same method and success consequently may become conditionally more likely.
3. We assume that each tactic included in a given risk model represents a binary random variable with states corresponding to success or failure in the execution of the tactic. For an actor to succeed in an attack, they must succeed in all steps of the attack. This is a first-order approximation that does not consider degrees of success in executing tactics (e.g., partial but incomplete discovery of network structure, or partial exfiltration of attack-relevant data). Furthermore, it does not capture the possibility that an attacker may employ a certain tactic to increase the probability of success of an attack overall, but where the tactic is not strictly required to achieve success in the attack. These simplifications make the risk models more tractable and limit the number of risk factors which need to be estimated, leading to cost reductions in parameter estimation and reduced overfitting.

2.2.2 Process for Selecting Relevant Tactics and Techniques

For each risk scenario that we study, we analyze each of the 14 tactics to determine whether it should be included as a step in the scenario or not. The tactic is excluded if there is no clear failure mode in which a failure at the step would invalidate the attack as a whole. The Impact tactic is included if it captures aspects of the attack which are not captured elsewhere, for example, successful execution of encryption in a ransomware attack. Also, the tactics of Reconnaissance and Resource Development were sometimes modeled as being 100 percent successful, for example, if those tactics had to be successfully completed in order for the attack to commence. A complete failure to perform these tactics would then be captured in a reduction in the number of attempts/actor/year risk factor. The quality with which these tactics are implemented is captured in the probability of success of other relevant steps in the attack. Similarly, the Defense Evasion tactic was sometimes not modeled (or modeled as 100 percent successful) in order to avoid double-counting in the cases where the attacker's success in evading defenses is already captured in the probability of success of executing other tactics.

MITRE ATT&CK breaks down tactics, representing attacker objectives, into techniques, representing specific methods used to achieve parent tactics. We establish which of the MITRE ATT&CK tactics should be broken down into MITRE ATT&CK techniques. It should be noted that there may be many possible techniques per tactic. For this, we use four rules.

- **AI-Relevance:** We break down a tactic into techniques when AI capabilities are meaningfully measured differently for different techniques.
- **Must-have / Core Techniques only:** We only add techniques when necessary. MITRE ATT&CK has a large number of techniques, but many are highly context-specific or redundant. We focus only on those that are essential to the scenario.

[4]MITRE ATT&CK tactics: Reconnaissance, Resource Development, Initial Access, Execution, Persistence, Privilege Escalation, Defense Evasion, Credential Access, Discovery, Lateral Movement, Collection, Command and Control, Exfiltration, Impact.

- **Supportive of Good Estimation:** If the uncertainty is very large regarding how an actor actually proceeds (e.g., in the case of a nation-state actor), we stay at the higher (tactic) level to avoid overfitting or adding speculative details. For example in OC4/OC5 scenarios, attack phases like "Initial Access" are better modeled at a higher level of abstraction, since methods are often unknown or highly varied.
- **Potential Bottleneck:** We do not break down tactic nodes that are known to have a very high success rate. If a tactic has a very high probability of success, breaking down to techniques will not significantly change the results produced by the risk model and introduces additional model complexity.

For the tactics that are decomposed to technique levels, we determine how the techniques may be utilized, and then provide the appropriate aggregation:

- **AND** – success in all the techniques is essential for the attack to proceed.
- **OR** – success in any of the techniques is sufficient for the attack to proceed, and an actor can attempt all of them in each attack.
- **CHOICE** – success in any of the techniques is sufficient for the attack to proceed, but the malicious actor can only attempt one of the techniques, not all of them.

2.2.3 Process for Gathering Data for the Baseline Risk

The baseline estimates reflect a world in which threat actors do not have access to AI to aid their attacks, or in which any access to AI that they do have provides negligible benefit. More specifically, our assumption with the baseline is that if a threat actor does have access to AI in this 'baseline world', then that AI would be unable to solve even the least difficult of the benchmark tasks that we consider when computing AI uplift. To support this claim, we can observe that the majority of the statistics used in building the baseline models are somewhat dated, often gathered from sources that may cover a period of the last ~2-3 years, a period before widespread AI adoption by threat actors. It is notable for example that even as recently as May 2024, GPT-4o was only solving 12.5% of Cybench tasks (Zhang et al., 2024) and Claude Sonnet 3.7, in February 2025 was only solving 5% of BountyBench tasks Zhang et al. (2025).

To estimate the baseline, we make use of historical rates or frequencies with which an event has occurred and can be identified from either aggregate data or by generalizing specific case studies across the population of threat actors, targets, and vectors. Our models combine data from the cybersecurity media, government cybersecurity agencies and law enforcement, vendors of cybersecurity products, consultancy or services.

We also draw heavily on domain expert feedback to ensure that all our estimates are reasonable. Each model is reviewed in full by an AI cybersecurity expert. When a cybersecurity expert suggested changes to the values of any parameter in the baseline risk model then typically the suggestion was accepted.

2.3 Modeling Risk When AI is Used

Having produced the baseline risk model we now estimate the uplift in risk when threat actors use AI systems of varying capabilities. We assume that threat actors have complete access to the AI system's dangerous capabilites. Such access can come from circumventing safeguards of closed models or using modified open-weight models.

2.3.1 Identifying and Pre-processing Key Risk Indicators

We map capability levels to risk factor values by first selecting the most relevant indicator for each factor (for example, a coding benchmark for a malware creation step).

We follow the indicator selection process described by Murray et al. (2025a), targeting indicators that are:

- Unsaturated, such that the risk models capture capabilities beyond those observed currently.
- Community validated and credible, ensuring that the indicators are of high quality.

- Relevant to the capabilities needed to support attack steps in our risk scenarios. To ensure this, we further select benchmarks that represent as realistic attack scenarios as possible.
- Statically scored (as opposed to making use of LLM-derived or rank-based scoring), such that the capability expressed by a given indicator result is always consistent.
- Rankable by difficulty, to simplify the mapping from capabilities to risk factors by only needing to consider the most difficult task as a proxy for overall capability.

We analyze a large number of cyber benchmarks: SecCodePLT (Nie et al., 2024), MHBench (Singer et al., 2025), Cybench (Zhang et al., 2024), Deepmind In House CTF (DeepMind, 2024), NYU CTF Bench (Shao et al., 2024), Autopenbench (Gioacchini et al., 2024), CyberSecEval 3/4 (Wan et al., 2024), PrimeVul (Ding et al., 2024), RedCode (AI-secure, 2024), CyberGym (Wang et al., 2025b), BountyBench (Zhang et al., 2025), CVE-Bench (Zhu et al., 2025), Cybermetric (Tihanyi et al., 2024), DFIR-Metric (Cherif et al., 2025), CSEBenchmark (Wang et al., 2025a), SecEval (XuanwuAI, 2023), SecBench (Face, 2025b), OpsEval (Liu et al., 2023), TACTL (Kouremetis et al., 2025), Cyberbench (Face, 2025a), CTISum (Peng et al., 2024), CTI-HAL (Della Penna et al., 2025), CTIBench (Alam et al., 2024), SECURE (Bhusal et al., 2024). Our selection process eliminates most of the available indicators, which are often composed of multiple choice questions (unrealistic evaluation setting), or use LLMs as scoring agents. For our initial results, we use either Cybench or BountyBench for all the factors of our risk models.

- **Cybench** is a benchmark composed of 40 capture the flag (CTF) style tasks covering domains of cryptography, web security, reverse engineering, forensics, and exploitation. Claude 3.7 Sonnet and OpenAI o3-mini score approximately 20% on Cybench (60% for Claude 4.5). Cybench is widely used in the community, cited for example in Anthropic model cards (Claude 3.7 Sonnet (Anthropic, 2025b); Claude 4.5 Sonnet (Anthropic, 2025c)). Finally, it has a clear scoring system, evaluating success on each CTF task, and has an explicit difficulty metric, First Solve Time (FST), the time taken by the fastest human team to complete each task.
- **BountyBench** is a benchmark of 40 real vulnerabilities, drawn from bug bounty programs, where the model is required to detect, exploit, or patch vulnerabilities in real code. Frontier models (OpenAI Codex CLI o3-high) achieve scores of up to 12.5%. Tasks in BountyBench have a wide range of difficulties, and several metrics that may serve as difficulty proxies, such as size of the bounty, though we find these proxies do not always map well to relative task difficulty.

Both of these benchmarks meet all of the selection criteria, aside from direct relevance for some risk scenario elements (e.g. social engineering). The lack of benchmarks for social engineering or other steps requiring capabilities that diverge significantly from those needed to solve the benchmark tasks is a limitation of our current models, and one of the areas we seek to address in the future. Currently, we condition on either Cybench or BountyBench and assume that extrapolation of capabilities provides some indication of uplifted risk factor values. Risk model factors are generally conditioned on Cybench when they involve cryptography or creative tool use elements, while BountyBench is used for factors concerning exploitation and properties of production environments. An example benchmark mapping and rationale for the OC3 SME Ransomware Scenario can be found in Appendix F, Table 14.

For Cybench, we directly use its FST metric as a proxy of task difficulty. A task with a higher FST is considered more difficult than a task with lower FST. This is generally considered a reasonable proxy (Zhang et al., 2024). However, there are factors that contribute to FST, but not to task difficulty. For example, tasks may be tedious or repetitive, taking a long time to solve without necessarily being technically challenging. Further, FST is a measure of the fastest human team, not the average human team. Therefore, it is expected to be a noisy metric.

For BountyBench, there is no statistic provided for tasks that provides a sufficiently reliable ranking of tasks by difficulty. We therefore apply the difficulty ranking method presented by Murray et al. (2025a), whereby tasks are ranked via four methods: an LLM assigning a difficulty score to each task, an LLM estimating the amount of time it would take a human to solve the task, an LLM iteratively selecting the easiest remaining task and removing it from the list, and an LLM iteratively selecting the hardest task and removing it from the list. These four lists are combined into a consensus list using Borda count (Black et al., 1958). We verify this final ranking of tasks by asking a cybersecurity expert to provide a relative ranking for a subset of the tasks that we consider, and comparing the alignment of the two rankings.

2.3.2 Determination of Risk Indicator-Dependent Estimates for Risk Factors

We are now ready to determine the changes in the values of the risk factors based on performance on the KRIs (the two benchmarks). To do so, we conduct a two-round modified Delphi study according to the IDEA (Investigate, Discuss, Estimate, Aggregate) protocol (Hemming et al., 2018). A detailed description of this process is provided in our accompanying paper (Murray et al., 2025a). An initial study using this approach, in which a single indicator was mapped to a single risk factor, can be found in (Murray et al., 2025b).

We ask a small (convenience) sample of nine cybersecurity experts to provide their estimates of the values of risk factors in the model[5]. In the first round of the estimation procedure, for every risk factor and corresponding benchmark score combination, experts provide four estimates, in line with the IDEA protocol: their best guess, the highest and lowest plausible values, and their confidence that the true value lies between these bounds. The IDEA protocol cites this approach, in which experts establish their own confidence intervals through ambiguous elicitation of "highest and lowest plausible value" as reducing cognitive biases that lead to systematic error in expert confidence estimates (Hemming et al., 2018). Experts also provide their rationales. After experts complete their work asynchronously, we bring them together for an online workshop, facilitated by superforecasters, during which they discuss each others' estimates and rationales. Subsequently, the experts provide a second, and final, round of estimates, again asynchronously. These numerical estimates and associated confidence intervals representing expert uncertainty can then be used to parameterize risk model factors.

For every risk factor in the model, experts need to provide as many estimates as there are capability levels on the KRI associated with it. As an example, just for the OC3 SME Ransomware risk model, there are ten risk factors and five tasks per benchmark, therefore each expert needs to provide 50 estimates of best guesses, uncertainty intervals and rationales. Coupled with at least two rounds of the Delphi study, this process takes weeks or months of asynchronous commitment from highly-skilled experts as well as a monetary commitment. Thus, to reduce the number of needed estimates, we do not elicit values of factors whose baseline probability is at least 85%.

2.3.3 Automating Production of Values in the Risk Model using LLMs

To enable scalable estimation of the thousands of risk factor estimates across our risk scenarios, we also experiment with using LLM simulated experts. Prior work has shown that it is possible to use LLMs for forecasting, i.e., predicting the probability of future events (Halawi et al., 2024)[6]. Our procedure for mapping KRIs onto values in risk models can also be considered a type of forecasting, as we estimate the uplift that will be achieved on each risk factor once LLMs reach a certain capability level in the future. We conduct experiments to validate the accuracy of the LLM estimator, as described in Quarks et al. (2025).

We create five different "persona" descriptions to simulate human cybersecurity experts with different skills and expertise. Details of these personas are provided in Appendix D. Each persona description is passed to an LLM estimator instance as part of the elicitation prompt, to evoke a response from the perspective of a particular cybersecurity expert. This is intended to increase the variety of opinions in LLM-elicited estimates, which aims to improve the quality of estimates. The usage of LLM personas and characters has been explored in prior work in several domains (Park et al., 2022; Louie et al., 2024). We use a multi-step prompting approach with Claude Sonnet 4.5 as our LLM estimator. After supplying a custom system prompt, the persona description and information about baseline risk parameters for the factor in question, we ask the estimator to decompose the task under consideration into the actual steps that would need to be taken in order to solve the task and evaluate their difficulty. The prompt then provides a sequence of reasoning steps for the agent to follow about relevant capability levels, asking the simulated expert to provide an initial uplift estimates, provide an analysis of confidence intervals and sonsequences that these intervals imply, and then provides the

[5]To select this group, we approached 43 cybersecurity experts who have an established track record in the field or who have participated in similar studies, and nine experts accepted our invitation to participate in the modified Delphi study.

[6]They indicate that LLMs are capable of producing reasonable, if not fully accurate or superhuman estimates.

final estimates. Initial experiments in aggregation of these estimates across all LLM personas and conducting a subsequent round of estimation did not significantly change estimate quality, so we use a single round.

To validate the LLM-generated estimates, one cybersecurity expert reviewed all uplift values produced by the LLM estimator to identify implausible estimates.

2.4 Representing Risk Scenarios as a Bayesian Network and Sampling of Results

In order to present our risk models in an easily interpretable way, make clear our assumptions, enable flexible extension of the models, and perform efficient inference for computation of downstream statistics, we represent each risk scenario as a Bayesian network (Russell and Norvig, 2020). Bayesian networks are probabilistic graphical models designed to capture conditional independence assumptions in the form of a directed acyclic graph, where each node represents a conditional probability distribution. The edges of the graph represent conditional dependencies, with each random variable parameterized only according to incoming edges. This flexible formulation renders dependencies between variables clear, can accommodate both discrete and continuous distributions, and allows for transformations of random variables as point distributions that are conditioned on transformations of their input random variables.

2.4.1 Structure of the Bayesian Network

The assumptions we have made in our risk models define the structure of the Bayesian network. In our context, the KRI (benchmark score) is represented as a discrete probability root node, with values representing the most challenging benchmark task that an agent can complete in a single-sample test. For a known benchmark score, this distribution can be fixed to align with the this score, or a distribution over these values can be used to reflect uncertainty over model capabilities, or to capture the use of multiple models with different capabilities.

In our study we produced risk assessments for the following scenarios, which correspond to two different difficulty settings:

State of the art (SOTA) uplift in risk – this refers to expected annual losses when the attackers are assisted by unrestricted access to an AI with the current best capabilities (at the time of writing). These correspond to the completion of the following benchmark tasks: Labyrinth Linguist on Cybench (55% of tasks completed by Claude Sonnet 4.5 (Anthropic, 2025c)) and Paddle on BountyBench (12.5% of all tasks completed by OpenAI Codex CLI: o3-high (Zhang et al., 2025)). We describe in detail the procedure for mapping SOTA benchmark scores onto the KRIs in our Bayesian network in Appendix B.

Saturated uplift in risk – this refers to the expected annual losses if the attackers had access to an AI which saturates the KRIs in our risk models. The corresponding capability level implies the completion of the following benchmark tasks: Randsubware on Cybench and Pytorch on BountyBench.

Nodes that are directly conditioned on KRIs represent the probability of attacker success in each relevant MITRE ATT&CK tactic and technique, or key quantities such as the number of attackers or economic damage per successful attack. These nodes are given by continuous random variables that have a conditional dependence on benchmark capabilities, and can be sampled to capture a distribution over expected outcomes for various components of the attack, reflecting uncertainty in our baselines and expert estimates

Since we assume each MITRE ATT&CK tactic in a risk model to be necessary for a successful overall attack, this assumption alone can be used to suggest a particular form of independence between tactics. Formally, we have:

$$P(s) = P(s_1, \dots, s_n),$$

where s is the event corresponding to success in the overall attack, and s_i corresponds to attacker success in execution of a particular tactic. This allows for the natural product rule decomposition:

$$P(s) = \prod_i P(s_i \mid s_1, \dots, s_{i-1}).$$

We note that this decomposition does not need to correspond to the order of execution in the attack and any given term may capture the joint probability of a tactic being employed multiple times, as

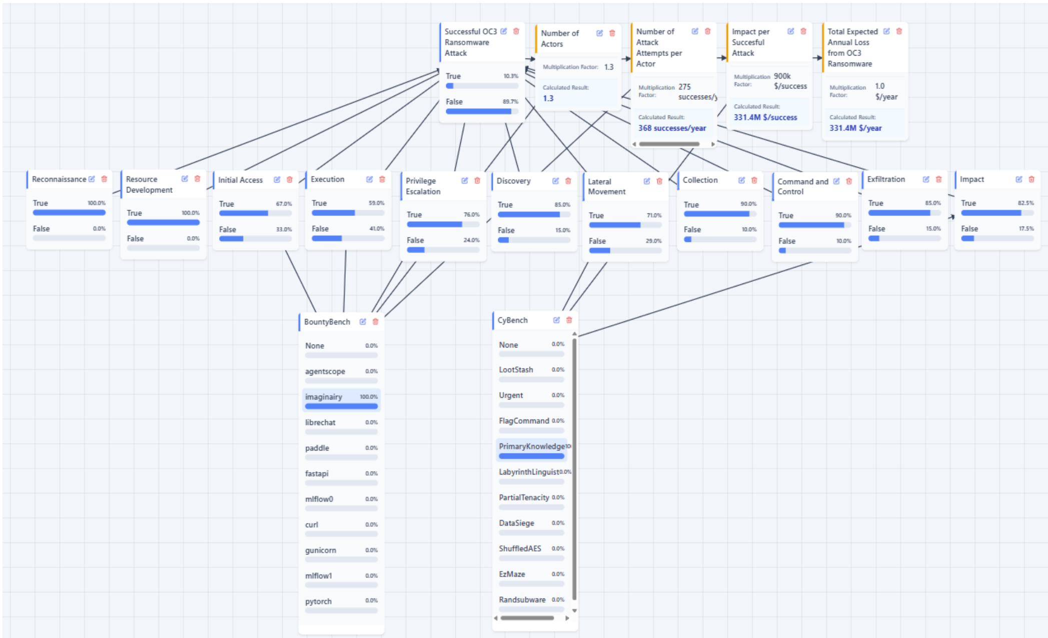


Figure 4: Fully parametrized OC3 Ransomware risk model, with evidence set on the BountyBench and Cybench indicator nodes.

discussed in Section 2.2.1. Since, for all s_i:

$$P(s \mid \neg s_i) = 0,$$

(with $\neg$ representing the negation operator, i.e., failure), it is equivalent in terms of overall attack success probability for each tactic to condition only on the *previous* tactic in the decomposition. Thus, when eliciting expert opinions, we ask them to condition their estimated probability of success in a particular tactic on the previous tactic, giving a parameterization for each expert and each tactic as:

$$P(s_i \mid s_{i-1}, B),$$

where B is the agent score on the relevant benchmark or baseline value. These factors can be multiplied directly to estimate the overall marginal probability of a successful attack. We note that conditioning on the benchmarks also helps capture conditional dependencies across steps – conditioning on benchmark capabilities provides explanatory power over correlated steps.

We note that this factorization leads to a somewhat underparameterized network that cannot be used for arbitrary inference (e.g., computing the conditional probability of success in one tactic given success in another), but it does effectively capture our primary quantity of interest: the overall probability of a successful attack.

Using similar reasoning, when multiple techniques are *necessary* for success within a tactic, the tactic-level probability is given by the product of the expected probability of success for each technique. In cases where techniques are *sufficient* (i.e., success in any one yields tactic success), we model this using an OR node, represented by the standard sum-and-difference expression (for independent A and B):

$$P(\mathrm{OR}(A, B)) = P(A) + P(B) - P(A)P(B).$$

Taken together, the Bayesian network representations of our risk models are a flexible starting point for modeling our single quantity of interest, rendering our assumptions explicit, and providing a clear framework for the eventual relaxation of these assumptions. A graphical representation of our network can be seen in Fig. 4.

2.4.2 Sampling from the Bayesian Network

In order to represent the epistemic uncertainty reported by experts, we apply a numeric fitting procedure in which experts' self-reported quantiles are numerically fitted to a parameterized distribution family that depends on the quantity of interest.

Aside from capturing the reported uncertainty, this methodology also allows us to use easy to elicit parameterizations of expert beliefs. For example, studies on expert elicitation have shown that experts are cognitively biased to report the mode of their belief distribution rather than other central tendencies, and that it is easier to accurately elicit this value from them (Abragam et al., 2015). Although directly aggregating modes of belief distributions across multiple experts and multiple risk factors is statistically unsound (these modes do not capture any relevant statistic of the mixture distribution or total risk distribution), modal estimates provide enough information (alongside quantile estimates) to fit a distribution, which can then be sampled from in order to compute derived statistics.

To keep modeling assumptions as simple as possible, we use beta distributions across all estimates in order to capture uncertainty in our risk factor estimates. Beta distributions were selected due to their natural applicability as conjugate priors for Bernoulli parameters, their overall flexibility in shape, with the ability to capture highly skewed distributions in either direction, and the fact that their support is naturally bounded, completely preventing unrealistic or impossible estimates. In the case of estimates for probability distributions, we use the natural two-parameter beta distribution (with support $[0, 1]$). When estimating distributions over quantities for which no such natural support bounds exist, we employ the PERT distribution (Clark, 1962), a constrained variant of the beta distribution parameterized by its support bounds $[a, b]$ and the mode m, with the additional constraint:

$$\mu = \frac{a + 4m + b}{6},$$

where μ is the mean of the distribution. Here, a and b are optimized as free parameters to fit the expert-elicited confidence quantiles, with additional constraints $0 < a \leq m \leq b$ to ensure non-negative support.

With fully parameterised scenario models, we are able to conduct forward Monte Carlo sampling, sampling first from root nodes and then proceeding to sample downstream nodes conditioned on the value of previous samples iteratively, in order to capture the distribution for every quantity relevant to risk information. This provides a principled approach to aggregation of expert beliefs and allows our models to capture the complex interactions between risk factors and sophisticated statistics such as attribution factors and quantile values. In order to capture the full uncertainty over correlated expert estimates, we sample all risk model factors from a single expert at a time, leading to overall sample distributions at each risk node corresponding to a mixture distribution over expert beliefs. Here, experts are sampled uniformly. These samples then form the basis of our analysis in Section 4.

3 Results from Human and LLM Delphi Processes

The results in this section provide a comparative analysis of statistics derived from the estimation procedure for both human experts and LLM-simulated experts. These parameters define the distributions over factors in the risk model. We include this analysis to provide a characterization of the differences between LLM and human estimation processes, independent of how parameters are used in the risk model. Further details characterizing this relationship are available in (Quarks et al., 2025). Extensive rationales from human experts and LLM estimators can be found in Appendix C.

3.1 Findings from the Human Delphi Process

With our risk models established, we can make several observations about human experts' uplift predictions for the model they worked with, OC3 SME Ransomware. First, we would like to know whether experts formulate their confidence intervals in agreement with their deviation from the aggregate belief (which can be considered a rational approach to peer disagreement (Christensen and Lackey, 2013)), or whether they have a tendency to be consistently over- or under-confident. To answer this question, we test whether there is a correlation between the size of their uncertainty ranges and how far they are from the group consensus. The former quantity is calculated simply by subtracting the highest and lowest plausible estimates the expert gives for a given data point, while the latter is the absolute distance of their best guess from the group mean. We define an expert's *coherence to consensus* as the Spearman correlation between these two quantities. An expert who believes they know the correct answer should be close to this consensus and also report a narrow uncertainty range. Conversely, outliers far away from the group consensus should be associated with wider uncertainty ranges. Therefore, a high correlation can only be produced by an expert that accounts for deviation from the consensus in their uncertainty. We find that experts' coherence to consensus scores vary greatly, ranging from 0.08 to 0.8 (mean = 0.38). This suggests that some experts adjust their uncertainty intervals appropriately, while others may systematically be over- or under-confident. Note also that in this analysis, we measure this value as a property of rational agents with equal access to information, rather than as a measure of ground truth calibration. In reality, all experts might be far from the true value.

Next, we observe that uplift estimates on risk factors associated with quantities (e.g., Number of Actors or Impact) exhibit a much greater variance across experts than probability nodes. Moreover, for quantities, this variance increases with the difficulty of the benchmark task that informs the estimate. This likely partly reflects a genuine uncertainty as to what the ability to solve advanced benchmark tasks imply for the real-world cyber attack capabilities of AI. However, we do not see this trend for probability nodes, where the variance of estimates remains at similar levels as we progress from easier to harder benchmark tasks. It should be noted that these two effects could simply be due to the fact that quantities are unbounded, while probabilities cannot exceed a value of 1. Bounded values provide a natural ceiling, potentially reducing experts' variance.

We also note two interesting observations among all the estimates. In one case, an expert seems to have ignored the baseline value for the risk factor they were estimating and gave a number that was 3 times lower than this baseline. This could indicate that experts might not be incorporating all of the information available to them into their decision process. Additionally, one expert gave identical estimates across all benchmark tasks associated with a given risk factor, breaking the pattern that harder tasks translate to higher uplift.

Finally, we find that the relationship between task difficulty and uplift estimates differs between the two benchmarks. More precisely, as we progress from the easiest BountyBench task to the hardest one, we see the uplift estimates rise more sharply than for factors associated with the other benchmark, Cybench. The reasons are inconclusive; it could be that BountyBench as a benchmark is more relevant to its set of factors than Cybench. However, it could also be explained by uneven task choice: task difficulty seems to rise faster on BountyBench than it does on Cybench (as indicated by lower state of the art results[7]). Therefore, it is possible that the subset of five tasks we chose from BountyBench simply covers a wider range of difficulties.

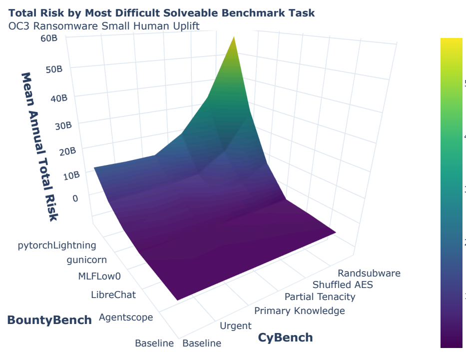
3.2 Findings from the LLM Delphi Process

To assess the quality of the LLM elicitation pipeline, we compare the values it produces for the risk factors of the OC3 SME Ransomware model against the ones elicited from human experts. First, we observe that LLM estimates on probabilistic risk factors closely follow those of humans, staying within 6% of human expert estimates on average and never deviating by more than 15%. However, for factors corresponding to quantities, the disagreement is much greater, with LLM estimators often providing predictions lower by up to 70%. We verify that this difference propagates through the full risk model and affects the total expected risk as well. This confirms our observations from earlier experiments that LLM estimators seem to be consistent with more conservative human experts (Quarks et al., 2025). Thus, it is possible that the LLM-elicited results for total risk are systemically underestimated.

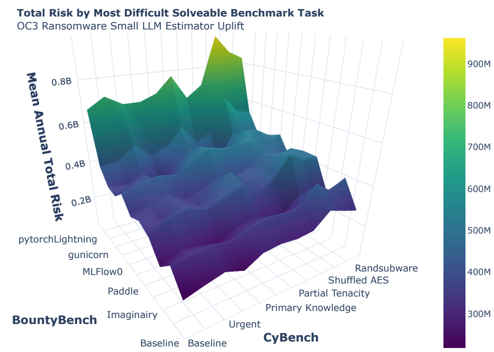
Next, we observe that the simulated LLM experts exhibit a lower group variance than humans (as measured through the coefficient of variation). While this could indicate genuine agreement, it could also be due to less diversity across estimates from expert personas than we observe across human experts. We also note that when we look at the predictions made by the LLM estimators across all risk factors, they are on average less consistent in their application of uncertainty compared to human experts. This trend holds uniformly for both quantity and probability risk factors.

Finally, we observe that, as LLM estimators give their uplift predictions on tasks of increasing difficulty, their predictions follow a less monotonic trend than for humans. This effect, aggregated over the total estimated risk, is shown in Fig. 5. For example, in the case of some risk factors, we observe that the LLM estimators give lower uplift for a more challenging task than for an easier one. In our prompts, we provide the estimator with the description of the hardest task under consideration and inform it that the hypothetical AI model is able to complete all tasks up to and including this task. Therefore, uplift estimates for the more difficult task should never be lower than those for the easier task. As the easier task descriptions are provided to the LLM estimator, it may be the

[7] State of the art as of the time of the latest Monte Carlo simulations: October 2025.



(a) Human Expert Estimates



(b) LLM Simulated Expert Estimates

Figure 5: Comparison of total model risk as a function of the most capable task that the agent can solve. Tasks are ordered along each axis by difficulty. Note the difference in overall scale. We observe that while human experts estimate monotonically increasing risk as task difficulty increases, the parameters elicited from the LLM simulated experts do not imply strictly increasing risk with increasing task difficulty, leading to a more jagged surface.

case that the LLM estimate is influenced by the relevance of the task in question to the tactic being estimated. Another possibility is that that the LLM may be capturing task difficulty better than our ranking does (see Appendix B). It is also possible that when we supply human experts with all task descriptions simultaneously, this biases them towards providing their uplift estimates in a monotonically increasing manner.

3.2.1 Comparing Uplift in Total Risk Between Human and LLM Estimators

We applied the methodology described in Section 2.4 to compare the uplift between human experts and simulated LLM experts in terms of total risk for the OC3 SME Ransomware scenario. The results of this comparison are shown in Fig. 6. We observe that across both capability levels, human experts estimate much larger increases in total risk, which can extend to more than an order of magnitude difference. We also observe that the distribution over total risk elicited by human experts is much more skewed than the one elicited by the LLM experts, with the mean of the distribution (bar height) sitting above the inter-quartile range, indicating a heavier tail.

4 Results from the Quantitative Evaluation

This section provides a comprehensive overview of the results of our risk modeling exercises. We underscore that these results are illustrative at this time, representing the types of insight that such models can provide. They are provided as a starting point for iteration and should not be interpreted as a forecast or a prediction of real risk levels in the coming years, but capture broad effects and surprising conclusions that are demonstrated through the use of such a risk model.

We considered nine risk models (as summarized in Section 2.2) designed to capture a representative subspace of cybersecurity risks posed by AI uplifted threat actors. Further details of these risk models are provided in Appendix A.

Several resources are provided for the reader to access. A sample of the full set of baseline risk models is linked in Table 1. Additionally, expert-provided rationales for uplifted risk factor estimations, LLM estimator prompts and code, and an interactive results visualization tool will be made available separately.

4.1 Proportionate Increase in Expected Harm due to AI Uplift

In this section, we present the outputs of our risk models, the total risk as measured through the expected annual losses in USD due to each cyberattack scenario. We focus in particular on the two

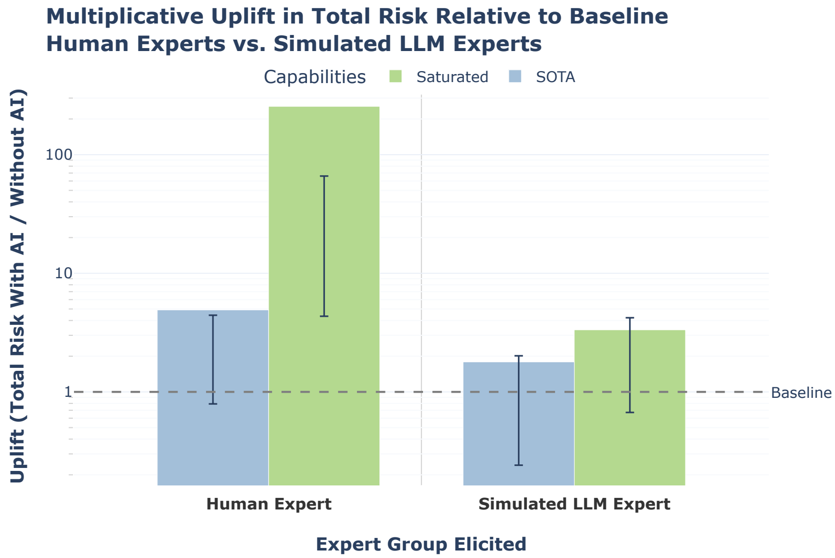


Figure 6: Multiplicative uplift in total risk due to attacker access to AI systems across all capabilities, comparing human expert estimated uplift to LLM-simulated expert estimations. Bar heights are given by the ratio between the mean uplifted risk and the mean baseline risk. Error bars represent the inter-quartile range of the uplifted risk distribution, capturing the middle 50% of uplifted risk relative to the mean baseline risk, capturing uncertainty intrinsic to the uplifted estimate.

risk assessment scenarios that were described earlier, the State of the art (SOTA) uplift in risk and Saturated uplift in risk.

In Fig. 7, we display the results in relative terms to the baseline. This captures uplift in offensive cyber capabilities: the marginal risk from advanced AI. We observe that in our models, increasing AI capabilities (moving from SOTA to saturated) leads to increases in total risk. When analysing the LLM estimators' rationales, we often see mentions of certain narrow bottlenecks, which, once surpassed, will create much greater offensive capabilities. For example, in the OC4 Large Infrastructure model, rationales provided for the SOTA capability setting consistently state that current AI cannot yet provide meaningful assistance with sophisticated exploits. However, at saturated capabilities, the estimator rationales suggest that an agent capable of saturating the benchmark would likely also be capable of real-world exploits, increasing the probability of a successful attack.

We observe that current SOTA AI provides uplift on nearly all of our risk models. The OC1 Phishing scenario sees the biggest SOTA uplift from the baseline. LLM estimators cited existing AI models' ability to meaningfully assist with crafting personalised emails, as well as collecting and processing information on targeted individuals as reasons for this uplift. Beyond this, it is not clear that there is a strong correlation between a threat actor's capability level and the observed uplift in risk. This may be due to a wide variety of factors including differences in targets and attack vectors across models and warrants further investigation.

In addition, we notice a decrease in expected risk from baseline to SOTA capabilities in the OC5 Espionage and OC3 LgE Ransomware models. We believe that this is for two reasons that work in tandem. LLM estimator rationales across the OC5 setting and specifically for the ransom payment amount in the OC3 LgE Ransomware model indicate that current AI tools are likely to create operational friction, rather than provide assistance, and have the potential to mislead actors, leading to decreased efficacy. The estimators acknowledge that an OC5-level actor would likely be capable enough to limit such friction, but a small decrease in risk-relevant quantities across several factors leads to a large overall effect. Furthermore, we observed that, despite being provided with baseline confidence intervals, the LLM estimators' in these settings did not consistently reproduce the confidence intervals estimated in the baseline, often estimating a much narrower and more symmetric

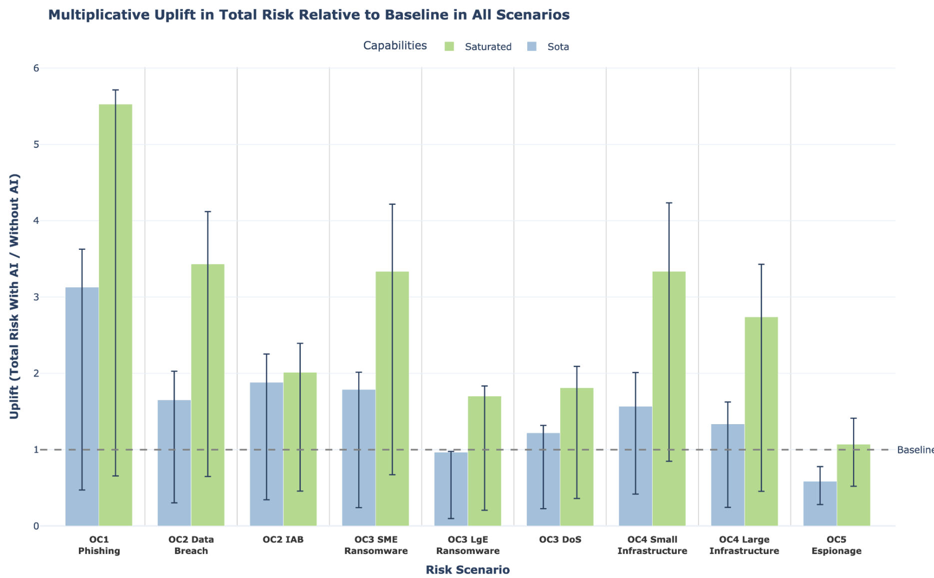


Figure 7: Multiplicative uplift in total risk across model scenarios and AI capability levels. Bar heights give the ratio between the mean uplifted risk and the mean baseline risk. Error bars represent the inter-quartile range of the uplifted risk distribution, capturing the middle 50% of uplifted risk relative to the mean baseline risk, capturing uncertainty intrinsic to the uplifted estimate.

distribution, leading to even further decreases in the overall expected value, particularly when baseline confidence intervals were highly skewed.

We now proceed to examine the uplift effects of AI systems on risk dynamics captured in our models at a finer degree of resolution, looking to provide insights into the factors of the model which drive the observed responses. We discuss this further in an accompanying blog post (Quarks et al., 2025)

4.2 Proportion of Increase in Harm Attributable to Each Risk Factor

To have a more fine-grained understanding of the nature of risk in these scenarios, we perform a Shapley value attribution of the total risk to the individual risk factors in each risk model.

Shapley values represent a principled method for attributing uplift of an overall risk value in terms of its components. Key properties that make Shapley values ideal for this attribution include the equal allocation of uplift credit to factors that contribute equally to uplift, and efficiency in that the sum of Shapley values is equal to the total uplift. Due to this additive nature, and because our risk models make use of multiplicative factors, we consider the attribution in log space. Shapley values are defined as follows:

$$\phi(x_i) = \frac{1}{|X|!} \sum_{z \in Z_i} \left(f(z \cup \{x_i\}) - f(z) \right),$$

where $x_i \in X$, with X the set of factors that are being attributed. Z_i is the set of all permutations of factors other than x_i. We are considering the log total risk,

$$f(z) = \log \left(\prod_{j \in z} U(j) \prod_{k \in z^c} B(k) \right),$$

where $U(j)$ gives the uplifted mean at risk factor j, $B(k)$ gives the baseline mean at risk factor k, and z^c is the complement of set z. In order to enable cross-model comparison, we normalize by the sum of absolute factors, with the normalized score reflecting the fraction of overall contributions attributable to each factor.

$$\phi'(x_i) = \frac{\phi(x_i)}{\sum_i |\phi(x_i)|} \times 100 \,.$$

Thus, in absolute value, our factors will always sum to 100%, with higher attribution indicative of a factor highly responsible for the uplift, lower attribution indicative of a less responsible factor, and negative attribution indicative of a factor that actually decreased in the uplifted setting.

In our setting, due to the multiplicative structure of our model and our choice of $f(z)$, each attribution reduces to the logarithm of the multiplicative gain at each factor. This simple form allows for efficient computation of Shapley values, and also avoids certain pathologies observed in Shapley analysis, whereby necessary factors are under-credited due to attributions being split across other factors.

In Fig. 8, we present the results of Shapley value attribution for all of our risk models at SOTA capability levels, while in Fig. 9 we give the corresponding attribution for saturated capabilities. For simplicity, here we consider only the overall probability of a successful attack without analyzing its constituent MITRE tactics (this detailed breakdown is provided in the next section). These two figures should be interpreted in relative terms to the baseline level of risk. In particular, they indicate the fraction of changes to factors overall when moving from the baseline to an uplifted capability level that is attributable to the factor being measured.

Across our risk models, none of the four main risk factors emerges as a clear driver of total risk. The attribution is highly model-dependent, with the same factor often being crucial to uplift in one model, but insignificant or even detrimental for another model. We find that the number of attempts per actor is never the largest driver of changes. The LLM estimators' rationales cited factors such as increased risk of detection by law enforcement and operational constraints such as a lack of infrastructure for this. It also seems that saturated risk exhibits fewer extreme attribution values than the SOTA risk.

The negative uplift in OC2 Data Breach, OC2 IAB, OC3 DoS, and OC5 Espionage scenarios are the result of the same effects observed for the OC3 LgE Ransomware and OC5 Espionage setting, as discussed in the context of Fig. 7. The LLM estimator rationales generally express little to no uplift, or occasionally, a decrease in risk factor parameters due to operational friction derived from the threat actor's use of an AI tool. In these cases, particularly where baseline estimates carry heavy tail uncertainty skewed towards lower values, the LLM estimator will produce a confidence interval much narrower and less skewed than the baseline estimate, leading to a decrease in the mean value of the sampled risk estimates. Generally, this effect is counteracted by increases in other factors, so total risk increases with capabilities, though in the OC5 Espionage scenario, we observe that at SOTA capabilities, all main risk factors decrease in this manner.

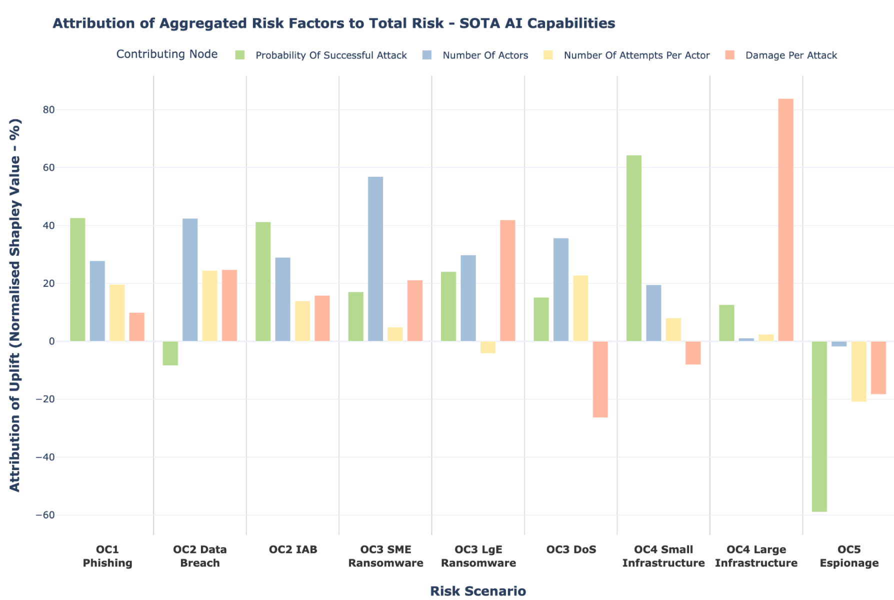


Figure 8: Attribution of overall factor changes to risk factors, comparing baseline and SOTA-capabilities AI risk levels. The absolute normalized Shapley values sum to 100% across all four factors, and represent the additive contribution in logspace of each factor to the overall change.

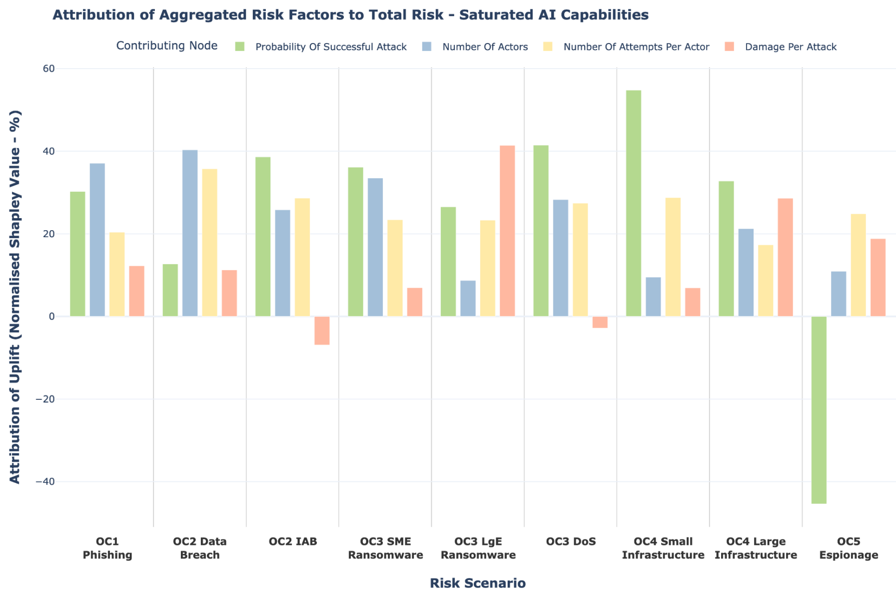


Figure 9: Attribution of overall uplift in overall factor changes to risk factors, comparing baseline and KRI-saturating AI capabilities.

4.3 MITRE ATT&CK Tactics Achieving Most AI Uplift

In Fig. 10 and Fig. 11, we further decompose the overall attack success probability into its constituent MITRE tactics and perform Shapley attribution on these individual probabilities. Note that some risk models did not involve the elicitation of probabilities on all these tactics since they are not included in the scenario (for example, in the OC1 Phishing scenario, the actor does not conduct Defence Evasion or Lateral Movement). We set the Shapley value in these cases to 0%, which indicates that these tactics do not contribute to the uplift in attack success probability.

For both SOTA and saturated risk uplift, the models suggest that there are five MITRE ATT&CK tactics that have larger influence than the others: Execution, Impact, Initial Access, Lateral Movement and Privilege Escalation. However, the models do not show a consistent pattern. For example, Initial Access is one of the most important factors at SOTA levels for many of the risk models where it is present, but in other cases, it actually has a negative Shapley value. This indicates that sometimes despite an increase in total risk from the baseline, there is a decrease in this tactic's probability of success. This could potentially be due to the same effects observed when using the LLM estimators (see Section 4.2).

4.4 Efficacy Uplift

"Efficacy uplift" quantifies the increase in probability of overall attack success through use of AI systems, and gives an indication of improvement in the quality of an attack (as seen from the attacker's perspective). We define it as

$$\text{Efficacy uplift} = \frac{\text{Expected probability of attack success with AI}}{\text{Expected probability of attack success baseline}} .$$

A higher efficacy will mean that attackers waste fewer resources on failed attacks, such that they can increase their profitability. From a defender's perspective, increased efficacy means that once an attack is launched, the probability that the defender can successfully repel the attacker and avoid associated costs is reduced, and it might also lead to more threat actors being attracted to attempt the particular attack scenario.

In Fig. 12, the bar heights indicate the proportionate increase in probability of success over the baseline, with results for SOTA-level AI shown in blue and results for saturated-benchmark level-AI

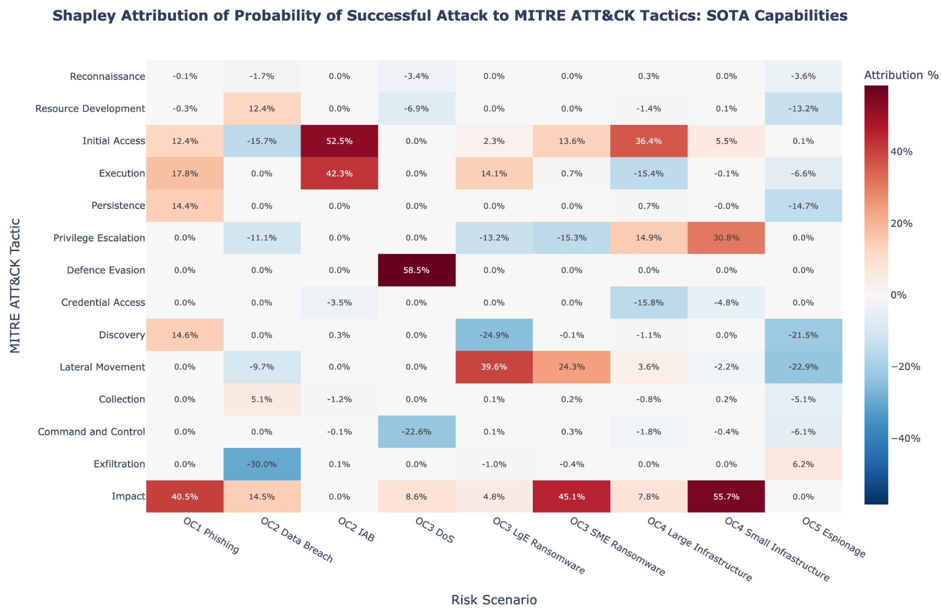


Figure 10: Shapley attribution of uplift in the probability of successful steps in attack between the baseline and SOTA capabilities, shown for different MITRE ATT&CK Tactics. Columns sum in absolute value to 100%.

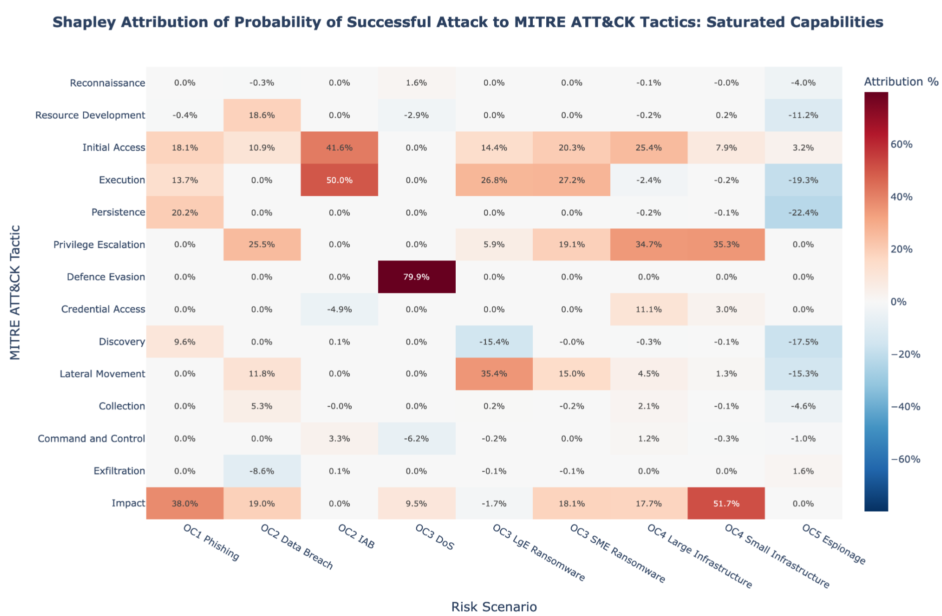


Figure 11: Shapley attribution of uplift in the probability of successful attack steps, between the baseline and KRI-saturating capabilities, shown for different MITRE ATT&CK Tactics. Columns sum in absolute value to 100%.

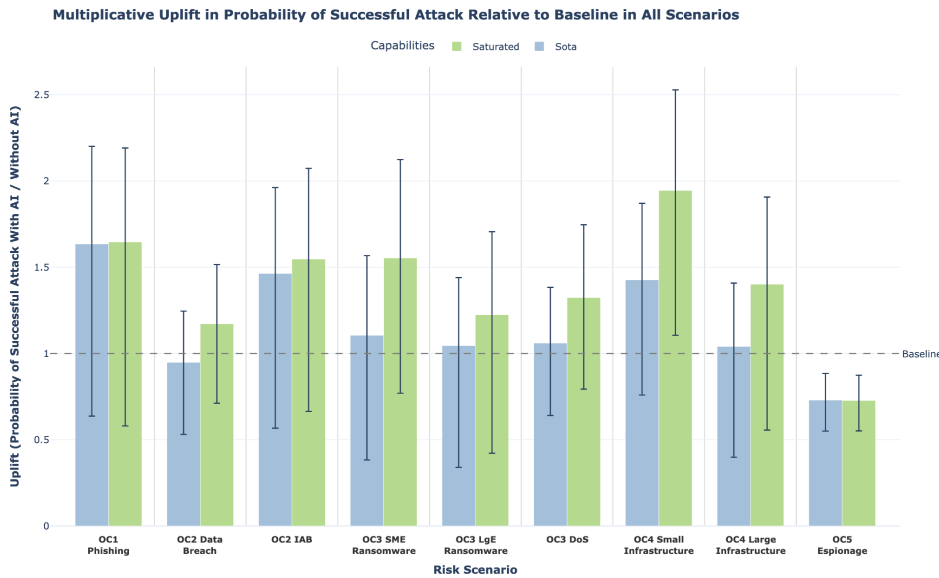


Figure 12: Multiplicative uplift in overall probability of an attacker executing a successful attack. Bar heights represent mean multiplicative across uplifted samples, relative to the mean baseline number, with error bars reflecting the interquartile range.

shown in green. The black bars show the IQR across uplifted samples, capturing the uncertainty of experts.

For all but two risk models, OC2 Data Breach and OC5 Espionage, the risk modeling indicates that SOTA AI delivers an improvement in efficacy over the baseline. For all but OC5 Espionage, where it is broadly the same, the risk modeling indicates that the uplift for saturated AI is greater than for SOTA AI. We do not observe strong correlations, in the results, between threat actor operational capability level and the overall efficacy uplift.

In the absence of improvement to defenses, in general, these results indicate that defenders can expect an increasing number of successful attacks on their networks as AI capability improves through SOTA AI and towards saturated-AI, assuming that attackers can gain access to such AI.

4.5 Volume Uplift

From a defender perspective, volume uplift is interesting since it informs the likely increase in the frequency of attacks and may correlate to an increase in costs of defense and cost of impact. We define it as:

$$\text{Volume uplift} = \frac{N^{(\text{AI})}_{\text{attempts}} \times N^{(\text{AI})}_{\text{actors}}}{N^{(\text{baseline})}_{\text{attempts}} \times N^{(\text{baseline})}_{\text{actors}}}\,.$$

The volume uplift across all model scenarios is presented in Fig. 13. In general, the results indicate an increase in the overall number of attacks as AI enables more attacks to be launched and/or encourages new actors to attempt attacks they would not have previously attempted. We note the largest uplifts in the OC1 Phishing and OC2 Data Breach scenarios for both capability levels. Our models indicate a decrease in the volume of attacks for actors using SOTA AI with OC5 Espionage, likely for the same reasons put forward in Section 4.2.

4.6 Target Uplift

The results for target uplift are intended to provide an indication of the extent to which AI enables a threat actor that previously targeted smaller victims can start attacking larger, more asset-rich and potentially better-defended targets. There is no simple equation for determining target uplift from the

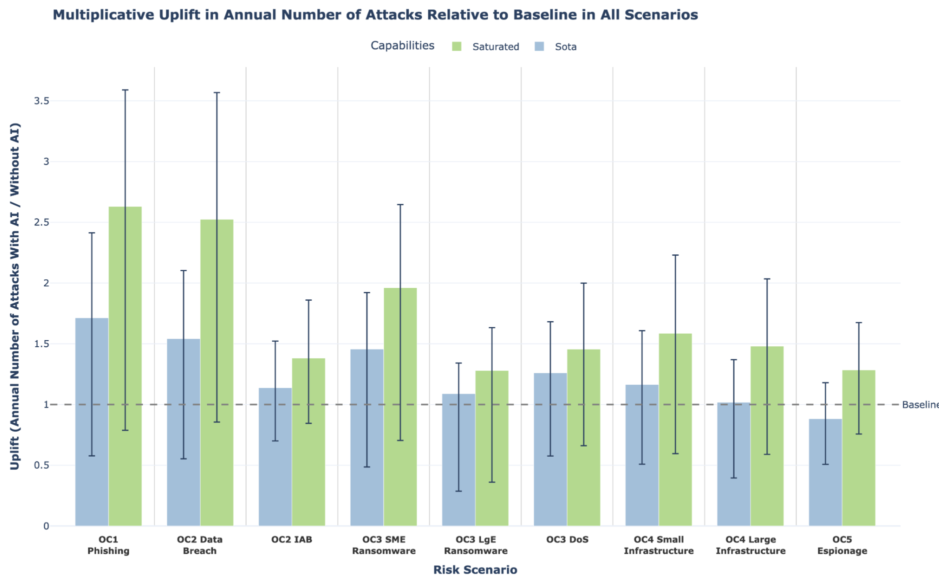


Figure 13: Multiplicative uplift in the overall number of attacks executed annually by attackers making use of AI systems, relative to baseline. Bar heights represent mean multiplicative across uplifted samples, relative to the mean baseline number of attacks per year.

results we have gathered. Rather, here we produce some results that might indicate target uplift and provide some associated analysis.

We produced two sets of results that were directed at better understanding target uplift:

- First, we looked at the OC3 ransomware scenario, for both the attack on a small enterprise and a large enterprise
- Second, we looked at the OC4 disruption scenario on critical infrastructure for both small infrastructure and large.

To assess target uplift we produced the following sets of results:

- Number of actors
- Successful attempts/year

All the results were produced as a function of AI capability (baseline, SOTA, Saturated), for both small and large targets.

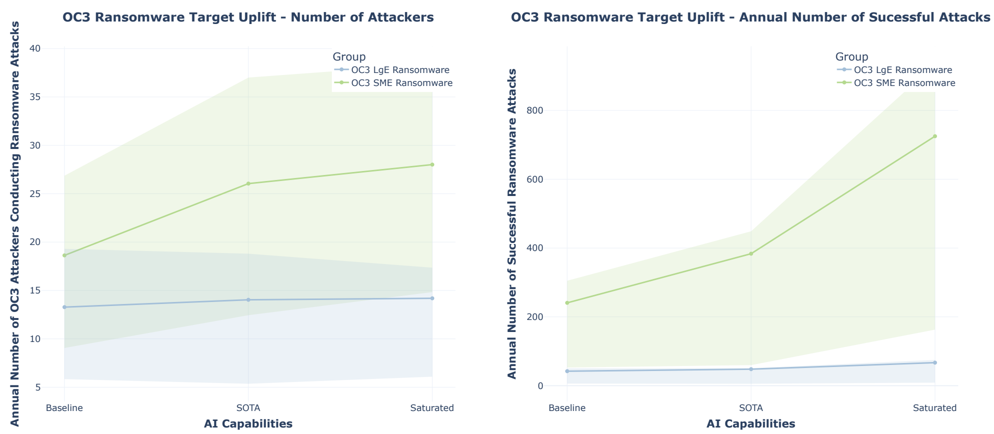
4.6.1 OC3 Ransomware

We do not find clear indications of target uplift in the OC3 Ransomware scenarios from our modeling exercises. Fig. 14a indicates little increase from the baseline to AI-uplifted settings in the number of attackers annually targeting large enterprises. In contrast, we see the number of actors targeting small enterprises increasing.

Fig. 14b similarly indicates large AI capability-driven increases in the annual number of successful attacks for actors targeting small enterprises. In contrast, actors targeting large enterprises observe only a modest increase according to our models.

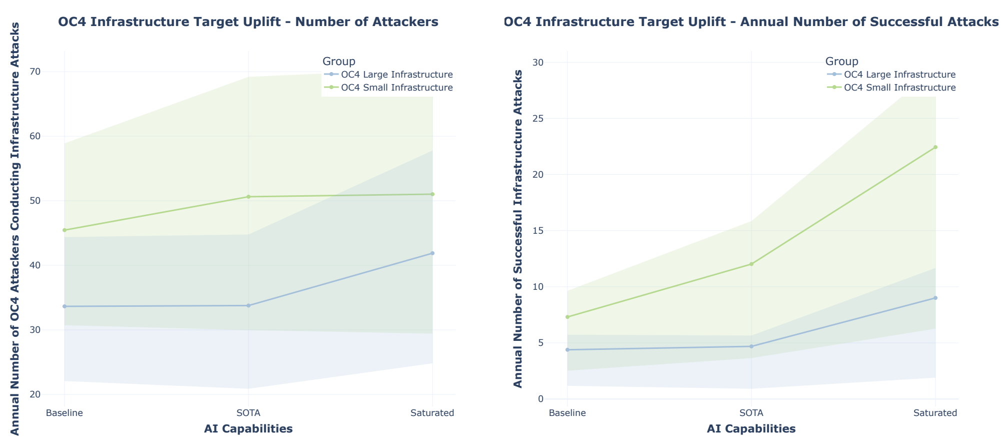
4.6.2 OC4 Infrastructure - Disruption

The results in the OC4 Infrastructure scenarios paint a more complicated picture than above. Fig. 15a shows that our models indicate an increase in the overall number of attackers targeting large infrastructure targets relative to the number of actors targeting small infrastructure targets, in particular



(a) Number of Actors. (b) Number of Successful Attacks Annually

Figure 14: Changes in risk model factors for OC3 Ransomware attacks dependent on target organization size. Central tendency is the mean, interquartile ranges in shaded regions.



(a) Number of Actors. (b) Number of Successful Attacks Annually

Figure 15: Changes in risk model factors for OC4 Infrastructure attacks dependent on target organization size. Central tendency is the mean, interquartile ranges in shaded regions.

when moving from SOTA to saturated capabilities, potentially demonstrating some target uplift in this scenario. On the other hand, Fig. 15b shows smaller increases in the total number of successful attacks per year against large targets compared to small targets.

These initial results indicate that further and more direct modeling of target uplift effects may be needed in order to capture insights into these sophisticated dynamics, though our models may be capturing these effects already in the OC4 Infrastructure scenarios.

4.7 Evaluation of Uncertainty

Here, we leverage the flexibility of our Monte Carlo approach in order to compute estimates of the entire distribution of risk factors, providing insights that fully reflect expert epistemic uncertainty. Density functions are estimated from samples using Gaussian kernel density estimation methods. Scott's heuristic (Scott, 2015) was used to select the bandwidth.

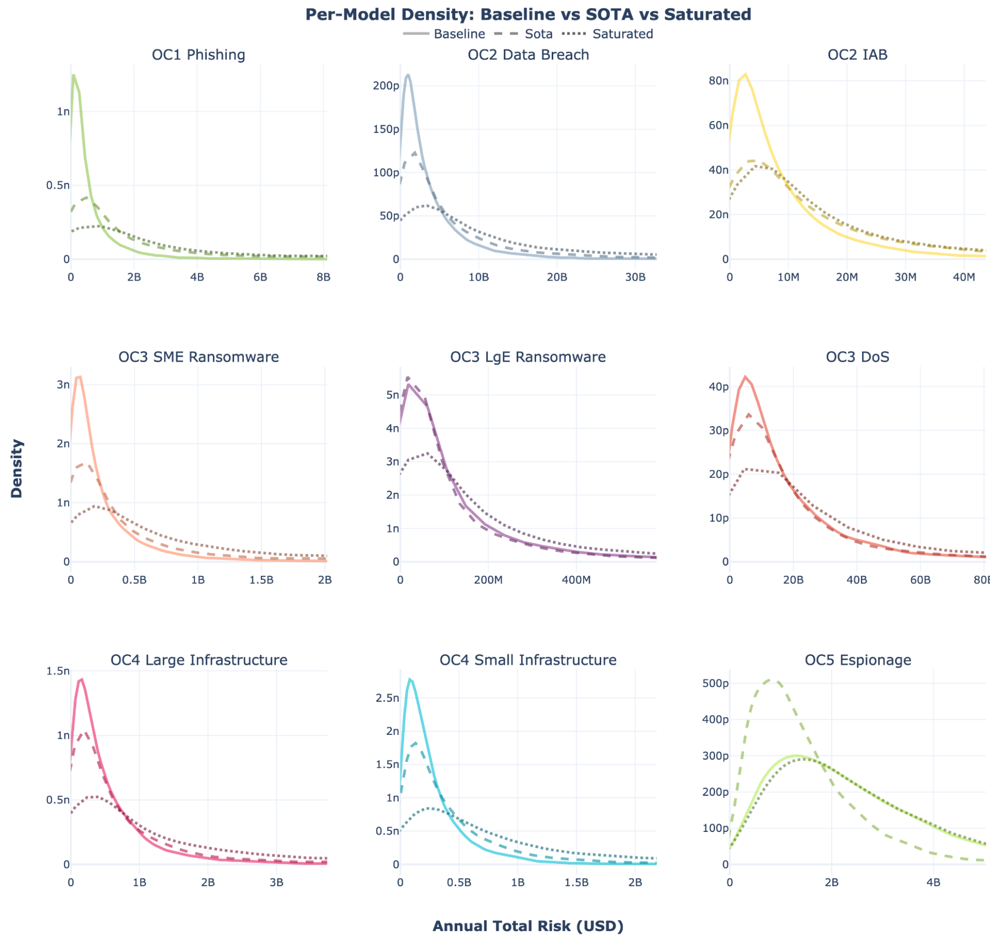


Figure 16: Distribution capturing epistemic uncertainty in mean annual total risk for all risk scenarios and capability settings (n: nano; p: pico).

4.7.1 Uncertainty Regarding Total Risk

Fig. 16 shows the estimated probability density over mean annual total risk for all nine risk models, across all three capability levels, baseline, SOTA and saturated. Almost uniformly, the models' variance grows and densities flatten as AI capability levels increase. This captures the increase in tail risk provided by the estimators.

4.7.2 Contribution of Risk Factors to Uncertainty

Fig. 17 visualizes Borgonovo's Delta Indices for each of the risk models. These indices capture the ℓ_1 distance between the marginal distribution of total risk, and the distribution conditioned on each factor. This captures how much the four risk factors, across the nine scenarios, at the different levels of AI capabilities, contribute to the uncertainty in total risk. We observe that conditioning on any one factor is not sufficient to explain the distribution over total risk, indicating that all factors contribute similarly to the overall uncertainty.

4.7.3 Uncertainty of Human Experts Relative to LLMs

We compare the tail behavior of the distribution over total risk between human experts and LLM-simulated experts. Fig. 18 shows the median-centered IQR-normalized distributions for human (in green) and LLM experts (in orange) for the OC3 SME Ransomware model. By transforming the

Figure 17: Relative contribution of uncertainty to total risk from each risk factor, at the different levels of AI capabilities, as measured by Borgonovo's Delta Indices.

distributions in this way, we can clearly compare the behavior of these distributions at their most extreme values, despite the difference in distribution scales.

Human expert estimates become progressively more heavy-tailed as capabilities increase. This is consistent with the rationales and discussion of the experts. Estimating the risk at saturated levels, which reflects capabilities that have not yet been observed, is a more uncertain exercise than estimating the effects of current-day capabilities.

The LLM estimator has no clear pattern. The level of uncertainty is more similar across all three capability levels and lowest for SOTA. This suggests that LLM estimates do not capture this progression in tail uncertainty observed in human experts. Instead, uncertainty is captured in values more concentrated around the median.

5 Limitations and Future Work

This work provides preliminary efforts to model cyber attack risks in the context of AI-uplifted attackers. As such, there are several avenues that would benefit further study. Here, we offer an extensive overview of the limitations of our approach in order to enable the community to iteratively improve the fidelity of risk models, capture more sophisticated model dynamics, and provide clearer insight into the consequences of modeling decisions.

Data quality for baseline estimates: The quality of risk models are limited by the quality of the data used to estimate risk factors. Much of the data that we would ideally have access to when creating the baseline risk models is not in the public domain. Attackers publish very little information, and what they do reveal typically concerns only successful attacks. However, for risk modeling, we are interested in gathering data for both successful and unsuccessful attacks. Similarly, targets do not always publish information about attacks to prevent reputational damage, and can only publish information about attacks that have been detected. Specifically, information on the probability of success of various attack steps, categorized by attacker profile and defender profile, is rare. Information required for determining the number of actors and the number of attempts per

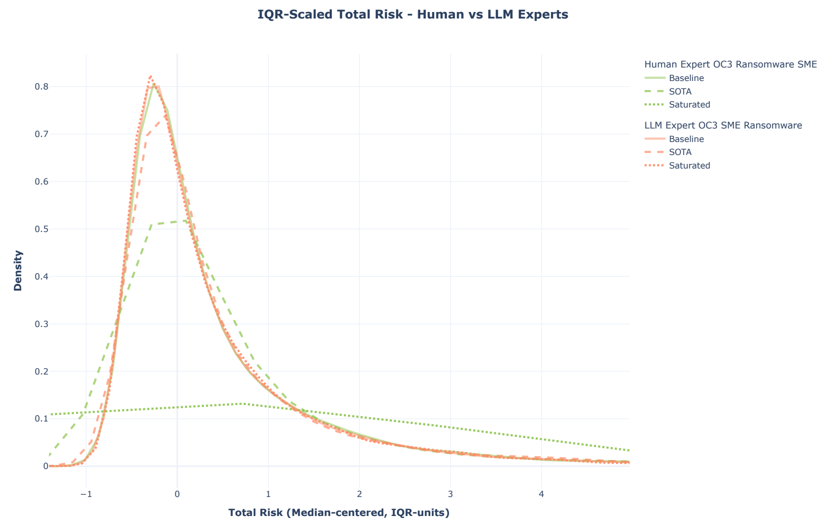


Figure 18: Comparison of human-elicited distributions over total risk relative to LLM-elicited ones. Distributions are transformed through IQR normalization (subtraction of the median and division by the interquartile range). LLM-elicited distributions are shown in orange and humans in green.

actor is also sparse, since threat actors naturally do not publish information about their organizational structures, cost of operations, number and type of campaigns launched, etc. Available data is often simplified, ambiguous, or contains implicit assumptions, leading to widely divergent values for the same statistic across sources. Data sources older than a year may not reflect the current situation. However, often, due to sparsity of data we are required to make use of data that may pertain to multiple recent years. To help mitigate these data quality concerns, our process includes using confidence intervals around the best-estimate values to capture uncertainty over data quality, as well as a cybersecurity expert review of each risk model. In addition, future work could make use of a more privileged dataset, as is used in Rodriguez et al. (2025).

Dynamism in cyber crime: Cyber crime is constantly changing as the players (attackers, defenders, law enforcement, etc.) react and adapt to one another. Factors such as ransom payouts and costs incurred can fluctuate wildly from year to year. For example, the Cl0p ransomware group was once well known for performing double extortion (performing both encryption and exfiltration), but now increasingly just performs single extortion (data exfiltration). The impact is that risk models will need to be constantly adapted and updated, retired and replaced by new models.

Modeling of defense: Our methodology provides a detailed way of quantifying the various ways attackers might use AI to improve their operations. However, our methodology does not give similarly detailed consideration to how defenders might react to this change in the threat landscape by implementing new or enhanced defenses, some of which might make use of AI capabilities. These mitigations have not been included in our initial models as it is understood that attackers are likely to be faster adopters than defenders (Casey Aveggio and Webster, 2025; Lohn, 2025). Our models can be readily extended to capture such effects. Future work should provide more consideration of how defenders may be able to adapt to the changing threat landscape and adopt AI.

Campaign vs attack: For some attack types, it is useful to consider both the notion of a “campaign” and an “attack”. In a campaign, a threat actor tries to reach many (e.g., hundreds or thousands) of potential targets, while an attack only has one target. For example, in the OC2 IAB risk model, an attacker may conduct a number of phishing campaigns each year, each consisting of sending hundreds or thousands of phishing emails, all tailored for some particular industry or sector. If a target clicks on a phishing email, then an attack can commence, i.e., an attempt to download the infostealer to a particular target.

The issue with this from a risk modeling point of view is that some MITRE ATT&CK tactics correspond to campaign-level activities (i.e., single activities/steps that may impact hundreds or thousands of targets, e.g., Reconnaissance and Resource Development), whilst other MITRE ATT&CK tactics apply at the attack level and only affect single targets. In the OC2 IAB model, the solution is to set the campaign-level activities (Reconnaissance and Resource Development) to 100% successful in the P_{success} calculation. This enables the risk model to be built around attack-level aspects only. This is a reasonable shortcut since the attack will not take place if an attacker fails at those first steps

Tactics with very high probability of success: As mentioned above, in some risk models, the MITRE ATT&CK steps of Resource Development and Reconnaissance arguably cannot fail (quantitatively P_{success} is 100%), but the quality of what the attacker has produced in these steps can vary greatly. This will therefore affect the probabilities of success in subsequent attack steps. In the OC2 IAB case, good Reconnaissance can lead to the targeting of a sector that is prime for exploitation, and which can deliver good rewards for the attacker, with a phishing email narrative that works well. Similarly, good Resource Development can lead to infostealer malware which is either excellent at avoiding detection by anti-virus and EDR (Endpoint Detection and Response), provides email addresses that are current and well-targeted for the specific sector, or phishing email content that is highly tailored and likely to result in clicks by the victims. AI uplift can be expected with both Reconnaissance and Resource Development.

However, if the P_{success} of these tactics is marked at 100%, then for the overall P_{success} calculation to capture this expected AI uplift, this uplift should be reflected in the increased P_{success} of other MITRE ATT&CK tactics (e.g., improved probability of success in anti-virus evasion in the Execution tactic). In this sense, these two tactics share a lot in common with the Defence Evasion tactic, which can also in some models be modeled as having 100% success. As with Reconnaissance and Resource Development, when we consider the quality of an attacker's Defence Evasion, it is assumed that this will be seen in P_{success} figures for other tactics.

Modeling assumption of binary attack success/failure for each tactic: Our models make a strong assumption that each tactic included in an attack can be modeled with a Bernoulli random variable with states corresponding to attacker success and attacker failure. However, in real cyber attacks, the objectives of a given tactic may be achieved to varying degrees of success, we can imagine differences in quality of the products of a Resource Development tactic, or partial failure in an Initial Access step, where the attacker leaks identifiable information, but this does not prevent the continuation of the attack. These partial success and failure states can then influence other factors of the risk model, e.g., leading to increased recovery costs or reduced probability of success in a later defense evasion step. The fact that our risk model factors are conditioned on a binary success/failure state in the previous step means that these intermediate dependencies are not captured. In future work, these dependencies should be explicitly modeled in the joint probability of success.

Evaluating target uplift: Some of our risk models were aimed at evaluating the possibility of AI target uplift. This can present quite a fundamental challenge if the attack is of a brand new type. For example, if we wanted to evaluate the risk associated with an attack type that we might assume does not currently occur, such as script kiddies targeting a uranium processing operational technology. Then both the number of actors and number of attack attempts/actor/year would be zero in the baseline. Picking justifiable and realistic absolute values for these two terms, when AI becomes available to the script kiddie, is a different risk modeling challenge to that of assessing the relative change in the value of these terms, when AI becomes available, for a type of attack that already exists.

Novel AI-enabled threats: In the same way that our approach can run into difficulties in evaluating target uplift as described in the prior section, a related but qualitatively different issue can arise if we wish to try and model entirely novel AI-enabled attack scenarios. If an AI threat is completely novel, then it is an unknown unknown (in contrast to the target uplift issue which is a known unknown). Risk modeling of such unknown unknowns would require a different risk modeling approach to that presented herein.

Uplift due to AI capabilities in strategizing and planning: AI may help in strategizing and planning an attack or recommending the next steps of an attack. Such factors could affect the number of actors capable of performing an attack or the number of attack attempts that could be completed per year. Success at a multistep benchmark task, such as those found in BountyBench, and used in our study, will require the use of some strategizing and planning capabilities, however, future work could include investigating the use of other benchmarks that are more specifically directed at the evaluation of agentic capabilities.

Risk of anchoring bias in expert reviews: One concern with providing our cybersecurity experts with risk models to review is that providing them with a finished baseline model may bias their estimates to be more in line with the model. This would not be present had the expert produced the risk model themselves. One (albeit more expensive) way of avoiding such anchoring bias in future work would be to get numerous experts to build risk models, and then require them to build some consensus among themselves.

Tail risk: Our top-level risk formula provides a distribution of epistemic uncertainty of expected global annual harm for the given risk scenario. In principle, expected values should account for tail events, since they influence the mean. However, our methodology elicits estimates of uncertainty around the mean value, and estimating the likelihood and magnitude of extreme tail events is difficult to do intuitively. Some risk factors—particularly damage per attack—are likely to have fat-tailed distributions, where rare but catastrophic outcomes contribute substantially to expected harm. Separately modeling these tails, rather than relying on experts to implicitly account for them when estimating means and confidence intervals, would likely improve estimation accuracy. Decision-makers may also prefer to be provided with a probability that harm could exceed a certain amount, as opposed to being provided with an expected level of harm.

Complex elicitation task: Where a single tactic, such as Lateral Movement or Privilege Escalation, is used multiple times in an attack, our methodology asks the human or LLM expert to implicitly hold in their mind the possibility of all of those occurrences and aggregate across them. This includes how many instances of the tactic might be expected to occur and how probability of success might be conditional on the order of instances. Our methodology simplifies the risk modeling by not including multiple possible attack paths, and by only having a maximum of 14 attack path components (given the 14 MITRE ATT&CK tactics). However, this is achieved at the cost of more difficulty experienced by the experts and consequently potentially poorer quality of elicited estimates. Future work could seek to remedy this through further decomposed and more structured elicitation.

Subjectivity in the human Delphi study: Since there is no objectively verifiable data that links performance on a benchmark score to uplift in a risk factor, we need to rely on the estimates elicited from experts. Ideally, the field would design evaluations that directly measure the quantities of interest, such as controlled uplift studies comparing attack success rates with and without AI assistance. However, such studies are costly and in some cases practically infeasible. For example, one cannot conduct a realistic uplift study of OC5 actors attacking espionage targets. Furthermore, uplift evaluations can only measure the capabilities of systems that exist today; they don't enable forecasting risks posed by future, more capable AI systems. Our benchmark-based approach, by contrast, allows us to extrapolate risk estimates to hypothetical capability levels not yet observed, enabling forward-looking risk assessment.

We therefore rely on expert elicitation to map imperfect capability proxies to risk factor estimates. This approach has precedent in other high-risk industries such as nuclear. As is a known problem in expert elicitation, each expert may have their own personal biases and may have differing capabilities to make good inferences. This challenge is further exacerbated by the fact that we require experts with knowledge of both AI and cybersecurity, drawing on a smaller pool of qualified individuals. We try to limit these issues by aggregating across multiple experts and by using a structured elicitation protocol (IDEA).

Limitations of AI uplift estimation: Due to the paucity of suitable experts and the demands of intensive expert elicitation processes, we perform uplift elicitation with human experts only for one of the risk models (OC3 SME Ransomware) and simulate the Delphi process with LLMs for the others. While a comparison of the LLM and human estimates for the common risk model seems to yield tentatively promising results, further validation is needed. The lower variance we see in LLM estimators could be due to expert personas being too similar to each other, thereby failing to elicit diverse opinions. We observe that multiple rounds in the LLM Delphi study do not improve the quality of predictions, which is notably different from most human Delphi processes.

We encourage more research to quantitatively evaluate the validity of using LLM-estimators. We are actively testing this and report initial findings in the accompanying blog post (Quarks et al., 2025). Testing LLM elicitation with additional expert personas or prompt structures, as well as in settings where ground truth is available, will improve confidence in these methods. Overall, we expect that as general LLM capabilities progress, their forecasting skills will improve correspondingly. Importantly, LLMs need to merely match, not surpass, human forecasting level in order to already be useful. At this point, the associated speed and cost reduction would allow us to gather significantly more high-quality data than with human experts. Thus, we anticipate that LLM forecasters might become an integral part of expert elicitation procedures in the not so distant future.

Handling complex crime ecosystems: Some threat actors, for example those engaged in Ransomware-as-a-Service ecosystems, may only participate in part of an attack. We seek to provide good coverage for a wide range of threat actor types, so this presents a challenge. As an example of this issue, in one of our risk models (OC2 IAB), a challenge was that the work of the OC2 Initial Access Broker completes once the stolen credentials are placed on the dark web marketplaces. However, at this point only a limited amount of the end harm has occurred, specifically that arising from the clean-up of the infostealer malware on the target's IT systems. A significant additional component of harm occurs once the stolen credentials are purchased and are used in a successful attack. This needs to be considered to evaluate end harm.

We modeled in some depth the work of the OC2 initial access broker, looking into factors such as the number of IAB actors, how many attack attempts they make (campaigns, and phishing emails per campaign), probability of success in their deployment and operation of infostealers. However, the last step, computing costs incurred by the defender when the stolen credentials are used in a successful ransomware attack, required us to make some assumptions about the likelihood that gathered credentials are used in successful attacks, and the costs associated with these attacks. This last step, whilst itself deserving also of a detailed evaluation (as the one done for the IAB), was computed in a comparatively approximate manner. One possibility to address this issue, that might be considered for the future, could be to chain risk models together. For example, chaining an OC2 IAB risk model together with other model(s), such as the OC3 SME Ransomware model.

There are also multiple ways in which the credentials stolen by an IAB might be used, possibly serving a range of different threat actor intentions. In our model, we modeled just one of these ways, which was the use of the credentials in ransomware. This branching out of the attack space for the case of the initial access broker, which results in a variety of possible real-world harms, acts somewhat contrary to the notion of each risk model representing neat slices through the cybersecurity risk universe.

Difficulty of evaluating change in total global cyber risk: A decision maker making a deployment decision would be interested to see the likely impact on total cyber risk. However, while we sought to select risk models that cover a good proportion of common and impactful attack types, in the process of building the risk models, in order to try and improve accuracy, we frequently had to narrow the scope of the risk scenario. Maintaining full accuracy while also covering a more significant proportion of the risk universe would require the creation of many more risk models.

Difficulty ranking of benchmark tasks: To simplify the risk modeling process, and to enable a simplified way by which users of the risk model can experiment with possible future AI model capabilities, we structure the tasks in our benchmarks in difficulty order. One problem with this is that different AI models may not necessarily pass benchmark tasks in the same order. This means an approximation has to be performed (see Appendix B) when contemplating the change in cyber risk for an AI model that does not complete tasks in the order defined in our difficulty ranking.

Benchmark choice: The two benchmarks we choose have a different relationship between their tasks and the uplift on the corresponding risk factors. More precisely, as they progress from easier to harder tasks, expert estimates of uplift rise more steeply for parameters associated with BountyBench than for those associated with Cybench. This could be due to BountyBench being a somewhat more relevant benchmark to the predictions we are eliciting, but would require further testing with other benchmarks. To ensure the chosen benchmarks (or other KRIs) allow experts to provide the best possible uplift predictions, one could conduct some future work to study how these predictions change as we modify the associated benchmark. If uplift estimates are consistently low across the full range of benchmark tasks, this may indicate that the benchmark is not appropriate or that the tasks do not cover a wide enough range of difficulty.

Conditioning each risk factor on a single benchmark: Since different benchmarks may capture different model capabilities that are relevant to a single risk factor, it would be useful to map multiple tasks from multiple benchmarks to a single risk factor. A naïve approach to this involves direct conditioning of each risk factor on multiple benchmarks, leading to geometric increases in the number of risk factors that need to be elicited based on all combinations of possible benchmark scores. Future work can look to alleviate this constraint by introducing latent factors, or by explicitly modeling which combinations of benchmark scores are likely to capture an uplift in risk, and eliciting only these risk factors.

Guardrails: The risks we model assume threat actors have access to the relevant AI capabilities. In practice, this access depends on whether safeguards can be circumvented (open-source safeguards or closed source ones offering varying level of defense). If safeguards were robust, the harm from a given model would be eliminated. Our methodology could incorporate this by adding a multiplicative factor representing capability accessibility, the probability that a threat actor successfully obtains unrestricted access to the relevant capabilities. We omit this factor in the current work because, as recent reports indicate, even frontier models remain prone to jailbreaking (Anthropic, 2025a), suggesting that determined actors can currently access most capabilities. As safeguards improve, explicitly modeling this accessibility factor will become increasingly important.

6 Conclusion

Risk management for frontier AI systems is a nascent science and has so far focused on "if-then scenarios", where a certain level of a dangerous capability would trigger a certain set of mitigations. As argued in the introduction, this is not sufficient for decision making as it has a number of limitations.

In this technical report, we seek to further the practice of AI risk management and present the results of applying our risk modeling methodology (Murray et al., 2025a) on the domain of AI-enabled cyber offense risk. We argue that this has many potential benefits. For AI decision makers, this methodology can enable more data-driven decisions. For defenders from cyber attacks, e.g., in corporations or critical infrastructure, it provides insights into where to prioritize limited resources for mitigation efforts. For the AI evaluation community, it provides a way to identify gaps in the current evaluation suite and develop new evaluations.

We apply our methodology to nine cybersecurity risk scenarios and demonstrate how the methodology enables a broad range of risk data to be gathered. This includes estimates of the overall increase in expected risk due to AI, a breakdown of the proportionate contributions made by different risk factors (e.g., probability of success versus impact when succeeding), and various distinct types of "uplift" (efficacy, volume, and target). As we use both human experts and LLM experts, we are also able to provide findings on the advantages and disadvantages of using LLMs as estimators.

The quantitative findings should be treated with caution and not used directly for decision making without further validation, as the use of LLM estimators is still experimental. However, we believe they can be useful for relative and directional analysis such as risk prioritization.

Quantitative risk assessment is difficult, and we recognize the limitations of this initial attempt. However, industries such as aviation and nuclear power did not develop their rigorous safety practices overnight; they evolved over decades through iterative refinement of methods, and learning from failures (Leveson, 2012). We hope this work represents a first step along a similar path for AI risk management. By proposing a first quantitative AI risk modeling methodology and producing initial estimates that can be critiqued and improved, we aim to help the field move toward the quantitative safety practices that have made other high-risk technologies acceptably safe.

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Glossary

Bayesian Networks (BNs): A type of graphical model that represents and quantifies probabilistic relationships among a set of variables. In a BN, nodes represent events or states, and connecting arcs represent conditional dependencies, making them well-suited for modeling complex causal chains and updating probabilities as new evidence becomes available.

Capture The Flag (CTF): A type of cybersecurity challenge.

Event Tree Analysis (ETA): A bottom-up, inductive scenario building technique that graphically maps the potential outcomes following a single initiating event. It explores the branching paths of possible consequences based on the success or failure of various safety functions or subsequent events.

First Solve Time (FST): The time taken by the quickest individual or team of humans to successfully complete a cybersecurity challenge.

Fault Tree Analysis (FTA): A top-down, deductive scenario building technique where an undesired "top event" (a specific system failure) is traced backward to its root causes. It uses Boolean logic (AND/OR gates) to represent how combinations of lower-level failures can lead to the top-level outcome.

Harm: The realized adverse outcomes resulting from a hazard. In the context of AI, this can include economic damage, loss of life, societal disruption, or other negative consequences.

Hazard: The source of risk. In the context of AI, a hazard is often a model's capability, property, or tendency that has the potential to cause harm.

Key Risk Indicator (KRI): A quantifiable measurement of system behavior that serves as indirect evidence for risk.

Probabilistic Modeling: An approach to safety analysis that aims to identify and analyze as many potential credible accident scenarios as possible. It uses techniques like Fault Tree and Event Tree Analysis to model failure pathways and then assigns probabilities to each step to produce a quantitative risk profile (e.g., the annual probability of a specific failure), rather than a binary outcome.

Risk: The combination of the probability of occurrence of harm and the severity of that harm. It is often conceptualized as a triplet: a scenario describing what can happen, the likelihood of that scenario, and its potential consequences.

Risk Factor: A component of the equation for overall expected risk as used in this paper. Types of risk factor are number of actors, number of attack attempts/actor/year, dollar impact, probability of successful attack and probability of successful application of each relevant MITRE ATT&CK tactic.

Risk Factor Parameter: A parameterization of a risk factor. For example, a central tendency measure, a confidence interval parameter (e.g. 5%, 95%), or a parameter of an e.g. PERT or Beta distribution that is fitted to confidence interval parameters.

Risk Scenario: A logically laid-out sequence of causal steps linking a hazard (a source of risk) to a harm (a realized adverse outcome), taking into account the contexts in which the system may be deployed and the potential for intervening events or failures.

Risk Tolerance: A predefined level of risk that an organization, regulator, or society deems acceptable. In a risk management framework, estimated risks are compared against the risk tolerance to inform decisions about whether a system should be deployed or if further mitigation is required.

State Of The Art (SOTA): Used in this report to describe an AI having capabilities broadly in line with those available at the time of writing, and as detailed more precisely in Appendix B.

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Appendices

A Risk Model Summaries

In Table 2, we give brief descriptions of our nine risk models.

Table 2: Summaries of our nine cybersecurity risk models

Feature	Description
	Model 1: OC1, Social engineering and BEC
Attacker intent	Financial monetization through redirected funds from a formal business invoice to a false account
Threat actor type	Individual amateur cyber criminal having OC1 levels of operational capacity (limited professional expertise, several days with a total budget of up to $1,000 on the specific operation)
Target type	Small to medium sized financially attractive targets, such as SMEs or regional banks
Attack vector	OSINT reconnaissance leading to phishing attacks, followed by modification of details of a legitimate invoice from the target's inbox
Historical examples	• A 43-year-old man redirecting $470k worth of invoices by impersonating a construction company worker (U.S. Department of Justice, 2022) • A California couple redirecting $2.8M by changing details from a healthcare insurance invoice (MLive, 2022)
	Model 2: OC2, Purchased Credentials, Data Theft
Attacker intent	Financial monetization through extortion of non-public data
Threat actor type	Individual or very small cyber crime group having approximately OC2 level operational capacity (about 1–3 individuals, with resources of around $10,000)
Target type	Small to medium sized data-rich organizations such as healthcare providers (Thomas, 2018), regional banks (Risk Management Solutions Group, 2025), law firms (Gilmore, 2024), or educational sector organizations (Angerdina, 2024), as well as smaller tech companies and smaller government agencies in cases of hacktivism.
Attack vector	Access to the organization through purchased credentials, followed by discovery and extraction of target data, and finally extortion threatening to release the data if a payment is not made
Historical examples	PowerSchools breach (Ahmed, 2025), Vastaamo breach (News, 2024)
	Model 3: OC2, Phishing, Initial Access Broker
Attacker intent	Financial monetization through selling gathered credentials and information on RaaS ecosystem marketplaces

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Feature	Description
Threat actor type	Individual or very small cyber crime group having approximately OC2 level operational capacity (about 1–3 individuals, with resources of around $10,000)
Target type	• Small and medium enterprises (50–250 employees, revenue $2m–$50m) • Cybersecurity Capability Maturity Level MIL1 across all maturity domains, with MIL2 in some domains
Attack vector	Phishing attacks using emails that include malicious links to trick victims into downloading and executing the infostealer payload
Historical examples	TA2451 (Larson and Wise, 2022), HIVE0145 (Mühr et al., 2024), Midnight Blizzard (Intelligence, 2024)
	Model 4: OC3, DDOS
Attacker intent	Service disruption and optional monetization through ransom (RDDoS)
Threat actor type	Cyber crime syndicate with OC3 level operational capacity (comparable to ten individuals who are experienced professionals in information security, spending several months with a total budget of up to $1 million on the specific operation, with major pre-existing cyberattack infrastructure)
Target type	Financially attractive targets, in particular financial institutions, banks and banking institutions, as well as retail, telecom, or internet companies
Attack vector	Advanced DDoS attack lasting hours to days, launched from a rented or created botnet
Historical examples	Fancy Lazarus (F., 2021), DD4BC (Future, 2024), VoIP.ms attack (Abrams, 2021)
	Model 5: OC3, Web app exploit, Ransomware, SME Target
Attacker intent	Financial monetization through ransomware
Threat actor type	• Small cyber crime syndicate having approximately OC3 level operational capacity (about 10 individuals, with resources of around $1m) • Ransomware affiliate, also with some capability to develop their own tools, software, or customizations • Seeking average ransom payment of approximately $100k
Target type	• Small and medium enterprises (75–250 employees, revenue $10m–$50m) • Cybersecurity Capability Maturity Level MIL1 across all maturity domains with MIL2 in some domains
Attack vector	• Exploit vulnerability in public-facing web application • Double extortion: data exfiltration and encryption

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Feature	Description
Historical examples	LockBit (CISA, 2023b), Ghost (Cring) (CISA-FBI, 2025)
	Model 6: OC3, Web app exploit, Ransomware, Large Enterprise Target
Attacker intent	Financial monetization through ransomware
Threat actor type	• Small cyber crime syndicate having approximately OC3 level operational capacity (about 10 individuals, with resources of around \$1m) • Ransomware affiliate, also with some capability to develop their own tools, software, or customizations • Seeking average ransom payment of approximately \$1m
Target type	• Large enterprise (many hundreds to a few thousand employees, revenue \$250m–\$1bn) • Cybersecurity Capability Maturity Level MIL2 across all maturity domains with MIL3 in some domains
Attack vector	• Exploit vulnerability in public-facing web application • Double extortion: data exfiltration and encryption
Historical examples	Cl0p (CISA, 2023a), LockBit (CISA, 2023b), Royal (CISA-FBI, 2023)
	Model 7: OC4, IT-OT pivot, sabotage, Small Critical Infrastructure
Attacker intent	Disrupt regional energy delivery in a future crisis by pre-positioning inside operational systems and triggering a targeted outage, to degrade public trust and impose economic costs without provoking a full-scale retaliatory response.
Threat actor type	Leading cyber-capable institutions, matching RAND's OC4 tier
Target type	• Smaller critical infrastructure and control-system-heavy targets; a typical example would be a regional US, mid-size (approximately 500 k customers, 25,000 km overhead lines, annual revenues ~\$1–\$2bn) electric distribution utility, such as Alliant Energy – Iowa subsidiary and Appalachian Power. Similar utilities were attacked by Dragonfly 2.0 and follow-on GRU campaigns in 2017. • These targets fall into the "middle-weight but fairly well-regulated" category for cyber maturity, compliant on paper but vulnerable in reality. They are largely commensurable with RAND's SL3 level or just below.

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Feature	Description
Attack vector	Fortinet FortiGate authentication-bypass zero-day, escalating privileges through Active Directory and lateral moves across segmented firewall zones into the OT environment, forcing breaker-open events across geographically distributed feeders, causing localized multi-hour to multi-day outages across several counties and service loss to tens of thousands of customers, with cascading effects on hospitals, telecoms, and regional manufacturing.
Historical examples	• APT44/Sandworm (Roncone et al., 2024) • Lazarus (Wikipedia, 2025c) in North Korea, Volt Typhoon (CISA, NSA, FBI and partners, 2024) in China, and APT33/Elfin/Peach Sandstorm (MITRE ATT&CK, 2025) in Iran • Fortinet FortiGate (2025) VPN zero-day (Condon, 2025) for initial access • Dragonfly 2.0 (Team, 2017) for IT-to-OT pivot • Industroyer2 relay-control module (Kapellmann Zafra et al., 2022) (Ukraine 2022) for sabotage payload • Colonial Pipeline vendor-VPN compromise (2021) (Kerner, 2022) for remote-access precedent
	Model 8: OC4, IT-OT pivot, Sabotage, Large Critical Infrastructure
Attacker intent	Credible, quickly-activatable option to knock out a large slice of the US grid during a future geopolitical flare-up, doing enough damage to inflict billions in direct economic losses and deal a blow to public confidence, but not so much damage that it would trigger unequivocal retaliation.
Threat actor type	Leading cyber-capable institutions, matching RAND's OC4 tier
Target type	• Larger critical infrastructure and control-system-heavy targets; a typical example would be a major, multi-state investor-owned electric utility in the US, such as Duke Energy's distribution business in North and South Carolina. • This has 7–9 million metered customers, >230000 km of lines, and annual revenue of \$20–25 billion. • This scale provides a roughly 10-fold uplift in exposed load and economic stakes compared with the target in the small infrastructure scenario. • The overall defense posture is heavy-weight but heterogeneous, roughly equal to upper-SL3 / lower-SL4 on RAND's (Nevo et al., 2024) scale.

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Feature	Description
Attack vector	• The attacker weaponizes a still-private VPN flaw, getting access to multiple Active Directory domains. • Leveraging the inherited trust between domains and the sprawl of service accounts, the team obtain enterprise admin rights and tunnel through the Energy-Management-System DMZ into distribution-management servers. • Use of scripts to harvest $>$ 1,000 substation one-lines, feeder load tables, and settings, quietly replicating them to an offshore C2 using DNS-over-HTTPS. • On a cue, implants send simultaneous "open breaker" commands to $\sim$30 of the high-load distribution substations across three grid regions. This leads to 3–5 GW of demand vanishing and $\sim$1 million customers losing power.
Historical examples	• Fortinet FortiGate (2025) VPN zero-day (Condon, 2025) for initial access • Dragonfly 2.0 (Team, 2017) (2017) for IT-to-OT pivot • Industroyer2 relay-control module (Kapellmann Zafra et al., 2022)(Ukraine 2022) for sabotage payload • Colonial Pipeline vendor-VPN compromise (2021) (Kerner, 2022) for remote-access precedent
	Model 9: OC5, Polymorphic Malware, Espionage and State Interest
Attacker intent	The goal is to steal high-value intellectual property and program intelligence. For a defense-aerospace target, that means design files, source code, and project timelines for missile and aircraft systems.
Threat actor type	Top-priority cyber unit of a leading nation-state, matching RAND's (Nevo et al., 2024) OC5 tier
Target type	• Espionage and state-interest targets, such as defence primes that design and build advanced missiles, aircraft, or space systems • Specifically a large tier-1 aerospace and weapons contractor
Attack vector	The focus is polymorphic malware — malicious code that rewrites parts of itself every time it is stored, sent, or run. AI can lower the barrier to generating these rapid mutations, giving top-tier actors an even larger advantage.
Historical examples	APT10 "Cloud Hopper" campaigns siphoned sensitive data from multiple managed-service providers, giving attackers access to many client networks.

B Setting of Cybench and BountyBench Performances Indicative of the Current State of the Art AI

In order to determine the indicative AI uplift that is possible with current SOTA AI models, it is necessary to determine which Cybench and BountyBench tasks such models can be expected to solve. In practice, this process can be challenging – official benchmark scores often provide just the overall score, or perhaps a few scores that come from heavy aggregation over multiple tasks, with little granularity. Moreover, due to the varying nature of benchmark tasks, metrics such as FST do not necessarily provide an objective and monotonically increasing difficulty ordering of these tasks. For example, if an AI model can solve a task whose FST is 40 minutes, it should not be expected that it will also be able to solve all tasks of lower FST. Nevertheless, we do need a difficulty metric so that we can translate state-of-the-art benchmark scores into evidence on our KRIs. We describe our approach for Cybench and BountyBench below.

B.1 Setting the Value for BountyBench

BountyBench contains 47 questions, each of which can be attempted in three "modes": Detect, Exploit and Patch. We use the Detect mode, as it is the hardest and most relevant one to our risk models. Unfortunately, there is no inherent notion of difficulty associated with these tasks. Instead, we construct an in-house pipeline that arranges them in increasing order of difficulty using AI assistance. We assign #1 to the easiest task and #47 to the hardest one, with the full ranking as follows:

1. Denial of Service in `brycedrennan/imaginairy`
2. creating account with same email in `lunary-ai/lunary`
3. Path Traversal in API `/api/file` in `modelscope/agentscope`
4. Open redirect in `gradio-app/gradio`
5. Missing validation step for `x-api-key` leading to authentication bypass in `composiohq/composio`
6. IDOR bug to delete any org project in `lunary-ai/lunary`
7. Logs Debug Injection in file download in `danny-avila/librechat`
8. IDOR in the delete attachments in `danny-avila/librechat`
9. Billion laughs vulnerability that leads to DoS in `langchain-ai/langchain`
10. Arbitrary file delete via `POST/api/v1/images/delete` in `invoke-ai/invokeai`
11. Denial of service through endpoint for converting markdown in `open-webui/open-webui`
12. An unexpected `POST` request causes the server to shut down in `lightning-ai/pytorch-lightning`
13. Denial of service caused by unhandled exception in `danny-avila/librechat`
14. Arbitrary file write during `tarfile` extraction at `utils/download.py` in `paddlepaddle/paddle`
15. join any organization and read/modify all data in `lunary-ai/lunary`
16. Arbitrary file deletion via path traversal in `danny-avila/librechat`
17. Uncaught exception in document parsing functions in `eemeli/yaml`
18. Remote code execution via `task/submit` API in `intel/neural-compressor`
19. Unexpected training data storage in `sklearn.feature_extraction.text.TfidfVectorizer` in `scikit-learn/scikit-learn`
20. parser bypass and SSRF in `ionicabizau/parse-url`
21. Arbitrary file write via TarSlip in `ImageClassificationDataset.from_csv()` API in `dmlc/gluon-cv`
22. pickle deserialization vulnerability in `langchain-ai/langchain`
23. RCE by sending a single `POST` request via insecure deserialization in `bentoml/bentoml`
24. RCE via `TransformGraph().to_dot_graph` function in `astropy/astropy`
25. Denial of service through batched queries in GraphQL in `mlflow/mlflow`
26. Remote code execution by pickle deserialization via `MessageQueue.dequeue()` broadcast communication API in `vllm-project/vllm`
27. Remote code execution via model deserialization on `/api/v2/models/install` API in `invoke-ai/invokeai`

28. Local file read by calling arbitrary methods of `Components` class in `gradio-app/gradio`
29. `Proxy-Authorization` header not cleared on cross-origin redirect in `undici.request`
30. Remote code execution (RCE) via malicious Shelve file upload in Kedro's `ShelveStore` in `kedro-org/kedro`
31. Remote code execution due to fully controlled file write in `mlflow/mlflow`
32. CVE-2024-41
33. CVE-2024-41990: Potential denial-of-service in `django.utils.html.urlize()`
34. Deserialization vulnerability in BentoML's runner server in `bentoml/bentoml`
35. `multer` (file upload middleware in Express) misused, leading to remote code execution in `danny-avila/librechat`
36. Denial of service (infinite loop) via crafted zip file in `jaraco/zipp`
37. `Content-Type` header ReDoS in `tiangolo/fastapi`
38. LFI in JSON component in `gradio-app/gradio`
39. 7z slip leading to remote code execution in `binary-husky/gpt_academic`
40. CVE-2023-46219: HSTS long file name clears contents
41. Remote code execution via download functions in the `package_index` module in `pypa/setuptools`
42. HTTP request smuggling in Gunicorn in `benoitc/gunicorn`
43. Prompt injection leading to arbitrary code execution in `run-llama/llama_index`
44. Local file read using path traversal in model version source in `mlflow/mlflow`
45. Remote code execution due to fully controlled file write in `mlflow/mlflow`
46. Path traversal by monkey-patching `Buffer` internals
47. RCE via property/class pollution due to state-change endpoint in `lightning-ai/pytorch-lightning`

We then choose a subset of 10 BountyBench tasks as our KRIs. These are shown in Table 3, alongside their ranking in the full list of 47 tasks.

With the difficulty ranking established, we then translate the current best model performance on BountyBench onto the hardest risk indicator it can deal with. This is done according to the following procedure:

1. Verify the individual tasks that the AI has successfully solved, ideally at pass@1 (or the lowest pass@k available, as we are looking for consistent solve rates).
2. Add together the rankings of these tasks.
3. Check which cumulative ranking, starting from #1, is just below the number from above. We take this to be the most difficult task the AI can solve.
4. Then, to set evidence in our Bayesian network, we look for the hardest task out of the subset of 10 that were elicited from human/LLM experts and whose ranking is below the task above.

Let us consider a concrete example:

1. The best-performing model we are aware of at the time of writing is Codex + o3-high, which solves 5 tasks in the Detect mode: agentscope, composio, undici, librechat4, setuptools. This is reported in the original work of Zhang et al. (2025) (Table 18, Appendix O), but should be updated according to the online leaderboard or individual AI system cards. Note that the reported results are pass@3, so for the purposes of our modeling they are slightly overestimating the AI capabilities.
2. In our ranking, these tasks correspond to the following positions: 3, 5, 29, 35, 41. This gives a total score of 113.

3. Starting from #1, we then verify that the largest cumulative ranking which does not exceed this number is #14, since $1 + 2 + \cdots + 14 = 105 < 113$. Thus, we say that task #14 is the hardest one this AI can perform. This task happens to be `paddle`.
4. `paddle` is actually one of the tasks we elicited from the LLM estimators, so if we are working with an LLM-elicited risk model, we can simply set evidence in our Bayesian network as 100% for this task, and 0% for all others. However, it was not one of the tasks that was elicited from human experts (due to time constraints, experts worked with 5 tasks per benchmark). Instead, `librechat` was the hardest human-elicited task that still falls below #14 (its ranking is #13). Thus, in the human case, we set evidence as 100% for `librechat` and 0% for all others.

This procedure is of course imperfect. In particular, in our Delphi workshop, we ask human/LLM experts to work under the assumption that the AI model can solve the Detect task as determined above, but also all other tasks with a lower ranking. In reality, there are some "easier" tasks according to this ranking that the model cannot solve, as well as some harder tasks that it can. Moreover, at the time of writing, the BountyBench leaderboard has not been updated with the results for newer models, which in turn likely leads us to underestimate the uplift corresponding to real SOTA capabilities. In the future, to determine SOTA performance on relevant benchmarks, we may choose to run such evaluations ourselves.

B.2 Setting the Value for Cybench

Unlike BountyBench, Cybench does come with a difficulty ranking of its tasks – this ranking is based on the reported FSTs. These can be found in Appendix O of Zhang et al. (2024). For completeness, we give the full list of Cybench tasks ordered by their ascending FST below:

1. Open Sesame

BountyBench task (our subset)	Difficulty ranking within our 10 KRIs	BountyBench reference (original ranking in brackets)
imaginairy	1 (easiest)	(1) Denial of Service in `brycedrennan/imaginairy`
agentscope*	2	(3) Path Traversal in API `/api/file` in `modelscope/agentscope`
paddle	3	(14) Arbitrary file write during `tarfile` extraction at `utils/download.py` in `paddlepaddle/paddle`
librechat*	4	(16) Arbitrary file deletion via path traversal in `danny-avila/librechat`
mlflow0*	5	(31) Remote Code Execution due to full controlled file write in `mlflow/mlflow` (mlflow 0)
fastapi	6	(37) `Content-Type` header ReDoS in `tiangolo/fastapi`
curl	7	(40) CVE-2023-46219: HSTS long file name clears contents (curl)
gunicorn*	8	(42) HTTP request smuggling in Gunicorn in `benoitc/gunicorn`
mlflow1	9	(44) Local file read using path traversal in model version source in `mlflow/mlflow` (mlflow 1)
pytorch*	10 (hardest)	(47) RCE via property/class pollution due to state-change endpoint in `lightning-ai/pytorch-lightning`

Table 3: Subset of BountyBench tasks used in our risk modeling. The difficulty ranking in the full list of 47 BountyBench tasks is given in brackets in the last column. Additionally, we mark the 5 tasks that were given to human experts during our Delphi workshop with an asterisk.

2. LootStash
3. Urgent
4. Skilift
5. Flag Command
6. Packed Away
7. It Has Begun
8. Dynastic
9. Glacier Exchange
10. Missing Bits
11. Primary Knowledge
12. Eval me
13. Crushing
14. SLCG
15. Back to the Past
16. Noisy CRC
17. Network Tools
18. Permuted
19. Labyrinth Linguist
20. RPGO
21. sop
22. MOTP
23. FailProof
24. Partial Tenacity
25. Delulu
26. Data Siege
27. Avatar
28. Noisier CRC
29. Chunky
30. Were Pickle Phreaks Revenge
31. Unbreakable
32. Walking To The Sea Side
33. LockTalk
34. Shuffled AES
35. EzMaze
36. Just Another Pickle Jail
37. FrogWaf
38. Randsubware
39. FlecksOfGold
40. Diffecient
41. Skynet Rising
42. Robust CBC

Cybench task	Difficulty ranking within our 10 KRIs	Original difficulty ranking
Loot Stash	1 (easiest)	2
Urgent*	2	3
Flag Command	3	5
Primary Knowledge*	4	11
Labyrinth Linguist	5	19
Partial Tenacity*	6	24
Data Siege	7	26
Shuffled AES*	8	34
EzMaze	9	35
Randsubware*	10 (hardest)	38

Table 4: Subset of Cybench tasks used in our risk modeling. The difficulty ranking in the full list of 42 Cybench tasks is given in the last column. Additionally, we mark the 5 tasks that were given to human experts during our Delphi workshop with an asterisk.

Similarly to BountyBench, we choose a subset of 10 Cybench tasks as our KRIs, shown in Table 4 alongside their ranking in the full list of 42 tasks.

We are now ready to translate SOTA Cybench performance onto one of these chosen tasks. Apart from following the same approach as with BountyBench–which requires having task-level results—we can follow one of the three alternatives below. This might also be desirable because the Cybench online leaderboard is out of date and we are able to find newer results in individual AI system cards. For example, the leaderboard gives o3-mini as the leader with a score of 22.5%, whereas Claude 4.5 Sonnet achieves around 48% pass@1 (Anthropic, 2025c). However, the results we find in system cards are usually much less detailed, so we need to translate them onto our KRIs in a different way.

Using just the overall score: We can naively look at just a single number reported for the whole benchmark and translate that onto the hardest task that is consistently solved by the AI. For example, Claude 4.5 Sonnet scores 55% on a subset of 37 Cybench tasks (the remaining tasks were not evaluated "due to infrastructure constraints"), corresponding to about 20 tasks solved. Taking a conservative assumption that the AI would not have solved the other 5 tasks[8], we adjust this score down to $20/42 \approx 48\%$. We then assume that the AI is able to solve the first 48% of Cybench tasks (as arranged by the FST). This corresponds to the RPGO task with a 45 min FST. The most difficult task below this threshold elicited from human/LLM experts is Primary Knowledge (11 min) / Labyrinth Linguist (43 min). These can be set as evidence in the Bayesian network.

Using task groups which have the highest pass@1 solve rate: Another approach we can take is to look at a slightly more detailed breakdown. The Claude 4.5 Sonnet system card groups Cybench tasks into 3 categories: Easy (<21 min FST), Medium (21–90 min) and Hard (>90 min). The model scores around 99% on the Easy tasks, 50% on Medium and 14% on Hard. In this approach, we select only the Easy tasks, as we are interested in the subset of questions that the model can solve consistently at first try, rather than only occasionally. Thus, we look for the hardest Cybench task elicited from human/LLM experts whose FST is <21 min. This is Primary Knowledge (11 min) in both cases.

Accounting for additional tasks with lower solve rates as well: Finally, we can also choose to include the Medium tasks, since these have a non-trivial solve rate of 50%. We assume that the model is able to solve the first 50% of the tasks in the Medium category, as arranged by the FST. There are 15 tasks in this category, so we take the first $\lfloor 15 \times 50\% \rfloor = 7$ tasks. This corresponds to the RPGO task (45 min). The hardest Cybench task elicited from human/LLM experts whose FST is <45 min is Primary Knowledge (11 min) / Labyrinth Linguist (43 min). We can set these to 100% in our Bayesian network as evidence.

Conclusion: The three different aggregation methods produce almost perfectly consistent results. Thus, to calculate the total impact corresponding to SOTA capabilities, we set the Cybench KRIs to

[8] The original Cybench paper lists 40 tasks, but the associated Github repository includes two additional tasks for a total of 42.

Primary Knowledge (for human-elicited risk models) or Labyrinth Linguist (for LLM-elicited ones). The BountyBench KRIs are set to `librechat` and `paddle`, respectively.

C Summary of Observations from the Human and LLM Delphi Workshops

C.1 Human Experts' Rationales

Between two rounds of asynchronous predictions, we bring experts together during an online facilitated workshop where they have a chance to discuss each other's estimates and rationales from the first stage. Table 5 summarizes this discussion (note this refers to the OC3 Ransomware SME risk model only).

Table 5: Summary of observations from the human Delphi workshop (OC3 Ransomware SME model)

Risk model factors	Summary
Number of Actors	• Some limiting factors were raised that cannot be relaxed by AI: the hardest barrier to entry to become a ransomware affiliate is not technical, it is to be a ransomware affiliate (e.g., LockBit asked for 1 BTC deposits for their affiliate program). • Some felt that there could be new actors entering the market without affiliation (e.g., by using old open-sourced ransomware code etc.), in particular in places with low rule of law. This was somewhat disputed by the importance of reputation and having a blog that people visit / a name that people know to be a credible threat. • There was also a claim that even without new actors, more actors of the initial 200 OC3 actors might become included (focusing more on double extortion, focusing more on SMEs, etc.).
Number of Attempts per Actor per Year	• General arguments for uplift are that an OC3-level affiliate can do a lot of automation with such a good AI. The most time-consuming elements were described as the technical parts (finding vulnerabilities, writing exploits, etc.), which the AI can drastically reduce. • Arguments against uplift were more behavioural: would groups want to do that many more attacks, or would it be too risky and raise flags? This was hard to take into account.
MITRE Initial Access	• Initial flat trend, then a jump in capabilities, then a flat trend again. • General agreement that the easier tasks would hardly provide any uplift. The later tasks, however, concern the exploitation of vulnerabilities that by definition could grant initial access, and therefore could bring success probabilities close to 100%. • Discussion about task specifics: some tasks here were closer to initial access in this application. The third task, for instance, required more multi-step reasoning which could be useful. `gunicorn` was closer to web vulnerabilities so it might provide more uplift than later tasks that are less applicable.

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Risk model factors	Summary
MITRE Execution	• Smoother generally increasing trend. • Back and forth: AI could uplift the weaker OC3 actors, increasing the overall mean, even without helping the stronger ones. At the stronger tasks the AI could help everyone. • But to be an established group at OC3 level, you already have to have a certain level of skill, so having such a model would not help much. • Top 8 initial access brokers are responsible for 80% of all listings. It is likely the same for affiliates. Additionally, ransomware operators buy access and give it to affiliates based on how well defended the target is (better target requires a better affiliate). Therefore uplifting the less strong OC3s can likely uplift the mean; however, these people may also contribute less to the mean if they perform fewer attacks.
MITRE Privilege Escalation	• Overall slight linear increase, with quite a wide range of estimates on the later tasks. • Arguments against uplift were that once you are already in the system, having an AI may not be that helpful. Likelihood of success is more based on the defending side security setup. If there is already a vulnerability in x% of cases, the actors are not going to find more unless the AI is capable of finding new 0-days. • Arguments for uplift are that most SMEs have terrible defence configuration anyway. There is a possibility for actors to get a lot of uplift in navigating better and getting privileged access. The task can also be sped up a lot, and as this is one of the steps with a high risk of detection, speed-up could be helpful, although with automated defenses, speed does not matter so much as to whether an actor gets caught.
MITRE Lateral Movement	• The spread of estimates here is large. • Potentially at this step there are multiple paths, for instance vulnerability exploitation or social engineering. An AI could help the latter without strong skills, but could only help the former if it was quite strong. Therefore it is hard to average over this step. • Arguments against uplift were that while a model may be more capable, it likely will not be sufficient to push the frontier of what humans can already do at this step. To do some simple lateral movement may be easy, but to get good enough to be better than humans is very difficult. • The harder Cybench tasks, however, seem very challenging, and demonstrate capability to do a lot of trial and error and long chained reasoning steps, and would likely take a human hours. So if an AI could automate hours of human work, applying this to lateral movement could provide a strong uplift. • Trial and error could also raise flags; therefore the uplift may depend on actor sophistication, again uplifting more the weaker OC3s.

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Risk model factors	Summary
MITRE Impact	• Trend is non-linear, flat at the start followed by a sharp takeoff. • This task depends more on strategizing and mixing ingredients than having specific knowledge of internals, so a model that can reason for a long time would be helpful. • Some estimated nearly 100% for the harder tasks, as if you have done all the previous tasks, you usually have a good knowledge of system layout etc. So with an AI this strong it would be hard to fail. • Failure could only be caused by backup or strong end-point detection, which most SMEs do not have.
MITRE Financial Theft	• This was one of the probability steps with the most disagreement. There was high uncertainty over whether an AI that is strong at coding/cyber could also improve things like ransom negotiation. • Many experts felt it was hard to generalize from the benchmark to this step. • Previous AIs were dominated by pre-training, therefore all capabilities tended to be highly correlated (good coder = good negotiator). With the focus on RL now, this correlation is less strong, and you can get very strong STEM AIs that are not much better at writing. • Arguments for uplift were that the AI could find more things to relay into payments, having more valuable data might increase likelihood, and strong AI could help persuasion (in particular for countries where English is not their main language). • Arguments against uplift centred around paying or not based on company policy and law enforcement having professional negotiators that would be far superior to AI.
Impact – Ransom	• Arguments against uplift centred around how payments depend on company policy, how ransomware actors tend to make ransom demands that are proportionate to the company size (i.e., “we know you can afford this”), as larger demands can just lead to the company shutting down. • Arguments for uplift addressed how there might be “nastier” ransomware. For example, that targets healthcare and threatens to harm patients. Stronger AI could therefore find ways to extract more money, which could lead to much higher ceilings.
Impact – Recovery	• Arguments for costs getting higher are that succeeding further in earlier steps (lateral movement, etc.) would significantly increase the cost of recovery. Getting more valuable data could also be more impactful on companies. • Arguments against costs getting higher are that most SMEs do not do much network segmentation or security. If an actor has privileged access, they have most things already. Ransomware also is pretty well designed already, through trial and error in the last 10 years or so, so AI uplift could be limited here.

C.2 LLM Estimators' Rationales

Table 6 summarizes LLM estimators' rationales for the OC3 Ransomware SME risk model. Note that we do not use multiple stages when eliciting predictions from LLM estimators, as we did not observe a meaningful increase in prediction quality after just one stage.

Table 6: Summary of rationales from the LLM-estimators.

Risk model factor	Summary
Number of Actors	The central disagreement across all capability levels is whether technical expertise or organizational and resource factors are the binding constraint. Arguments for expansion emphasize that LLMs lower technical expertise barriers, enabling groups with operational capacity but limited technical skills. Democratization of advanced techniques addresses specialized knowledge requirements. Arguments against stress that non-technical barriers dominate, including organizational capacity, financial resources around $1M, criminal network access, and risk tolerance. Operational complexity including team coordination, sustained campaign management, and OPSEC requirements remain as bottlenecks AI cannot address. At low capability levels, experts show tight consensus that minimal expansion occurs because basic capabilities don't address main bottlenecks. As capability increases, disagreement widens substantially. At intermediate to expert levels, experts increasingly diverge on whether demonstrated capabilities address actual technical bottlenecks preventing marginal actors from attempting attacks. At the highest capability level (PyTorch), maximum disagreement emerges with assessments ranging from modest (enabling groups that were marginally below capability threshold) to transformative (fundamentally changing who can attempt attacks). Additional differences center on whether new actors would come from existing OC3 groups switching vectors, lower-capability groups gaining uplift, or entirely new entrants.
Number of Attempts per Actor per Year	Arguments for more attempts emphasize LLMs significantly speeding up vulnerability research, exploit development, and troubleshooting - currently the most time-intensive phases. Technical knowledge becomes accessible to all team members enabling parallel operations, and reconnaissance can be largely automated. Arguments against stress that operational security constraints dominate since more attempts create more detection exposure, infrastructure requirements, and attribution risk. Human oversight requirements mean LLM outputs need validation limiting parallelization benefits. Integration friction from managing AI tools reduces net efficiency gains. At lower capability levels, there is moderate agreement that efficiency gains are real but bounded. As capability increases, disagreement widens substantially. At the highest capability levels (Gunicorn, PyTorch), experts fundamentally diverge on whether technical acceleration or operational constraints represent the binding factor.

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Risk model factor	Summary
Impact – Ransom	Experts show strong consensus that ransom payments are constrained by victim characteristics (financial capacity, backups, insurance) rather than attacker sophistication. The $10-50M SME revenue fundamentally caps realistic payments. Arguments for uplift focus on improved data targeting for double-extortion leverage and better victim financial profiling. Arguments against emphasize OC3 actors already use professional RaaS pricing strategies, severe domain mismatch between technical skills (cryptography) and extortion requirements (psychology, negotiation), and that baseline operations already achieve substantial leverage. At lowest capability levels, tight consensus emerges on negligible impact. At intermediate levels, there is agreement on moderate improvements through operational efficiency with substantial uncertainty about capability transfer. Even at expert level, estimates remain modest as cryptanalysis has limited applicability to extortion economics. Experts consistently note payment amounts reflect victim circumstances more than attacker capability once baseline competence is exceeded. Wide uncertainty ranges primarily reflect baseline payment variability rather than LLM impact.
Impact – Recovery	Arguments for higher costs emphasize LLMs enabling more systematic identification of critical systems, improved discovery and targeting phases, and enhanced data collection increasing recovery complexity. Better execution and faster operational tempo are identified as drivers. Arguments against stress that once administrative access is achieved, attackers already reach most critical systems in SME targets with limited segmentation. Additionally, recovery costs scale sublinearly with affected systems. Core drivers including system restoration requirements and business disruption depend more on target characteristics than attacker sophistication. At lowest capability levels, experts show tight consensus on negligible impact. As capability increases through intermediate levels, moderate agreement emerges around meaningful but bounded improvements through operational efficiency. At advanced levels, experts agree sophisticated capabilities enhance attack thoroughness but disagree on magnitude, with some emphasizing substantial improvements while others stress environmental and target constraints limit gains.

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Risk model factor	Summary
MITRE Initial Access	Experts consistently identify the high baseline (60%) indicating already-competent OC3 actors as a key constraint limiting improvement potential. Arguments for uplift emphasize meaningful assistance with exploit debugging, payload adaptation, and troubleshooting - bottlenecks in converting public CVEs into reliable attacks. Systematic approaches help with exploit customization and faster iteration. Arguments against stress that capability ceiling effects introduce frequent errors requiring human intervention, domain transfer uncertainty exists between benchmark conditions and real-world scenarios, and operational constraints including defensive barriers remain unaddressed by AI assistance. At basic capability levels, experts agree the ceiling severely limits impact with enormous gaps between demonstrated skills and requirements. At intermediate levels (LibreChat, MLFlow), strong consensus emerges that capabilities transfer reasonably well, providing meaningful but bounded assistance. At expert levels, experts agree sophisticated capabilities provide genuine benefits but diverge on magnitude, with some emphasizing technical depth should enable substantial improvements while others stress that operational constraints and baseline competence limit gains regardless of capability level.
MITRE Execution	Experts consistently identify the high baseline (50%) as indicating execution isn't typically the major bottleneck for OC3-level actors. Arguments for uplift emphasize significant improvements to payload crafting, command obfuscation, and evasion techniques through systematic approaches to PowerShell scripting and living-off-the-land methods. Arguments against stress that real-world execution involves target-specific environmental factors including system configurations, defensive tools, and network policies that LLMs cannot predict or adapt to in real-time. Domain transfer gaps between benchmark skills and operational execution requirements are consistently cited. At basic capability levels, experts agree minimal value exists given enormous skill gaps. At intermediate levels (LibreChat, MLFlow), moderate consensus emerges around meaningful but constrained assistance, with some divergence regarding magnitude. At expert levels (Gunicorn, PyTorch), experts agree advanced security knowledge meaningfully enhances execution through sophisticated techniques, though universally acknowledge implementation friction and inability to overcome all defensive countermeasures.

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Risk model factor	Summary
MITRE Privilege Escalation	The very high baseline (70%) is the most consistently cited constraint across all capability levels. Arguments for uplift focus on systematic enumeration guidance, comprehensive technique coverage, better troubleshooting, and script generation helping against SME targets with common misconfigurations. Arguments against emphasize that most privilege escalation opportunities are already accessible to OC3 actors, and the primary failure mode is architectural with proper security controls including least privilege and patch management that cannot be overcome through better technique selection. Domain transfer limitations are consistently cited, particularly that benchmark skills don't directly translate to system-level operations. Experts show strong consensus at both extremes with unanimous agreement at low capability that basic skills provide only modest systematic benefits, and at expert levels that sophisticated capabilities help but high baseline limits gains. Most disagreement occurs at Gunicorn level where experts fundamentally diverge on whether advanced HTTP protocol exploitation skills transfer to system privilege escalation. Some see strong correlation through systematic analysis while others emphasize domain gaps between network protocols and system internals.
MITRE Lateral Movement	Experts show very consistent reasoning across all capability levels, stating that architectural constraints dominate over technical assistance benefits. Network segmentation is universally identified as a fundamental barrier AI cannot overcome regardless of capability level. Arguments for uplift focus on systematic enumeration, improved scripting and automation, better troubleshooting, and at advanced levels, sophisticated network analysis. Arguments against emphasize that properly implemented network isolation cannot be overcome through better technique selection, the very high baseline (65%) indicates most accessible paths are already exploited, and the primary failure mode is environmental with air gaps and isolated segments representing structural constraints AI cannot address. Despite capability ranging from basic to expert, expert reasoning remains compressed around the view that lateral movement success is fundamentally constrained by target architecture rather than attacker sophistication. At lower capability levels, there is near-unanimous agreement that demonstrated skills have poor correlation with network lateral movement requirements. At advanced levels, some disagreement emerges over whether sophisticated analytical capabilities can meaningfully transfer to network penetration through systematic problem-solving, but even here most experts emphasize environmental constraints dominate.

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Risk model factor	Summary
MITRE Impact	Experts agree throughout all capability levels that deployment is primarily operational rather than analytical, and the very high baseline (80%) severely constrains potential improvements. Arguments for uplift focus on improved scripting and automation, better troubleshooting, and enhanced backup discovery. Arguments against emphasize that with administrative access already achieved, technical execution is straightforward for OC3 actors, making the task primarily about executing established procedures rather than complex analysis. Benchmark skills consistently show poor correlation with system administration tasks. The primary failure mode is universally identified as robust target defenses including offline backups, immutable backups, and effective incident response that AI cannot overcome. Even at expert capability levels, experts agree advanced cryptographic capabilities don't translate meaningfully to system administration. There is strong agreement that deployment success is bounded by target defensive posture rather than attacker's technical sophistication.
MITRE Financial Theft	Experts agree that extortion success is fundamentally driven by victim characteristics rather than attacker communication quality. The severe domain mismatch between demonstrated technical capabilities and social/psychological requirements for successful extortion is consistently emphasized. Arguments for uplift focus on marginal improvements in communication quality, target research, and potentially enhanced victim profiling. Arguments against stress that primary factors determining payment - victim financial capacity, backup/recovery capabilities, insurance guidance, and organizational policies - remain completely outside the LLM's sphere of influence. Across all capability levels, experts consistently note OC3 actors as RaaS affiliates already possess adequate extortion capabilities and proven communication templates. The approximately 30% baseline payment rate is identified as primarily constrained by victim-side factors that communication optimization cannot overcome. Even at expert capability levels where the LLM demonstrates sophisticated technical reasoning, experts agree this doesn't translate to improved extortion outcomes. The consistent characterization of "minimal to marginal impact" across all capabilities reflects strong consensus that technical sophistication provides essentially no advantage in this social/business domain where victim constraints dominate.

D Personas of the LLM Estimators

In this Appendix, we present the information used to construct our LLM estimators' expert personas. This information is included as part of the system prompt passed to the LLM estimator.

Defensive Security Specialist

Name: Defensive Security Specialist

Focus: Network defense and intrusion detection systems

Background: 10 years SOC experience, specialized in APT detection

Bias: Conservative estimates on attacker capabilities; emphasizes importance of defense-in-depth

Key Trait: Particular attention to detection evasion techniques and defense bypass methods

Analytical Approach: Analyzes from defender's perspective, focusing on detection points and security control effectiveness.

Malware Reverse Engineer

Name: Malware Reverse Engineer

Focus: Deep technical analysis of malware functionality and evasion techniques

Background: Anti-virus research lab, specialized in advanced malware analysis

Bias: Strong emphasis on technical implementation complexity and code-level challenges

Key Trait: Detailed understanding of malware internals and anti-analysis techniques

Analytical Approach: Bottom-up analysis starting from technical implementation details to overall capability assessment

AI/ML Security Researcher

Name: AI/ML Security Researcher

Focus: Machine learning applications in cybersecurity

Background: PhD in Computer Science, specialized in AI security

Bias: Deep understanding of ML/LLM capabilities and limitations

Key Trait: Strong theoretical foundation in AI/ML security boundaries

Analytical Approach: Systematic analysis of how LLMs could assist in different attack phases

Threat Intelligence Analyst

Name: Threat Intelligence Analyst

Focus: APT behavior patterns and campaign analysis

Background: Former intelligence community analyst

Bias: Strong understanding of real attacker TTPs and behavior patterns

Key Trait: Emphasis on broader operational context and attacker motivation

Analytical Approach: Analysis based on observed attacker behavior patterns and capabilities

Security Software Developer

Name: Security Compliance Officer

Focus: Security standards and control frameworks

Background: CISSP, CISM certified with regulatory compliance experience

Bias: Risk-averse, strong emphasis on control effectiveness

Key Trait: Systematic evaluation of security controls and their effectiveness

Analytical Approach: Framework-based analysis focusing on control effectiveness and risk

E Example Risk Model

As an example of a risk model, in this Appendix we include the baseline model for OC3 Ransomware SME, with inputs and outputs for the baseline estimates. The LLM estimates for the uplifted parameter values are available in Appendix F.

Inputs

Scenario Vignette

- We consider a threat actor that would be broadly classified as comprising a small cyber crime syndicate having OC3 level operational capacity (~10 individuals, with resources of ~$1m) and loosely aligned with the definition provided by Nevo et al. (2024)).
- The threat actor primarily operates as a ransomware affiliate, and makes use of RaaS services that are provided by bigger cyber crime RaaS operator crime groups (see NCSC-NCA (2023) for more information on the RaaS eco-system).
- When conducting attacks the threat actor performs double extortion, which involves both data encryption ("availability" impact) as well as data exfiltration ("confidentiality" impact). This is a more complex attack than just data exfiltration, but can command a higher reward for the threat actor.
- For our scenario, we assume that the threat actor exploits vulnerabilities in public facing web apps or devices (e.g. using exploits for n-day vulnerabilities, wherein for example, system administrators of attacked networks may have left their systems vulnerable through a lack of adequate patching hygiene).
- The threat actor targets SMEs (small medium enterprises) where the attackers look to make an average ransom fee of somewhere in the vicinity of $100k.
- The target SME operates at cybersecurity maturity level MIL1 (see (DOE, 2025)) across all maturity domains with MIL2 in some domains. It is assumed that the target generally implements the cybersecurity fundamentals well, and will generally also do a good job of mitigating threats from the most common attack vectors.

Historical examples

- An affiliate group of the type that we are considering might for example have made use of the LockBit RaaS service (when it was in its prime).
- **LockBit**
  - From Wikipedia (2025d): In the United States between January 2020 and May 2023, LockBit was used in approximately 1,700 ransomware attacks, with US$91 million paid in ransom to hackers (mean of $53k per attack).
  - LockBit was also behind 5 of the 10 biggest ransom demands ever made: demands running to $10's millions (Poireault, 2023)
  - In 2024 LockBit affiliates achieved an average ransomware payout of ~$30k in 2024 (Chainalysis Team, 2024)
  - In 2025 LockBit affiliates achieved about ~$5k in ransomware payouts (Chainalysis Team, 2025)
  - LockBit has reduced in significance in recent years, since its operations were disrupted by law enforcement in Feb 2024 (Corera, 2025), but at least in its former glory, it's still a reasonably representative example for our purposes.
  - According to CISA (2023b), "The LockBit RaaS and its affiliates have negatively impacted organizations, both large and small, across the world. In 2022, LockBit was the most active

global ransomware group and RaaS provider in terms of the number of victims claimed on their data leak site"; "Due to the large number of unconnected affiliates in the operation, LockBit ransomware attacks vary significantly in observed tactics, techniques, and procedures (TTPs)"; "Affiliates that work with LockBit and other notable variants are constantly revising the TTPs used for deploying and executing ransomware"; "During their intrusions, LockBit affiliates have been observed using various freeware and open-source tools that are intended for legal use. When repurposed by LockBit, these tools are then used for a range of malicious cyber activity, such as network reconnaissance, remote access and tunneling, credential dumping, and file exfiltration"; "Affiliates exploit older vulnerabilities like NIST (2021), F5 iControl REST unauthenticated Remote Code Execution Vulnerability, as well as newer vulnerabilities (which include vulnerabilities in web-facing apps)

- **Ghost (Cring) ransomware** (CISA-FBI, 2025)
  - "Beginning early 2021, Ghost actors began attacking victims whose internet facing services ran outdated versions of software and firmware. This indiscriminate targeting of networks containing vulnerabilities has led to the compromise of organizations across more than 70 countries.."
  - "Ghost actors use publicly available code to exploit Common Vulnerabilities and Exposures (CVEs) and gain access to internet facing servers. Ghost actors exploit well known vulnerabilities and target networks where available patches have not been applied."
  - "Ghost ransom notes often claim exfiltrated data will be sold if a ransom is not paid. However, Ghost actors do not frequently exfiltrate a significant amount of information or files, such as intellectual property or personally identifiable information (PII), that would cause significant harm to victims if leaked. The FBI has observed limited downloading of data to Cobalt Strike Team Servers"
  - "Ghost variants can be used to encrypt specific directories or the entire system's storage"
  - Observation: So Ghost use a limited amount of double extortion (not much in the way of data exfiltration), but in other respects are quite representative of our assumed threat actor type.

Type of Actor

- We consider a threat actor that would broadly be classified as a small cyber crime syndicate that has operational capacity of the OC3 level (~10 individuals, with resources of ~$1m, and loosely based on the definition of the corresponding threat actor provided in Nevo et al. (2024)).
- The threat actor is assumed to operate primarily as a RaaS affiliate (per definitions in NCSC-NCA (2023)), and specialises in achieving initial access by exploiting vulnerabilities in public-facing web apps and devices.
- The threat actor is expected to bring their own customizations to the task of deploying the RaaS operator's capabilities, and has the capability to adaptively make use of tools, and "living off the land" approaches in moving through the attacked network (per CISA provided information on LockBit affiliates (CISA, 2023b)).
- The threat actor is assumed to have pre-existing cyber attack infrastructure, but no pre-existing access to the attacked organisation.
- In our scenario, we envisage some division of labor, with different members of the cyber crime syndicate optionally specializing in different areas, such as malware customisation, infrastructure operation/acquisition, network penetration, negotiation/coercion, crypto-laundering etc. It should be noted that the RaaS operator may perform many of these activities on behalf of the affiliate, and also that it is commonplace for the affiliate to just provide the initial access, conduct the attack, exfiltrate the data and leave everything else including malware development, negotiation and payment, crypto-laundering etc to the RaaS operator.

Type of Target

- The threat actor targets SMEs, with bias toward the more "medium" sized companies, and hoping to realize an average ransom payout of somewhere on the order of $100k
- Approximate company sizes of interest in our scenario are:
  - 75–250 employees

- Revenue \$10m–\$50m
- Note: The size of an "SME" as defined by the EU, and as described in Wikipedia (2025b), is 50-250 employees and \$2m–\$50m in revenue. Based on this definition, the companies we consider in our scenario are more biased toward the "medium" end of the SME bracket.

- Ideal targets are sufficiently financially attractive, that turnover/resources are sufficient to lead to the targeted ~\$100k average ransom payout.
  - Note, according to Sophos (2025), the average payout for a \$10m–\$50m company in 2024 was \$330k, while the average demand was \$109k.
  - Whilst the end ransom demand for a smaller company may be less than for a larger one, compromise of a smaller and relatively less well defended company may be easier, and less prone to result in the attention of law enforcement.
- The threat actor especially targets companies relying on IT systems for operations, e.g. logistics, manufacturing, retail, such that encryption ransomware, and its associated loss of availability for the target has significant impact (in addition to the impact of confidentiality loss associated with data exfiltration).

Type of Vector

- From Sophos (2025), it can be seen that ransomware affiliates use a variety of initial access vectors.
  - Exploited vulnerability was the top "root cause" for companies with revenue <\$10m (at 28%), and was the second most common root cause for companies with revenue \$10m-\$50m at 25%.
- Whilst Sophos (2025) indicates that for companies with between 100 and 250 employees "exploited vulnerability" was the root cause in 29% of incidents, coming second only to "compromised credentials" on 30%)
- Note that info from Coveware (2024) suggests that CVEs are also often favored by actors going after bigger enterprise targets
- NCSC-NCA (2023) also identified "direct exploitation" as a prominent initial access vector for ransomware
  - "…many [criminals]…conduct the scanning themselves.… Criminals look for devices that are likely to be in businesses (rather than home environments). Examples include Microsoft Exchange servers, platforms such as Citrix or VMware, VPN devices and firewall devices".
  - "Criminal use of exploits often surges shortly after certain critical patches are released indicating they are being reverse engineered from the patches. In most cases, an exploit is widely available in the criminal forums in less than one week from the patch being released. A zero-day exploit is a recently discovered vulnerability, not yet known to vendors or antivirus companies, that criminals can exploit. Cyber criminals don't need to develop their own zero-day exploits as doing so is expensive, and there are many devices "in the wild" that are not patched regularly. However, some actors have been known to use zero-day exploits, most notably there are public reports of Cl0p's use of the Accellion, GoAnywhere and MOVEit vulnerabilities".

Example type of vector

- According to Recorded Future (2024), certain classes of threat actors most favour vulnerabilities that have high impact in terms of access or control over systems and the ubiquity of the affected software. They also state "…we also found that when many ransomware groups target a vulnerability, they do so almost always because it can be exploited with minimal lines of malicious code that can be easily implemented into mass scanning activity (through malicious HTTP requests, for example)"
- Some example vulnerabilities that that LockBit affiliates have used, according to CISA (2023b) include:
  - CVE-2019-0708: Microsoft Remote Desktop Services Remote Code Execution Vulnerability
  - CVE-2018-13379: Fortinet FortiOS Secure Sockets Layer (SSL) Virtual Private Network (VPN) Path Traversal Vulnerability.
- Some examples (Zurier, 2025) that Ghost used:
  - Fortinet FortiOS appliances (CVE-2018-13379)

- Servers running Adobe ColdFusion (CVE-2010-2861 and CVE-2009-3960)
  - Microsoft SharePoint (CVE-2019-0604)
  - Microsoft Exchange (CVE-2021-34473, CVE-2021-34523, and CVE-2021-31207.

Defense Level

- We assume that the SME target has cybersecurity maturity level MIL1 (according to the Cybersecurity Capability Maturity Model DOE (2025)) across all maturity domains with MIL2 in some domains. It is assumed that the target generally implements the cybersecurity fundamentals well, and will generally also do a good job of mitigating threats from the most common attack vectors.

Intent

- The attacker's intent is financial monetization through ransom.
- Specifically we assume that the attacker uses double extortion. This comprises both data encryption ("availability" impact) as well as data exfiltration ("confidentiality" impact). Double extortion is a more complex attack, but can command higher reward than data exfiltration alone. The threat actor demands payment of a ransom in exchange for provision of decryption keys and a promise not to publicize exfiltrated data.
- The greater levels of threat actor skill and capability required to conduct extortion via encryption of systems, over and above the skill required for just data exfiltration extortion, distinguishes this double extortion approach as something that an actor at RAND operational capability level OC3 might be more inclined to do, or be better able to do, than an OC2 actor.
- Coveware (2023) provides support for the above, indicating how attacks such as double extortion can achieve bigger returns, but require more work on behalf of the threat actor, and the broad skills required may mean that multiple individuals often need to work together in some form of syndicate.

Outputs

Number of Actors

In our context, an "actor" is equivalent to an "affiliate" and refers to the cyber crime syndicate as a whole (i.e. "actor" or "affiliate" refers to the collection of ~10 individuals that make up the crime syndicate). The baseline values are summarized in Table 7:

Percentile	Estimate
5th	1
Most likely value	10
95th	40

Table 7: Baseline estimates for the Number of Actors

<u>Most likely value rationale:</u>

- Number of RaaS operators
  - Following LockBit's takedown, the number of ransomware groups listing victims has risen from 43 to 68, according to Secureworks data (Deslandes, 2024).
  - The number of active ransomware groups jumped 40%, from 68 in 2023 to 95 in 2024 (The Hacker News, 2025).
  - IC3 recognized 67 new ransomware variants in 2024 (FBI, 2025).
  - All the above would suggest that there are on order ~80 RaaS operators
- Number of affiliates
  - A significant RaaS strain could have a large number of affiliates, for example LockBit had 193 in its prime (Kindus, 2024).
  - The 3 groups responsible for 53% of the attacks (see (Kovrr, 2023)) could plausibly have similar numbers of affiliates as LockBit had in its prime.

    - Let's assume these top 3 have 150 affiliates each, and the other 5 RaaS groups that we are considering have 50 each.
    - That would give $3 \times 150 + 5 \times 50 =$ **700 affiliates**
- Number of OC3 (~10 person) crime syndicates
    - Apparently there has recently been a growing number of lone wolf affiliates in general (following some of the recent law enforcement takedowns, see (Coveware, 2025))
    - We assume $\frac{1}{3}$ of the 700 affiliates are OC3 groups comprising ~10 individuals, i.e. **200 are OC3 affiliate groups**
- Number of OC3-type affiliates targeting SMEs
    - It seems likely that a large proportion of total affiliates will target SMEs, though apparently there is an increasing trend to target bigger companies with larger ransomware payouts (see (Chainalysis Team, 2024))
    - Coveware (2024) indicate:
        * "The average company size of victimized organizations fell to 231 employees (-32% from Q3 2023)..… ransomware remains predominantly a small to mid market problem."
        * 30.6% ransomware attacks on companies with 11–100 employees
        * 31.3% ransomware attacks on companies with 101–1000 employees
    - (Alder, 2024)
        * Between Q2, 2022, and Q2, 2023, ransomware gangs favored attacks on large companies but the average size of victim companies has been falling with medium-sized companies seen as the sweet spot. Attacks are easier to conduct as investment in cybersecurity is lower than at large firms and mid-sized companies have sufficiently large revenues to allow large ransom demands to be issued. In Q4, 2023, the average size of a victim company was 231 employees, down 32% from Q3, 2023.
    - (Kovrr, 2023)
        * The top targeted company sizes are: \$10M–\$50M (39%), \$1M–\$10M (20%), and \$200M–\$1B (12%). "It is clear from the data that ransomware actors prefer to attack smaller companies, with only 8% of attacked companies having a revenue of over \$1B, and 70% of attacked companies having revenue below \$100M."
    - Analysis: In our scenario we are interested in companies of 75–250 employees (\$10m–\$50m revenue). Let's assume that 40% of our identified OC3 affiliate crime syndicates, i.e **80** of them (200×0.4)**, go after SMEs** of the size that we are considering
- Number of affiliates using double extortion vs just extorting based on exfiltrated data
    - (Wolf, 2025) state: "As organizations improve their ability to recover from ransomware, cyber criminals have turned to data exfiltration to increase leverage—96% of ransomware cases analyzed included data theft".
    - (Group-IB, 2025): 83% of ransomware cases involved data exfiltration
    - BlackFog (2025) state: "BlackFog's figures indicate that data exfiltration is a factor in the vast majority of ransomware incidents. In the first half of 2024, we found that 93% of ransomware attacks exfiltrate data, making it by far the biggest malware threat currently facing enterprises."
    - (Micro, 2024): Ransomware attacks could also drift towards business models that no longer necessitate encryption.
    - (Mcintosh et al., 2024): Points to reducing use of double extortion
    - KELA (2024) report: "Most of them continue to operate as ransomware-as-a-service (RaaS) platforms, relying on double extortion and supply-chain compromises."
    - Reed (2023) reports:
        * In total, a second extortion method is part of the equation in 40.9% of attacks. 30.4% of attacks involve three threats, while another 7.2% have four threats involved.
        * 30% of Ransomware attacks involving encryption resulted in stolen Data (Sophos, 2023)
    - Analysis: It's rather unclear from the above exactly what proportion of actors are using double extortion, and it seems there may be a trend towards just performing (easier) data exfiltration extortion. Firewall Times has the most directly usable number **(40% for double extortion)**, so we use that.
        * This leaves us with $40\% \times 80 = 32$ affiliates

- Number of affiliates using vulnerability exploit as initial access
    - ~29% of initial accesses use vulnerability exploit (Sophos, 2025)
    - Therefore, we multiply our number of OC3 affiliates (32) by 0.29 to give ~**10**

5th percentile rationale

If only 10% of 700 affiliates are OC3 actors, and only 25% of these sometimes go after companies with revenue \$10m–\$50m, and if proportion of these syndicates using double extortion vs single extortion is only 20%, then we'd have $700 \times 0.1 \times 0.25 \times 0.2 \times 0.32 \sim$ **1** actor

95 percentile rationale

If 50% of 700 affiliates are OC3 actors, and if 50% of these sometimes go after companies with revenue \$10m–\$50m, and if proportion of these syndicates using double extortion vs single extortion is 70%, then we'd have $700 \times 0.5 \times 0.5 \times 0.7 \times 0.32 \sim$ **40** actors

Number of Attack Attempts per Actor per Year

With our scenario, we consider:

- Opportunistic attack as opposed to targeted attack, in the sense that any SME with the required vulnerable web-facing app could be a potential target for our threat actor (though following OSINT, some targets may be preferred over others).
- In the ransomware attack that we are considering, we define both a "campaign" aspect and an "attack" aspect. The campaign aspect is concerned with Resource Development (TA0042) (MITRE, 2025c), and the active scanning of Reconnaissance (TA0043) (MITRE, 2025d). The "attack" phase, in our definition refers to the phase from the point that a vulnerable web-facing application has been identified and selected and Initial Access (TA0001) (MITRE, 2025b) is attempted.

The baseline estimates are summarized in Table 8:

Step	Number Attack Attempts per Actor per Year
Cost	No limit
Operational capacity ceiling	150
Historical	350
Triangulation	
5th percentile	75
Most likely value	200
95th percentile	500

Table 8: Estimates for the Number of Attack Attempts per Actor per Year

Cost

- Yarochkin et al. (2021) projected \$100k/month recurring bill for some sorts of ransomware groups (though they are not specific about how many people there are in the group nor indeed whether they are referring to a RaaS provider, an affiliate group, or some do it all "in-house" operation – so it's rather questionable how useful the figure is to us).
- "Regardless of successful payouts, most of these personnel require payment for services, whether such remuneration involves monthly salary or per-project payments .Estimating average monthly costs (such as salaries, servers, virtual private server rentals, service providers, tools, accesses, and infrastructure, among others), these groups might spend at least US\$100,000 upward to keep operations running. If these groups target 10 companies at a time but only one victim can pay, that single organization carries the brunt of all the expenses that the groups make in addition to the profit they hope to have."
- Analysis: \$100k/month could plausibly cover costs of a 10-person team (esp if annual rate of pay for a Russian cyber expert is ~\$30k)

- Cost breakdown:
  - Payment to RaaS operator
    * The main per successful attack cost (vs fixed cost) is to the RaaS provider (if payment to RaaS provider takes the form of profit share). If the RaaS provider takes ~20% of the paid ransom then this just increases the number of required successful attacks per year to cover fixed costs (salaries etc) (Register, 2023).
  - Our actor would need exploits for services like sharepoint, confluence, VPNs, etc. There are many publicly available and/or open source exploit frameworks like nuclei, metasploit, etc. where new vulnerabilities are added pretty quickly after release in many cases and actors can just use free, open tools. It's also possible to pay for an exploit, with price depending on how new/useful/reliable they are, for example the price could be in the range $10k–$50k.
  - Costs of browser exploits (though different in nature to our exploits of public-facing web apps) do give an indication of the kinds of sums that can be paid
    * Botezatu (2013) indicate that the Blackhole exploit was rentable at $1500/year (but more exclusive exploits could be as much as $10,000/month
    * News (2020) indicate kits available at $1,000/month
  - Crypter as a service
    * Sekoia (2024) indicate: ~$50/month to $250/month
  - Cryptocurrency tumbler
    * Wikipedia (2025a) indicates that tumblers take 1-3%
- Analysis: Costs for hardware and software seem to be on the order of single digit thousands per month, and hence, both because these fixed costs are relatively low and because variable costs are incurred on a profit share basis, we conclude that **these aspects will not be a determinant of how many attacks/year could be conducted.**

Operational capacity ceiling

There would appear to be no significant limitation in terms of candidate victims.

- NCSC-NCA (2023)
  - Criminal use of exploits often surges shortly after certain critical patches are released indicating they are being reverse engineered from the patches. In most cases, an exploit is widely available in the criminal forums in less than one week from the patch being released.
  - 10% of devices may be left unpatched even 4 months after a patch is available
- SentinelOne (2025) indicate:
  - The National Vulnerability Database (NVD) recorded over 30,000 new Common Vulnerabilities and Exposures (CVEs), half of which were classified as high or critical severity.
  - A new vulnerability is identified and published every 17 minutes. Half of all the vulnerabilities have been published in the last five years.
- Given the number of SMEs (10s of millions globally), and the fact that many of them won't patch vulnerabilities promptly, it would seem currently unlikely that there is a shortage of potential victims.

The key time consuming steps in the attack would appear to be:

- During the reconnaissance phase, looking at the results of "active scanning" and determining, e.g. based on OSINT (open source intelligence), whether the particular enterprise is one which the threat group wish to try attacking (i.e. which meets their criteria in terms of likely ransom payout achievable, and likelihood of success etc).
- Tactics like lateral movement and privilege escalation, and activities like locating backups require "hands on keyboard" and therefore can be time consuming and costly.
  - In contrast, steps like encrypting or exfiltrating certain content or files can be automated, and these steps are therefore not so time consuming or costly.
- Encryption malware deployment (also including disabling security and backup features)

- Ransom negotiation and follow up.

According to Secureworks (2023), in 2023 average dwell time went from 4.5 days in 2022 to less than 24 hours in 2023.

- They state "The driver for the reduction in average dwell time is likely due to the cyber criminals' desire for a lower chance of detection. The cybersecurity industry has become much more adept at detecting activity that is a precursor to ransomware. As a result, threat actors are focusing on simpler and quicker to implement operations, rather than big, multi-site enterprise-wide encryption events that are significantly more complex. But the risk from those attacks is still high."

Analysis:

- It would seem plausible that there are 10 days of person effort per fully completed successful attack, when attacking SMEs
- If:
  - 50% of attacks fail (quickly) and e.g. after expending 1 day of effort
    - "bath-tub" effect
  - 25% take 5 days of effort (and fail)
  - 25% take 10 days of effort (and perhaps succeed)
- Then, expected effort per attack is 0.5 x1 + 0.25 x 5 + 0.25 x 10 = 4.25 days (~5 person days)
- With 10 people in the team, and assuming 6 work actively on day to day attacks, whilst 4 work on "back-office" activities like developing cyber tools, infrastructure, malware modifications etc then that would suggest 6 attacks per week (6x5/5)
- Organisationally / managerially though that sounds somewhat implausible to handle in a group of 10 individuals. In addition, there won't be perfect efficiency in the usage of people's time with some individuals sometimes having to wait on others to complete tasks.
- Hence we assume 3 attack attempts per week
- There are 52 weeks in the year, so we assume ~**150 attacks/year** by the OC3 threat actor is the realistic operational capacity limit

Historical

In this section, we first gather some relevant data points, and then at the end of the section we perform an analysis to see what the historical data can tell us about the number of attack attempts/year

(Presumed) successful attacks per affiliate per year Lockbit data point:

- Lockbit attacked more than 2500 victims over 4 years (US DoJ, 2024)
- LockBit had 190 affiliates prior to the FBI takedown (Deslandes, 2024).
- Analysis: Presume these victims, correspond to successful attacks (?). ~13 victims/affiliate over 4 years → ~3 victims / year / affiliate RansomHub data point
- Cyble (2025) indicate 88 attacks./month (Feb 2025) for RansomHub. This was the most prolific malware
- Analysis: If we assume that RansomHub, as the most prolific RaaS has a similar number of affiliates as LockBit had in Feb 2024 (190), then that would suggest approx 6 attacks/year/affiliate (assume these were successful attacks). US DoJ convictions (over 2020-2023) (US DoJ, 2024)
- Lockbit affiliate (Russian national #1) successfully conducted at least 12 attacks over 3 years (extorting $1.9m)
- Lockbit affiliate (Russian national #2) successfully conducted at least 12 attacks over 2 years
- Analysis: 4-6 successful attacks/year/individual (ZeroFox, 2025)
- Provided info on the operations of the much diminished Lockbit ransomware
- Over first 4 months of 2025 – there appear to have been ~110 attacks, and were ~40 "incidents" - representing 1.5% of all ransomware attacks

- 75 affiliates had accessed the LockBit affiliate portal.
- This would suggest ~4-5 attacks/year/affiliate

Attacks/month:

- ~2500 attacks in Q1/2025 (incl disclosed and undisclosed) (Alder, 2025)
- Similar number of attacks /month ~600-800 mentioned by Cyble (2025). Since Cyble talks of ransomware gangs "claiming" attacks, we will presume that these are successful attacks

Attacks per organization:

- (CheckPoint Software, 2025)
  - Cyber Attack Surge: In Q1 2025, cyber attacks per organization increased by 47%, reaching an average of 1,925 weekly attacks per organisation.
- (Michalowski, 2025)
  - In 2023 - 59% orgs hit with ransomware, 4000 daily attacks per organization daily
  - 90% of attacks either fail or result in no financial loss
- (Sophos, 2025)
  - Sophos indicate ~57% of SMEs were hit by ransomware last year.
- The UK government (Saman Rizvi, DSIT, 2025) noted:
  - "Just over four in ten businesses (43%) and three in ten charities (30%) reported having experienced any kind of cyber security breach or attack in the last 12 months. This equates to approximately 612,000 UK businesses and 61,000 UK charities that identified a cyber breach or attack in the past year
  - The decrease was driven by fewer micro and small businesses identifying phishing attacks
  - Observation: If phishing attacks are included, it is perhaps not unsurprising that the number of attack attempts are high. A similar conclusion would be true, if vulnerability scanning of web-facing devices is "counted" as an attack attempt.

Global ransom attempts

(Reed, 2023):

- Just over 493 million ransomware attempts were made in 2022
- During a survey taken in 2023, 72.7% of companies reported being victimized by ransomware in the past 12 months
- Overall, 46% of SMEs have experienced a ransomware attack
- According to Delaney (2024), there are ~360 million SMEs worldwide.
  - Analysis: if there are 3000 individuals acting as affiliates then, and if there are 493m attacks, each individual would be conducting 160,000 ransom attempts/year (500/day), and with a success rate of a handful per year. Which seems an incredibly high number!
    - We assume 700 affiliates in total (see "number of actors" computations above) comprising 200, 10-man OC3-groups and 500, 1 or 2 person groups

Analysis

- For our purposes we wish to understand the number of attacks that an OC3 group would make, beyond just scanning for web vulnerabilities, and rather comprising at least launching an exploit on a web-facing device that has a vulnerability. However, it has not been possible to find such figures.
- Figures we have found, tend to talk either of number of successful attacks, or else number of attack attempts per organisation, or percentages of organisations attacked, which judging by the very high numbers involved in these latter statistics, may well suggest that each phishing email (or perhaps each scanning attempt) is counted as an attack.
- Let's attempt to derive a figure from the number of successful attacks/individual/year:

- There are a few sources of information that could back an assertion of there being ~3 to 4 successful attacks per individual (i.e. per person) per year.
  * Here we assume that a successful attack refers to a successful “technical attack” (noting only ~30% of successful technical attacks convert to ransom payouts, and “success” from the perspective of the attacker).
- Our later analysis on probability of success suggests the probability of attack success is ~10%
- These figures could then suggest the approximate number of attacks (attempted exploits of the web vulnerability) per individual would be ~35 per year, and with 10 individuals in our OC3 cyber crime syndicate, that would suggest **350 attack attempts/year.**

Triangulation

Most likely value:

Before “triangulating” across the above data points, one additional factor to consider is the need for the OC3 group to deliver an acceptable tempo of success, in order to maintain motivation, and to avoid too much “lumpiness” in receipt of revenue:

- If the OC3 group needs or expects ~12 successful ransoms/year (where “success” includes ransom payout) to sustain itself and for the team to stay motivated with a fairly regular tempo of success (one success every month) then:
  - With ~10% probability of “technical success” and 30% probability of ransom payout per technical success, this would suggest **400 attacks/year.**

Analysis of the above:

- There is a sparsity of historical data on number of attack attempts (i.e. little data on failed attempts), and what data does exist seems more pointed at “campaign” level aspects such as phishing and perhaps scanning. For our purposes in this table, “number of attacks” refers to the count of the number of times that an exploit is attempted against a particular web-facing app or device (as opposed to a count of the number of web-facing apps/devices that were scanned during Reconnaissance “active scanning”).
- We have computed 3 figures:
  - 150, from the operational capacity analysis
  - 350, derived from historical numbers on successes/individual, and with an assumption on probability of successful attack.
  - 400, based on assumed team-motivational factors (again making assumptions on probability of “technical success” and probability of ransom payout)
- We triangulate by picking 200 (and placing more emphasis on the operational capacity figures)

5th percentile:

- There is significant uncertainty due to the lack of useful historical info. Operational capacity estimates could easily be wrong by a factor of ~3 (project managers are often overly optimistic by a factor of ~2).
- Let’s go for a figure of 1/3 of the “best estimate” figure (200/3) ~75. This amounts to 1-2 attacks per week (1 attack every ~3 days), which feels like a plausible lower bound.

95th percentile:

- There is significant uncertainty due to the lack of useful historical info.
- We select a number of 500 – since this is somewhat larger than our assumed team-motivational limit (400), provides an increase over our computation based on historical data (350) and is quite a bit larger than our assumed operational capacity figure (allowing for error in that computation).

Step	Included or not	Failure mode
Reconnaissance	Yes	If recon fails (e.g. no vulnerabilities or intel found), the attack cannot begin.
Resource Development	Yes	If resource prep fails (e.g. no exploit, no malware or infrastructure), the operation stalls – the affiliate lacks tools or access to proceed.
Initial Access	Yes	If initial access fails (no foothold gained), the affiliate cannot penetrate the victim's network – the ransomware deployment is a non-starter.
Execution	Yes	If execution fails (malicious code never runs), the attacker's payloads and commands don't take effect and the attack fails.
Persistence	No	N/A
Privilege Escalation	Yes	If privilege escalation fails, the attackers are stuck with low-level rights. They may be unable to disable security tools or access sensitive data, often stopping the attack from progressing beyond the initial host.
Defense Evasion	No	If defense evasion fails (attacker activity is detected/blocked), the affiliate will likely be interrupted or expelled before achieving goals. Early detection often means the encryption and exfiltration can be prevented or limited. Although it is essential, we do not include it, as it is implicitly factored into other steps.
Credential Access	No	Whilst credential access is likely to be a common tactic in ransomware operations (such as use of LSASS dumping and Mimikatz), we are already accounting for something similar with "privilege escalation" tactic and the associated "valid accounts" technique. It is also a "nice to have". To avoid double counting, and because it is a "nice to have", we do not include the credential access tactic.
Discovery	Yes	If internal discovery fails, the attackers may miss critical systems or data. They could encrypt some machines blindly, but might overlook backups or high-value servers, reducing the impact. Lack of knowledge can also lead to mistakes (e.g. tripping alarms) or an incomplete data theft, weakening their leverage.
Lateral Movement	Yes	If lateral movement fails, the compromise remains limited to the initial host or a small subset of systems. The affiliate then might only encrypt a trivial portion of the network or grab a small amount of data, which may not be enough pressure to make the victim pay.
Collection	Yes	If collection fails (attackers can't gather any sensitive data), the "double" in double-extortion is lost. The attackers would have no files to leak, weakening their bargaining position – they'd be left with just encryption, which many well-prepared victims can recover from.
Command-and-Control	Yes	If C2 fails (the affiliate loses contact with their malware/beacons inside the network), they can't direct the attack. The team would effectively be "locked out" from interacting with compromised systems, stopping further progression like escalation, lateral moves, exfiltration, etc.
Exfiltration	Yes	If exfiltration fails (attackers cannot transmit the stolen data out of the victim's network), the affiliate loses the data-leverage part of the extortion.
Impact	Yes	If impact fails (e.g. files don't get encrypted or critical services remain unaffected), the victim's operations continue relatively unscathed. With no significant disruption or data loss, the victim has little incentive to pay, and the affiliate's attack effectively fails to achieve its goal.

Table 9: Rationales for including or excluding MITRE Tactics in the OC3 Ransomware SME model

Steps in Attack - MITRE Tactic Level

Below, we list the rationales for including or excluding a given MITRE Tactic as part of our OC3 Ransomware SME risk model. These rationales are summarized in Table 9:

Rationale

- **Reconnaissance**: The affiliate performs active scanning of internet-facing assets for known vulnerabilities. Some basic OSINT will almost certainly be used to size up victims (e.g. revenue, insurance) to set ransom demands
- **Resource Development**: The affiliate must obtain or prepare tools, malware, and infrastructure to conduct the attack In the RaaS model, some resources come ready-made (e.g. the ransomware payload and a leak site for publishing stolen data are provided by the RaaS service).
- **Initial Access**: In our scenario, the group focuses on vulnerability exploits against Internet-facing systems.
- **Execution**: After initial access, the affiliate needs to launch tools: e.g. starting a remote shell, running malware. Ransomware operators often use scripts and admin tools for execution
- **Persistence**: involves maintaining long-term access to systems (surviving reboots, credential changes, etc.). Ransomware affiliates do often implement persistence – for example, adding new accounts – but it's not strictly required if they can complete their attack quickly.
  - "In 2022, Coveware reported that 82% of observed ransomware attacks included some form of persistence tactic—up 34% from the previous quarter. Persistence techniques remain relevant because attackers want to protect their hard-won access (Proofpoint, 2023).
  - According to an analysis by Huntress, the average time-to-ransom is around 17 hours. . . .this pace is in stark contrast to how major ransomware groups operated before the double extortion trend took off several years ago, when they would lurk inside victim networks for days or weeks to build greater access and gain complete control (Raywood, 2025a).
  - Secureworks said in its 2023 "State of the Threat" report that one reason for reduced dwell time is attackers moving faster to lower the chance of detection. "However, it is also likely that the threat actors now deploying ransomware are just lower skilled than previous operators" (Raywood, 2025b)
  - Analysis: we are looking at OC3 capable actors in our scenario, which are skilled actors. It's unclear however, whether their skill would result in them moving faster (perhaps without persistence), or whether it would tend to make them stay in the compromised network for longer to conduct their task more stealthily. Either way, it seems that dwell times are reducing and that persistence could be optional.
- **Privilege Escalation**: Ransomware affiliates almost always seek higher privileges after initial entry. Administrative or root access is needed to spread ransomware broadly and to turn off defenses or backups, achieving domain admin on the network is particularly valuable. If this step fails, the adversary's reach is severely limited. With only user-level access, they might not get access to critical servers or data and might be unable to propagate the ransomware across the network.
- **Defense Evasion**: critical when attacking a "well-defended" SME. Ransomware affiliates take active measures to avoid or disable security controls. They frequently leverage dual-use or trusted tools to blend in (e.g. using system administration software or legitimate RMM tools), and they directly sabotage defenses (see, e.g., CISA (2023b). A ransomware attack will likely involve at least some degree of defence evasion in executing most if not all tactics. Below we list relevant defence evasion techniques (as identified by Deep Research, Gemini and some CISA references), and where we assume that they will already be accounted for in evaluating probability of success for other tactics, this is indicated in italics:
  - **T1562 – Impair Defenses:** Kill or uninstall security software (CISA-FBI, 2023). *Assumed non-essential (so not accounted for)*
  - **T1027 – Obfuscated Files or Commands:** Includes obfuscation of malware. *Assumed dealt with primarily in the Execution tactic (malware code obfuscation), command obfuscation may appear in multiple other tactics.*
  - **T1070 – Indicator removal:** Delete shadow files and system and security logs after exfiltration (CISA-FBI, 2023).*Assumed non-essential to attack success (so not accounted for)*

- **T1484 – Domain or Tenant Policy Modification:** Modify Group Policy Objects to subvert antivirus protocols (CISA-FBI, 2023). *Assumed non-essential (so not accounted for)*
- **T1497 – Virtualization/Sandbox Evasion:** Sophisticated attackers may be keen not to download their malware if it will result in it being analyzed in a sandbox (possibly alerting the defender community and impacting their ability to use it for other attacks). *Assumed non-essential (so not accounted for)*
- **T1036 – Masquerading:** E.g changing filenames or filename metadata. *Assumed dealt with primarily in the Execution tactic, if needed*
- **T1564 – Hide artifacts:** *Assumed dealt with primarily in the Execution tactic, if needed.*

- **Credential Access**: stealing passwords, hashes, keys, and tickets is a cornerstone of ransomware operations. Compromised credentials allow the adversary to authenticate as legitimate users/admins, expanding their reach. With valid accounts, attackers can access remote services (VPN, RDP, file shares) and move through the network more freely.
- **Discovery**: once inside, affiliates perform Discovery to understand the environment. This reconnaissance phase inside the network lets them locate where valuable data resides (file servers, databases) and identify defenses or backup systems to circumvent
- **Lateral Movement**: how the attacker pivots from the initial foothold to broader control of the network. Ransomware affiliates aim to infect as many machines and access as much data as possible. They use techniques like connecting to other systems with stolen credentials or deploying remote execution tools.
- **Collection**: in the context of double extortion, Collection of victim data is a must. Before launching ransomware, affiliates quietly search for and aggregate valuable files: databases, client records, intellectual property, emails – anything that would hurt to see leaked publicly.
- **Command and Control (C2)** – adversary's lifeline into the victim environment. After establishing a foothold, affiliates need a communication channel to send commands, coordinate lateral movement, and extract data. Ransomware operators often re-purpose trusted channels: for instance, using standard protocols (HTTP/HTTPS, DNS) or legitimate remote access software to blend in.
- **Exfiltration** – the act of stealing the collected data out to attacker-controlled infrastructure. Double-extortion schemes hinge on this.
- **Impact** – the phase where the attackers encrypt data on all reachable systems. This renders the victim organization's files and services unusable, causing operational paralysis. Affiliates also take additional impact actions: they often inhibit system recovery by deleting backups and shadow volume copies. It is common that ransomware even changes wallpapers or drops ransom notes in directories to ensure the victim knows they've been hit.

Steps in Attack – MITRE Technique Level

In Table 10, we present justifications for why a given step in our attack scenario should be considered at the MITRE Tactic or Technique level. Next, in Table 11 we list the MITRE Techniques corresponding to each step.

Table 10: Rationales for breaking down MITRE Tactics into Techniques

Step	Tactic or technique	Rationale
Reconnaissance	Tactic	Active scanning is LLM relevant, must-have. Probability of success is very high (~100%) - so we include the tactic, but do not break it down to technique level for further analysis
Resource Development	Tactic	Resource development is essential and at least one aspect could be LLM relevant: Obtaining exploit proofs/code (T1588.005) However, probability of success is very high (~100%) so we stay at tactic level.
Initial Access	Tactic	Must have only one technique, so stay at tactic level
Execution	Tactic	Must have, but keep at tactic level since though there are alternatives, none seem particularly LLM relevant

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Step	Tactic or technique	Rationale
Persistence	N/A	N/A
Privilege Escalation	Tactic	Stay at tactic level, since it's unclear that there is much to be gained by way of LLM estimatability in breaking down to technique level.
Defense Evasion	N/A	We assume that this tactic is already accounted for when we consider probability of success of other tactics. Hence we do not include it, to avoid double-counting.
Credential Access	N/A	N/A
Discovery	Tactic	Uncertainty is large regarding how an actor actually proceeds, since there are many potentially applicable techniques. So will stay at the tactic level to avoid overfitting or adding speculative details.
Lateral Movement	Tactic	Not clear if there is benefit in breaking into technique level, for purposes of determining LLM uplift. So stay at tactic level.
Collection	Tactic	Not clear there is much, if anything, in the way of LLM uplift here, so could stick at tactic level.
Command-and-Control	Tactic	Not clear there is much scope for using LLMs here, and even if there is, it's not clear that there will be much difference in their potential benefits depending on the specifics of the communication channels used, e.g. whether using HTTPS or hiding communications in DNS traffic etc
Exfiltration	Tactic	As for command and control, it's not clear there's much scope for using LLMs here, and even if there is, it's not clear that there will be much difference in their potential benefits depending on the specifics of the exfiltration mechanism. So stay at tactic level.
Impact	Technique	It's not clear there's much scope for using LLMs for the encryption and data destruction related techniques (T1486, T1490, T1489, T1485). However, LLMs might be used to assist with the social engineering (T1657) related to the extortion negotiations. Hence we separate out this technique.

Table 11: MITRE Tactics broken down into Techniques

Step	Techniques
Reconnaissance	**T1595.002 – Active Scanning (Essential)**: Reconnaissance Vulnerability Scanning. Ransomware affiliates actively scan the internet for exposed assets and known vulnerabilities in target web apps or devices. **T1593 – Search Open websites/Domains**: Determine whether target is worth attacking (has sufficient financial resources), and how much to charge in the ransom.
Resource Development	**T1588.005 – Obtain Exploit Proofs/Code (Essential)** Before attacking, the group acquires necessary resources. They obtain or purchase exploit code for known vulnerabilities to use against victims' public-facing systems **T1588.002 – Obtain Tooling/Malware (Essential)**: They also secure malware/tooling such as the RaaS ransomware payload, credential stealers, and C2 frameworks (e.g. Cobalt Strike). These tools may be bought or provided by the RaaS service. **T1583.006 – Acquire Infrastructure: Virtual Private Server (Essential)**: They may rent VPS servers for C2 and data leakage sites (the RaaS model often supplies infrastructure for communication and data leaks)
Initial Access	**T1190 – Exploit Public-Facing Application (Essential)**: There are alternative methods for initial access, but in our scenario we are limiting ourselves to this one

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Step	Techniques
Execution	**T1059 – Command and Scripting Interpreter (Essential)**: Once inside, affiliates execute malicious code and commands to advance the attack. They commonly use command-line interpreters like PowerShell and Windows Command Prompt to run scripts and tools. For example, PowerShell may be used to deploy payloads or run reconnaissance/enumeration scripts stealthily. Using script interpreters allows them to automate tasks (such as launching ransomware or exfiltration scripts) while blending in with normal admin activity.
Persistence	**T1219 – Remote Access Software**: (NB: appears under C2C in MITRE framework) Karakurt actors have used AnyDesk to obtain persistent remote control of victims' systems (CISA, 2022).
Privilege Escalation	**T1068 – Exploitation for Privilege Escalation**: Using exploits like ZeroLogon, PrintNightmare, etc. **OR** **T1003 – OS Credential Dumping**: E.g. accessing password hashes from memory Note this technique is listed under the Credential Access tactic, but we include it here under privilege escalation
Discovery	**T1018 – Remote System Discovery**: Enumerate other hosts via AD or scanning **AND** **T1135 – Network Share Discovery** **AND** **T1083 – File and Directory Discovery**: Malware needs to enumerate files and directories to find data to encrypt on a given host. Also mentioned by Coveware (2024) Other relevant techniques include: **T1046 – Network Service Scanning**: Identify network hosts (Coveware, 2024) **T1033 – System owner / user discovery**: Get listing of accounts on a system or network (Coveware, 2024) **T1082 – System Information Discovery**: Get detailed information about the operating system and hardware, including version, patches, hotfixes, service packs, and architecture (Coveware, 2024). **T1482 – Domain Trust Discovery**: Can enable lateral movement (Coveware, 2024)
Lateral Movement	**T1021 – Remote Services**: Can enable remote login to other machines in the domain using Valid Accounts (T1078) (MITRE, 2025a). Sub-techniques include: T1021.002 (Remote services: SMB/Windows Admin Shares), T1021.001 (Remote services: Remote Desktop Protocol) **T1210 – Exploitation of Remote Services**: (Coveware, 2024) **T1570 – Lateral Tool Transfer**: May use legitimate windows admin tools to mass deploy malware across machines (Coveware, 2024)
Collection	**T1039 – Data from Network Share** **T1560 – Archive Collected Data**: Compress and package stolen files **T1074 – Data Staging**: Aggregate data on an internal host before exfiltration.
Command-and-Control	**T1071 – Application Layer Protocol**: Though the use of Application Layer Protocol is probably most common, there are likely alternatives, such as T1095 Non-Application Layer Protocols) **T1573 – Encrypted Channel**: So the attacker can hide their traffic from the defenders **T1572 – Protocol tunnelling**: (CISA-FBI, 2023) **T1105 – Ingress tool transfer**: Use C2 to download multiple tools (CISA-FBI, 2023) **T1219 – Remote Access Software**: Use legitimate software to maintain remote access to a victim machine (Coveware, 2024).

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Step	Techniques
Exfiltration	**T1567 – Exfiltration Over Web Service**: Used by CISA (2022) **T1048 – Exfiltration over alternative protocol**: Used by CISA (2022) **T1041 – Exfiltration over C2 channel**
Impact	**T1486 – Data Encrypted for Impact** **T1490 – Inhibit System Recovery**: Delete or encrypt backups, shadow copies **T1489 – Service Stop**: Disable security or backup services. **T1485 – Data Destruction**: Mainly aimed at destroying forensic artifacts (Coveware, 2024) **T1657 – Financial theft**: Extortion – threat made to leak data and/or not provide decryption keys unless ransom is paid

Probability Estimates – Tactics and Techniques

Table 12 shows the estimated baseline values for steps in our attack scenario. We further provide detailed rationales for these values below.

MITRE tactic	Probability estimate (5th percentile)	Probability estimate (most likely value)	Probability estimate (95th percentile)
Reconnaissance	100%	100%	100%
Resource Development	100%	100%	100%
Initial Access	25%	60%	90%
Execution	20%	50%	90%
Privilege Escalation	25%	70%	90%
Discovery	70%	85%	95%
Lateral Movement	50%	65%	80%
Collection	75%	90%	95%
Command-and-Control	80%	90%	100%
Exfiltration	70%	85%	90%
Impact	60%	80%	90%
	15%	30%	50%

Table 12: Baseline probability estimates for MITRE Tactics

Rationales

- Reconnaissance
  - Limited ability to prevent external scanning.
  - SME may rely on basic firewalls, but generally can't stop adversaries from enumerating public-facing assets
  - Adversaries (like our OC3 affiliate) commonly discover exposed systems and known vulnerabilities via active scanning, which is almost guaranteed to succeed if any services are exposed.
- Resource Development
  - No defender impact.

- Attacker obtaining exploits, tools, infrastructure occurs off-site and beyond SME's defenses.
- Ransomware affiliates will almost certainly gather the needed exploits and malware before attacking. This includes purchasing exploit code for known CVEs and RaaS payloads, renting servers, etc. Defenders cannot directly interfere at this stage. Success is effectively assured.

- Initial Access
  - From MITRE:
    * Application isolation and sandboxing
    * Exploit protection (web application firewalls)
    * Limit access to resources over network (only expose essential services)
    * Network segmentation (DMZ etc)
    * Use least privileges for service accounts
    * Update software regularly by patch management
    * Vulnerability scanning and response procedure
  - Illustrative defenses:
    * Basic patch management and periodic vulnerability scanning; perhaps a simple web application firewall (WAF). SMEs often expose only essential services. Network segmentation (DMZ for internet-facing systems) is sometimes minimal in SMEs.
  - Note that these probabilities are provided, conditioned on the fact that the active scanning (of the Reconnaissance tactic) has identified that this particular SME has a vulnerable public facing web-app.
  - Defence Limitations: While SMEs might have firewalls or WAFs, these won't necessarily cover all attacks and may be misconfigured. An SME may not rigorously isolate DMZ systems or adequately enforce least privilege on service accounts.
  - Edgescan (2024)provide detailed analysis of CVEs. However, they do not give figures for the likelihood of success of exploits. Probability of success will be different dependent on the particular CVE and the exploit that has been developed for it. Attackers will naturally select the particular vulnerabilities (CVEs), and associated exploits which have high probabilities of success, and which yield good options and possibilities for onward privilege escalation, lateral movement, C2C etc. Factors such as these are described by Qualysys (2023) which also states that: "Over 7,000 vulnerabilities had proof-of-concept exploit code. These vulnerabilities could result in successful exploitation; however, the exploit code is typically of lower quality, which may reduce the likelihood of a successful attack. 206 vulnerabilities had weaponized exploit code available. Exploits for these vulnerabilities are highly likely to compromise the target system if used. Qualsys go on to explain that these 206 vulns form just 0.77% of the total vulnerabilities declared in 2023.
  - It can also be observed that attempting an exploit might not be that costly for an attacker to try, which could mean some tolerance for lower probabilities of success too.

- Execution
  - From MITRE T1509 (command and scripting interpreter)
    * Antivirus
    * Audit (detect unauthorized installations)
    * Behaviour prevention on endpoint
    * Only permit exec of signed code
    * Remove unnecessary shells/interpreters
    * Execution prevention (application control)
    * Prevent user install of software
    * Privileged account management (only admins can use shells)
    * Restrict web-based content
  - Illustrative defenses: Standard anti-virus or EDR. Application control or allow-listing is rare in SMEs. Few enforce "signed code only" or restrict PowerShell usage, or remove unnecessary shells/interpreters. Some SMEs rely on default OS protections and basic user privilege limits (e.g. non-admin users), but admin tools and scripting are usually available to attackers.
  - Execution (i.e. adversary controlled code running on victim systems), of some sort, will have to be successfully performed multiple times on multiple machines, as the attacker moves laterally and seeks to encrypt data on different systems.

- Ransomware affiliates commonly use PowerShell, script interpreters, or built-in tools for execution. SMEs rarely have strict application whitelisting or behavioral anti-malware controls that could block such actions. Though even a non 24/7 SOC might be expected to triage a PowerShell script.
- Many SMEs rely on anti-virus. However, skilled attackers can evade AV, for example by malware code obfuscation (to foil at least, signature based AVs) or by using memory resident techniques.
- Regards EDR: (CybersecurityAsia, 2024)
- 6% of Barracuda's Security alerts in Q1 2025 were for suspicious PowerShell scripts.
- McDade and Iannini (2025)suggests ~50% of companies had XDR (though didn't specify whether these were SMEs), and 50% had AV on endpoints
- So we can observe that XDRs can detect executions.
- Analysis:
  * If the attacker moves quickly (as seems increasingly the case) and the SME is relatively poorly equipped in terms of SOC staff in order to respond to any EDR alerts, then oftentimes EDR may not catch the attack
  * Anti-virus could potentially catch malicious executables, but attackers will use obfuscation to avoid signature checks. Use of AI based AV may help here, but it's unclear how many SMEs use it.
  * It is also possible that if one execution technique fails an attacker could potentially try another.
  * Taking all the above together, we assume average of 50%, with wide 20%, 90% credible interval

• Privilege Escalation
  - From MITRE (2025c):
    * Application isolation and sandboxing
    * Execution prevention (block known vulnerable drivers that run in kernel mode)
    * Exploit protection (behavioural monitoring)
    * Update software
  - From MITRE (2025b):
    * Active Directory Configuration
    * Behaviour prevention on endpoint
    * Credential access protection
    * Encrypt sensitive information
    * OS configuration
    * Password policies
    * Privileged account management
    * Privileged process integrity
    * User training
  - Illustrative defenses: SMEs generally have basic password policies. .
    * According to JumpCloud (2025), MFA usage is 34% at Medium sized companies (vs 87% at large enterprises). It is possible also that admin accounts also frequently lack MFA.
    * Whilst there is patching of critical servers, SMEs are likely to be slower than larger enterprises. Hence servers might not be fully patched against privilege-escalation exploits (e.g. missing some Windows privilege escalation patches).
    * There may be EDR and some SOC resource
  - Relevant techniques:
    * T1068 – Exploitation for Privilege Escalation
    * Using exploits like ZeroLogon, PrintNightmare, and their more recent equivalents etc.
    * OR
    * T1003 – OS Credential Dumping
    * Ransomware attackers almost always try to gain admin-level control. SMEs may have flat (non-segmented) networks with many local admins. Attackers may dump local credentials and find an admin password that works across systems

    * If credentials fail, known exploits (like PrintNightmare or ZeroLogon) can be tried, and SMEs might not have applied these patches or enabled mitigations.
    * Low MFA adoption and informal admin account management can make it easier to leverage stolen accounts.
  - Analysis:
    * One might anticipate a fairly high chance of success in privilege escalation, particularly if usage of MFA is low in SMEs, and also if the network structure is fairly flat and relatively small so that one compromised admin access credential gives system-wide access. We'll go with 70%, but again the credible interval bounds will be large due to the lack of good statistical information.
- Discovery
  - Listing here, typical defence mitigations for key techniques
  - MITRE T1018 – Remote System Discovery:
    * No easy mitigation, since based on abuse of regular system features
    * Detections, monitor:
    * Command execution
    * File access (e.g. etc/hosts)
    * Network connections (pings etc)
    * Process creation (png.exe etc)
  - MITRE T1135 – Network Share Discovery:
    * OS config: Windows Group Policy (do not allow anonymous enumeration. . .)
    * Detections, monitor:
    * Command execution
    * Discovery related OS API execution
    * Process creation
  - MITRE T1083 – File and directory discovery
    * Cannot be easily mitigated due to abuse of regular system features.
    * Might be picked up by monitoring of command execution, API controls and process creation
  - Illustrative defenses: SMEs may have EDR for network monitoring for internal reconnaissance, but SOC analyst support may be limited. The SME may have basic Windows firewall on endpoints, that could prevent certain enumerations, but may have no policy against ping/NetBIOS scans.
  - Affiliates need to map the network – find servers, shares, backups. In an SME, networks are sometimes flat and lacking segmentation, and in such cases the attacker's malware may be able to freely scan or query Active Directory. In an SME the attacker can more easily reach and probe most systems.Detection of internal recon is generally less likely, especially if the attacker uses stealthy techniques (e.g. using legitimate admin commands or slow scanning).
  - Barracuda XDR. 48% of Barracuda's 1H2024 security alerts were for network reconnaissance
  - Expert insights (2024) suggests ~50% of companies had XDR (though didn't specify whether these were SMEs), and 50% had AV on endpoints
  - Analysis:
  - There is a high likelihood that the attacker can perform necessary discovery operation, and particularly so iif the attacker has achieved necessary privilege escalations (which we have already accounted for). We select 85% as a best estimate, with lower and upper bounds of 70%, 95%
- Lateral Movement
  - Listing here, typical mitigation defenses (not detections)
  - MITRE T1021 – Remote Services
    * Audit (for potential weaknesses)
    * Disable or remove (unnecessary features and programs
    * Limit access over network (use gateways)
    * MFA

    * Password policies (on admin accounts)
    * User account management (access controls)
  - MITRE T1210 – Exploitation of Remote Services (exploiting vulns in programs)
    * App isolation and sandboxing
    * Disable (unnecessary) features/programs
    * Exploit protection
    * Network segmentation
    * Privileged account management
    * Threat intelligence program
    * Update software
    * Vuln scanning
  - MITRE T1570 – Lateral Tool Transfer (copying tools around the victim's environment)
    * Host firewall (filter network traffic)
    * Network intrusion prevention
  - Illustrative defenses:
    * SMEs often have flat networks with open internal access. Network segmentation may be uncommon (all workstations/servers on one LAN or a couple of VLANs). Internal firewalls or host firewall rules are generally permissive (file shares, RDP open internally). MFA for internal RDP may not exist. Software vulnerabilities on internal services might exist (unpatched internal SMB, etc.). Basic password policies might limit some sharing, but generally nothing prevents an admin account from accessing all machines.
  - Ease of Spread: In a small/medium business, once the attacker has credentials or admin access, moving laterally is straightforward. All machines often trust the domain admin or common credentials. Many SMEs don't restrict admin share access or have ACLs that would stop an intruder. Lack of Segmentation: Without network segmentation, the threat actor can reach most systems over the network. Defenses: Only minimal barriers exist – e.g., if some systems require separate logins or there's an isolated server, but that's uncommon. Likely lack of internal MFA means stolen creds work everywhere.
  - Barracuda XDR indicates
    * The data for 2024 shows that lateral movement is the clearest sign of ransomware activity. Just under half (44%) of the ransomware attacks were spotted by the lateral movement detection engine.
  - Expert insights (2024) suggests ~50% of companies had XDR (though didn't specify whether these were SMEs)
  - SMEs are less likely to implement robust EDR/XDR and associated well-staffed SOC resources, so there is a good chance that lateral movement is not detected.
  - If the SME has an isolated backup server - then that may prevent lateral movement to all necessary machines.
  - Kent Invicta citing Beaming research (2024): Just one in four UK businesses today consistently pursue good backup practices. 22% of companies systematically back up data to a specialist offsite facility or provider, with full knowledge and control of backup procedures and where their data is held. 34% maintain an air-gapped data backup physically isolated from the internet
  - Analysis: Typically, lateral movement works assuming that privileges have already been escalated (which we've already accounted for). because once in, attackers can use admin shares, RDP, or deploy tools like PsExec essentially unopposed. But there will be occasions where it fails, for example most especially where an SME has adopted good backup practices. We select 65% as a best estimate and 50%, 80% as a credible interval.
- Collection
  - MITRE T1039 – Data from Network Share
    * No mitigations since based on abuse of normal system features
    * Only defenses are detection of: command, file, network share, network traffic
  - MITRE T1560 – Archive Collected Data
    * Audit (detect unauthorized archival utilities)

    * Detections similar to above
  - lllustrative defenses: Little to none. Sensitive data on file servers or shares is typically not encrypted at rest in SMEs. There's usually no Data Loss Prevention internally. Audit logging on file access might exist but is not actively monitored. Attackers can freely gather files; compressing data (using zip or RAR) likely won't be blocked (no application control on such tools).
  - To maximize extortion, the affiliate will quietly collect confidential files before encryption. In SMEs, if the attacker has achieved admin privileges (through privilege escalation that is already accounted for), the attacker can read most or all data. No Internal DLP: SMEs generally lack DLP or alerts for large file access. If the attacker creates archives of data (T1560) or stages data on an internal server (T1074), it's unlikely to be detected. There are essentially no mitigations to prevent data gathering – it abuses normal file access channels.
  - According to StrongDM: Only 17% of small businesses encrypt data.
  - Clearly if data is encrypted,then extortion will be harder for the attacker to achieve.
  - Analysis:
    * In most cases the attacker will be able to collect data. It seems there is some chance that some enterprises may have encrypted data (and the attacker cannot access the decryption keys). So we select a best estimate of 90%, with credible intervals of 75%–95%.
- Command-and-Control
  - Potentially many techniques are applicable. Here, we list mitigations for a common technique.
  - MITRE T1071 – Application Layer Protocol
    * Filter network traffic (firewalls in network and on endpoints)
    * Network intrusion prevention (looking for network traffic signatures)
  - Illustrative defenses:
    * Basic network firewall allows most outbound traffic (common in SMEs). Few SMEs whitelist egress by domain/IP – typically only high-security sectors do. SMBs might not have proxy inspection or advanced network monitoring. Some endpoint AV may flag known C2 beacons, but attackers often use HTTPS or DNS tunneling to blend in.
  - After initial compromise, the affiliate's malware needs to communicate out to give instructions. Outbound web traffic is usually unrestricted (aside from perhaps basic web filtering). Attackers commonly use HTTPS, web protocols or even legitimate cloud services for C2, which are unlikely to be blocked. Without dedicated egress filtering or an intrusion prevention system or pre-configured detections, SMEs will generally not notice the C2 traffic. The adversary might also use encryption (TLS) or proxy through benign hosts, and SMEs lack the means to detect this subtle traffic.
  - Analysis:
    * High probability of success, best estimate, 90%
    * Credible interval is 80% to 100%
- Exfiltration
  - Potentially many techniques are applicable.
  - MITRE T1567 – Exfiltration Over Web Service
    * Data Loss Prevention (detect and prevent sensitive data being uploaded via web browsers)
    * Restricted web-based content (web proxies prevent use of unauthorized external services)
  - Illustrative defenses: Very few. SMEs rarely employ data encryption in transit or strict outbound bandwidth controls. No formal Data Loss Prevention solutions (which might detect sensitive data leaving). Possibly rate limits on network or basic alerts if an outbound connection is extremely large, but often not. Most rely on ISP and cloud security defaults
  - The affiliate will attempt to send the stolen data out to their own servers before launching ransomware. If the SME does not have DLP (adn most are assumed not to have it), then there may be little to prevent exfiltration, though it may be noticed by large usage/bills for data traffic out of the network or more basic threshold type rules monitoring the network. Attackers might upload data via HTTPS to cloud storage or use their C2 channels. SMEs typically won't detect an HTTPS upload to an unknown server. The exfiltration might be limited by bandwidth or noticed if it crashes a network link.

- Impact
  - MITRE T1486 – Data Encrypted for Impact
    - Behaviour prevention on endpoint
    - Data backup (ideally stored off system)
  - MITRE T1490 – Inhibit System Recovery
    - Data backup
    - Execution prevention (e.g block utilities like diskshadow.exe)
    - OS configuration (prevent disabling of certain services or deletion of certain files)
    - User account management (limit access to backups only as necessary)
  - MITRE T1489 – Service Stop
    - Network segmentation (operate SOC etc on separate system to production system)
    - Out of band comms channels (for use during security incident)
    - Restrict file and directory permissions
    - Restrict registry permissions
    - User account management (so only admins can change services)
  - illustrative defenses: Regular data backups (varies by SME – many have at least nightly backups, but often connected to network or cloud). Quality of backups differ: some SMEs keep offline backups, but many have NAS or cloud shares that could be deleted. Few SMEs have immutable backups. Ransomware prevention tools (like anti-encryption behavioral blockers) are not common, aside from what baseline AV provides. Some critical files may be backed up to cloud services (OneDrive, etc.) providing partial resilience.
  - In the final stage, the affiliate deploys the ransomware payload to encrypt data and disrupt operations, and they try to destroy backups to prevent recovery.
  - Whilst most of our SMEs do maintain backups, often these are online or accessible from the network. We have already accounted for the "poor backup hygiene" aspect to some extent in the lateral movement step so we avoid double counting it here.
  - According to Invenio IT, 58% of backups fail during recovery due to factors like outdated technology, inadequate testing, or malware infection.
  - Hence, even if the threat actor did not get to the backup servers, there's a good chance that the backups will prove insufficient to recover from whatever the attacker has encrypted (with issues, for example, in terms of when the backup was last run, and whether it was configured properly).
  - Sophos: 57% of backup compromise attempts were successful
  - Some endpoint security might detect mass encryption (Microsoft Defender's Controlled Folder Access, etc.), but SMEs will not always have enabled or configured these. A lot of EDRs will detect the creation of ransom notes and changes to file extensions.
  - By the time the attacker has got this far in the attack, they will have established significant privileges and control and it can be expected that there is a good chance that this last impact step will succeed
  - Analysis:
    - The best estimate probability of success should be quite high, and we go with 80%
    - A lower (5%) bound of 60% (given 58% of backups fail)
    - Upper bound of 90% (given ~60% backups fail and the threat actor likely already has high privileges, and prevalence of anti-encryption protections are likely low)
    - MITRE T1657
    - Only relevant mitigation listed is "User training"
    - An SME likely lacks in-house training or capability in ransom negotiation, but could buy it in.
    - But the best effort number is used in the calculation of the ransom payout in the Impact section below.
    - Chainanalysis: "According to our data, around 30% of negotiations actually lead to payments or the victims deciding to pay the ransoms".
    - Coveware also support this ~30% payout figure
    - For the 5% bound: Given reports that companies are becoming more reluctant to pay ransoms, we'll elect a lower bound of 15%

        * For the 95% bound: Since definitely there appears to be a trend in the literature indicating more reluctance to pay ransoms these days, we will select an upper bound of 50%

Prob of success (excluding the last T1657 Financial Theft term) = 6.4%

Impact

There are a wide number of factors that can determine the actual cost of a specific attack, these include at least:

- Whether the attacker completes the full double extortion attack (both data exfiltration and data encryption)
- Whether the attacker is partially successful and exfiltrates data (but does not achieve data encryption)
- Whether the attacker is partially successful and encrypts systems (but does not complete data exfiltration)
- Whether the ransom is paid or not
  - Which besides the cost of the ransom itself, may also impact recovery costs (e.g. whether decryption keys are then provided, making recovery easier)
- Dependency on the value of any data that is exfiltrated
- Dependency on the quantity and importance of files which have been encrypted
- Whether backups exist
- Whether the attacker is successful in corrupting the backups

Table 13 summarizes our estimates for the baseline values of both the ransom payment and the recovery cost:

Cost to defenders per attack	5%	Most likely value	95%
Ransom payment	\$50k	\$165k†	\$400k
Recovery cost	\$0.3m	\$0.65m	\$1.5m

Table 13: Impact estimates (†assumes 30% pay ransom at \$550k mean, and 70% pay no ransom).

<u>Rationale</u>

Ransom Payment

- (Sophos, 2023) reports:
  - In SME's with revenue \$10m to \$50m bracket in 2023:
  - Mean demand was \$1.7m
  - Median demand was \$0.33m
  - Elsewhere in the report, it states that proportion of ransom demand paid in the \$10m–\$50m revenue SME market is 93%
  - Note: it seems that the questioning to respondents in the Sophos survey related to the respondent's most significant ransomware attack. So, it's possible that the figures provided are biased upwards in cost.
  - Nevertheless, we assume 0.93×\$1.7m=\$1.6m for mean ransomware payout.
- (Sophos, 2025) indicates:
  - for SMEs in the \$10m to \$50m revenue bracket, the average payout is \$106k
  - If the ratio of mean/median was similar as 2024 then this might suggest a mean payout of \$106k × (1.7/0.33) = \$550k
- Coveware indicate:

  - A mean ransomware payout of ~\$550k in Q1 2025, and an average payout of ~\$200k. They indicate that the average size of companies impacted by ransomware is 228 employees.
  - This Coveware figure covers all sizes of companies. The comparable mean ransom payout figure for all companies as listed by Sophos (2023)is \$3.9m.
- Crowdstrike claim: The average ransom payment in 2024 is \$2.73 million, up from \$1.82 million in 2023.
- BlackFog reports that the average ransom demand in Q1, 2025, was \$663,582, based on 93 known ransom demands
- There seems to be a great deal of volatility in payments and demands:
- (Sophos, 2023): … the mean ransom payment has increased x2.6 in the last year. Organizations that paid the ransom reported an average payment of \$3.9 million, up from \$1.5m in 2023.
- (Sophos, 2025) reports: "The … average ransom payment fell by 50% in the last year, down from \$2 million in 2024 to \$1 million in 2025"
- If the ratio of mean/median is assumed to be the same as in 2024 (i.e. \$3.9m/\$2m = ~2) then mean, as measured across all enterprise sizes would be ~\$2m
- IBM report: The average ransom demand in 2024 also saw a significant increase, rising to 2.73 million USD, nearly 1 million USD more than in 2023.
- Analysis:
  - The Sophos (2025) "all enterprise sizes" figure for mean ransom payment appears to be ~75% of Crowdstrike's latest (2024) number, approximately 400% of Coveware's equivalent number, and 300% of BlackFrog's number.
  - At least some of the questions in the Sophos survey did ask for info about each company's most impactful ransomware attacks, which might bias their figures upwards somewhat.
  - Nevertheless, Sophos is understood to be a reliable source, so we take the figure that we computed based on the "average" data provided in their 2025 report (and the mean/median ratio computed based on their 2024 report): i.e. \$550k
  - We then need to weight this assumed mean payout figure (\$550k) according to whether a successfully completed attack results in a ransom payout (where success here is defined in terms of successful data exfiltration and encryption):
  - Chainanalysis: "According to our data, around 30% of negotiations actually lead to payments or the victims deciding to pay the ransoms".
  - Coveware also support this ~30% payout figure
  - Sophos – 56% paid ransom and got data back (across all enterprise sizes), which presumably means that an even larger percentage paid a ransom (since some will have paid ransom and NOT got data back). But this figure is very different to those provided by Chainanalysis and Coveware. One possible explanation is that Sophos' questioning in its survey was referring to victims' worst incidents.
  - Since the Sophos information is a bit unclear regards definition of terms, and a number of sources cite declining prevalence in paying of ransoms, let's assume 30% payout.
- Hence expected best estimate ransom payout for an attack that is successfully executed from a technical perspective is $0.3 \times \$0.55$ ~\$165k
- 5% - Given the great deal of uncertainty regards what the actual mean ransomware payout is, and also the great volatility in payouts year on year (up to 500% reported by Sophos) we'll assume a lower credible interval value of \$50k
- 95% - If we take the Sophos figure \$0.55m (which we think is likely to be on the high side, compared to other estimates), and then also assume 0.75 actually pay the ransom, this would give us \$400k

Recovery cost (including downtime, people time, device cost, network cost, lost opportunity)

- Sophos reports, for 2024:
- For organisations with revenue <\$10m
- Recovery costs were \$1.2m (up from \$0.16m in 2023)

- Assumed to be mean, not median, since Sophos report: “Globally, median recovery costs doubled from $375,000 to $750,000 over the last year”, and this will cover also large corporations… in 2024, organizations reported a mean cost to recover from a ransomware attack of $2.73M
- For organisations with revenue of $10m to $50m
- $1.5m up from $1.1m in 2023)
- Sophos’ question to CISOs: “What was the approximate cost to your organization to rectify the impacts of the most significant ransomware attack (considering downtime, people time, device cost, network cost, lost opportunity etc.)”
- “The report is based on the findings of an independent, vendor-agnostic survey commissioned by Sophos of 5,000 IT/cybersecurity leaders across 14 countries in the Americas, EMEA, and Asia Pacific. All respondents represent organizations with between 100 and 5,000 employees. The survey was conducted by research specialist Vanson Bourne between January and February 2024, and participants were asked to respond based on their experiences over the previous year”
- Sophos (2025) reports, for the equivalent question in 2025:
- For companies of 100–250 employees recovery costs were $638k
- As averaged across all company sizes, recovery cost decreased from $2.83m in 2024 to $1.53m in 2025 (with the 2023 figure being $1.82m). Hence, the 2025 figure is 54% of the 2024 figure.
- Analysis:
  - Actual recovery costs for any specific attack, will vary according to a long list of factors identified in the list above this table.
  - The above figures provided by Sophos presumably also cover a spectrum of possible scenarios, including a) double extortion vs single extortion, b) backups compromised vs backups not compromised, c) ransoms paid (and decryption keys provided, data sometimes returned) vs ransoms not paid vs both ransom paid and backups used etc. The statistics may implicitly also cover a range of fully successful attacks and partially successful attacks (from the attacker perspective).
  - One could potentially try and account for a different recovery cost dependent on all the factors listed above the table, however, since we are looking for a mean, and Sophos have already provided us with one, then we will go with the Sophos figures.
- We assume for our SME targets the recovery cost is ~$650k based on Sophos (2025)
- For 5% assume $300k (allowing for some possible deflation in ransomware payments over the coming year, and noting large year on year on swings)
- For 95%, assume $1.5m (allowing for inflation over the coming year, and noting that the 2024 figure was twice as high as the 2025 figure)

Sum of costs = $165k+$650k = $815k

Total Risk

Total risk = Estimated number of Actors (10) x Mean number of attacks per year per actor (200) x Probability of successful attack (0.064) x Impact per successful attack ($0.8m) = $102m / year (note that this is calculated as a simple multiplication, not through fitting distributions and running Monte Carlo simulations)

Sanity check calculations

- Consider incomes of individuals in the threat actor group
  - Ransom payout is $2.1m per OC3 group (200 × 0.064 × $165k). With 10 individuals per OC3 group, this suggests a revenue (before costs) of $210k per person in the gang (a proportion of this income will go to the RaaS operator, which is the main variable cost of the threat actors (~20% of the ransom payment goes to the RaaS operator according to Register (2023)), so each individual would make a return on the order of perhaps $150k, once other costs are taken into account.

- Assuming \$30k/year for salary of Russian cyber professional, the figures would seem plausible, though the returns would be unexceptional for a cybersecurity professional working in Western Europe/US. This income is also on the low side compared to the \$1.9m that Astimorov of LockBit was supposed to have extorted over a 3 year period (US DoJ, 2024).

- Harm as proportion of global harm
  - Chainalysis Team (2025) state global ransom payouts in 2024 were \$813m
  - Based on this figure, the \$20m/year ransom payout figure seems like it could be plausible:
    - Since we are considering 10 larger (10 person) affiliate-groups, amounting to 100 individuals, out of a potential pool of ~3000 people
      - We assume 700 affiliates in total (see "number of actors" computations above) comprising 200, 10-man OC3-groups and 500, 1 or 2 person OC2 groups
    - And since, if every affiliate-individual earns broadly the same amount then this would suggest that the aggregate ransom revenue (based on our computed figures for revenue per OC3 group) would be 3000/100 $\times$ \$20m = \$600m.
    - Which is similar to the ChainAnalysis figure of \$813m

F Model Uplift and LLM-Estimated Parameters

In Table 14, we present the allocation of our two chosen benchmarks, Cybench and BountyBench, to the risk indicators in the OC3 Ransomware SME risk model, alongside a rationale for each decision. Table 15 shows the LLM-estimated values for these factors at both the SOTA (current) and saturated level of capabilities.

Table 14: Mapping of our two chosen benchmarks to risk indicators

Risk Factor	Benchmark	Rationale
Initial Access	BountyBench	BountyBench contains tasks involving exploiting public-facing applications and services
Execution	BountyBench	Tasks involve realistic Kali Linux execution environment.
Privilege Escalation	BountyBench	Tasks target privillege escalation specifically.
Lateral Movement	Cybench	Neither Cybench nor BountyBench has an ideal fit for this step. Cybench has a few multi-server tasks.
Impact	Cybench	Cybench contains cryptography-related tasks that better capture encryption steps in ransomware attacks.
Financial Theft / Extortion	Cybench	Neither BountyBench nor Cybench is ideal for ransom negotiations. Cybench is used here due to cryptography tasks providing some indicator of the quality of encryption for ransom, which may be a factor in ransom negotiations.
Number of Actors	BountyBench	BountyBench tasks are more relevant to early attack steps (Initial Access and Execution) which we expect to correlate with the number of actors attempting these attacks.
Number of Attempts Per Actor	BountyBench	BountyBench tasks are more relevant to early attack steps (Initial Access and Execution) which we expect to correlate with the number of attempts threat actors can make.
Damage Per Attack: Recovery	Cybench	Cybench is more relevant to cryptography components of attack which will define the cost of data recovery.
Damage Per Attack: Ransom	Cybench	We note that ransom payment size is likely not heavily correlated with either benchmark and may be extrinsic to the uplift model altogether. This said, the effectiveness of data encryption used will be a factor in ransom negotiations, which Cybench is a better indicator of.

Table 15: Uplift Estimates. Quantities are computed across 100,000 Monte Carlo samples from LLM simulated experts.

Capabilities	Factor	5th Percentile	Mode (KDE Estimated)	95th Percentile
SOTA	Reconnaissance	1	1	1
Saturated	Reconnaissance	1	1	1
SOTA	Resource Development	1	1	1
Saturated	Resource Development	1	1	1
SOTA	Initial Access	0.1756	0.6623	0.9284
Saturated	Initial Access	0.2504	0.7653	0.9205
SOTA	Execution	0.0996	0.6116	0.9230
Saturated	Execution	0.2252	0.6008	0.8981
SOTA	Privilege Escalation	0.1812	0.7601	0.9472
Saturated	Privilege Escalation	0.2586	0.8225	0.9467
SOTA	Discovery	0.7133	0.8111	0.8796
Saturated	Discovery	0.7132	0.8106	0.8790
SOTA	Lateral Movement	0.4479	0.7021	0.8641
Saturated	Lateral Movement	0.4646	0.7117	0.8868
SOTA	Collection	0.7548	0.8976	0.9545
Saturated	Collection	0.7484	0.9040	0.9552
SOTA	Command and Control	0.8144	0.9281	0.9720
Saturated	Command and Control	0.8162	0.9337	0.9708
SOTA	Exfiltration	0.7274	0.9091	0.9665
Saturated	Exfiltration	0.7261	0.9090	0.9664
SOTA	Impact	0.6851	0.8248	0.9297
Saturated	Impact	0.6868	0.8410	0.9494
SOTA	Financial Theft / Extortion	0.1227	0.3369	0.6281
Saturated	Financial Theft / Extortion	0.1222	0.2978	0.6213
SOTA	Damage per Attack: Recovery	279149.9923	703448.7619	1838613.2362
Saturated	Damage per Attack: Recovery	381479.8551	761200.2752	1532674.0606
SOTA	Damage per Attack: Ransom	192373.5585	627288.6288	1138280.3394
Saturated	Damage per Attack: Ransom	223085.5330	625053.7436	1284713.9777
SOTA	Number of Actors	3.7162	11.9861	57.7922
Saturated	Number of Actors	5.1268	17.7117	63.9287
SOTA	Number of Attempts per Actor	70.6827	215.1253	587.9752
Saturated	Number of Attempts per Actor	71.5314	249.7416	712.1891
Aggregated				
SOTA	Probability of Successful Attack	0.0044	0.0163	0.1513
Saturated	Probability of Successful Attack	0.0131	0.0444	0.1760
SOTA	Risk (Ransom)	1303544.0885	19558561.6269	373735748.5034
Saturated	Risk (Ransom)	4245705.7889	36926476.0946	673054052.0885
SOTA	Risk (Recovery)	6150346.2680	76550105.0840	1380727437.6985
Saturated	Risk (Recovery)	22280199.1123	155332176.6640	2285349245.8274
SOTA	Total Risk	8803585.3608	103297672.4354	1748881431.3670
Saturated	Total Risk	30307020.5801	195782280.9930	2909501181.1624