

ZETAR: Modeling and Computational Design of Strategic and Adaptive Compliance Policies

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Abstract—Compliance management plays an important role in mitigating insider threats. Incentive design is a proactive and non-invasive approach to achieving compliance by aligning an insider’s incentive with the defender’s security objective, which motivates (rather than commands) an insider to act in the organization’s interests. Controlling insiders’ incentives for population-level compliance is challenging because they are neither precisely known nor directly controllable. To this end, we develop ZETAR, a zero-trust audit and recommendation framework, to provide a quantitative approach to model insiders’ incentives and design customized recommendation policies to improve their compliance. We formulate primal and dual convex programs to compute the optimal bespoke recommendation policies. We create the theoretical underpinning for understanding trust, compliance, and satisfaction, which leads to scoring mechanisms of how compliant and persuadable an insider is. After classifying insiders as malicious, self-interested, or amenable based on their incentive misalignment levels with the defender, we establish bespoke information disclosure principles for these insiders of different incentive categories. We identify the policy separability principle and the set convexity, which enable finite-step algorithms to efficiently learn the Completely Trustworthy (CT) policy set when insiders’ incentives are unknown. Finally, we present a case study to corroborate the design. Our results show that ZETAR can well adapt to insiders with different risk and compliance attitudes and significantly improve compliance. Moreover, trustworthy recommendations can provably promote cyber hygiene and insiders’ satisfaction.

Index Terms—Insider threat, information design, incentive mechanism, zero-trust, incentive learning, Bayesian persuasion.

I. INTRODUCTION

Insider threats in cyberspace refer to vulnerabilities and risks posed to an organization due to the misbehavior of its trusted but not trustworthy insiders, such as insiders, maintenance personnel, and system administrators. In 2021, insider threats have caused around 39% of breaches [1], which have resulted in significant operational disruptions, data loss, and reputation damage.

This paper has been accepted for publication in IEEE Transactions on Computational Social Systems

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This work was supported in part by the National Science Foundation (NSF) under Grant ECCS-1847056, Grant BCS-2122060; in part by Shuimu Tsinghua Scholar Program 2022SM046; in part by International Postdoctoral Exchange Fellowship Program(Talent-Introduction Program) YJ20220128; and in part by National Natural Science Foundation of China No.62341109, No.62341106, Shanghai Municipal Science and Technology Major Project, and Tsinghua University Initiative Scientific Research Program.

Digital Object Identifier 10.1109/TCSS.2023.3323539

Many organizations design insider threat countermeasures based on the presumption that insider security violations are either malicious or unintentional [2]. This dichotomous perspective, however, overlooks the sizable middle ground of intentional yet non-malicious violations, which often emanate from self-interested insiders who place personal convenience or advantage above organizational security. The task of managing these non-compliance behaviors entails a strategic shift from straightforward deterrence and awareness training to the subtler approach of aligning insiders’ incentives with the security objectives of the organization. By properly designing insiders’ incentives, the organization can elicit proper behaviors in a *proactive* and *non-invasive* way; i.e., the insiders voluntarily reduce non-compliance and misbehavior.

Existing studies [3]–[5] have recognized the critical role of incentives in mitigating insider threats and emphasized the integrated usage of various incentive methods, including monetary rewards, recognition and penalties, peer comparisons, and cultural cultivation. These studies have laid the empirical and experimental foundations for identifying the key incentive factors. However, there lacks a unified model to formally define incentives and systematically quantify the impact of those factors on the insiders’ incentives and their resulting behaviors. Our work aims to address the above challenges of modeling the abstracted concept of incentives, characterizing the impacts of incentive factors, and ultimately developing a quantitative and automated design framework to guide the changes in insiders’ incentives to enhance compliance and mitigate insider threats.

To this end, we develop a modeling and computational framework called ZETAR (ZEro-Trust Audit with strategic Recommendation) for the defender whose goal is to improve the insiders’ compliance and organizational cyber hygiene. As illustrated in Fig. 1, ZETAR consists of two functional modules for the defender: the zero-trust audit and an incentive mechanism, both targeting the insiders’ decision-making loop. The zero-trust audit mechanism assigns no prior trust to the insiders and inspects each insider’s behaviors. Based on the audit outcome, the audit mechanism changes the incentive factors (e.g., creating penalties or rewards), which indirectly affect the insider’s behaviors through the insider’s decision model.

An audit enables the defender to detect non-compliant behaviors and implement post-event remediation. Yet, given the vast landscape of non-malicious violations, pinpointing malicious infractions might strain the defender’s time and budget. Therefore, ZETAR further introduces an incentive mechanism that recommends compliance policies for the in-

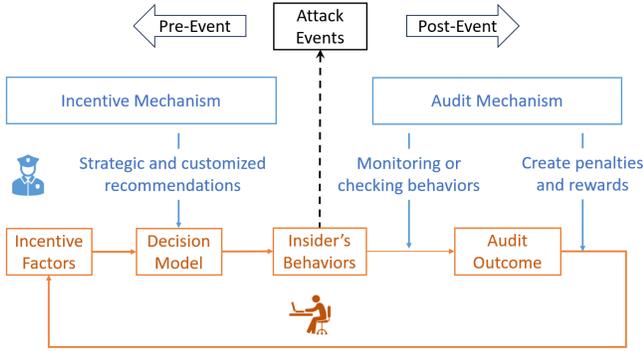


Fig. 1: ZETAR affects the incentives and behaviors of the insiders (depicted in orange) through a social-technical approach (highlighted in blue) that integrates the incentive and audit mechanisms. The technical approach of audits provides post-event remediation after the insiders have taken actions that could potentially lead to attack events. In contrast, the social approach of recommendation delivers a pre-event preemptive approach by actively shaping the insiders' motivations to enhance compliance.

siders. The defender strategically designs these recommendations to be trustworthy and informative, based on the selected audit mechanism and each insider's incentive. The aim is to influence the decision-making process of the insider and promote compliant behaviors. In this way, the defender can preemptively curtail non-malicious breaches from self-motivated insiders, allocating limited defense resources more effectively towards malicious violations. As illustrated in Fig. 2, ZETAR tailors recommendations for each insider based on their individual incentives, ensuring the same audit mechanism can cater to diverse motivations and facilitate population-level compliance.

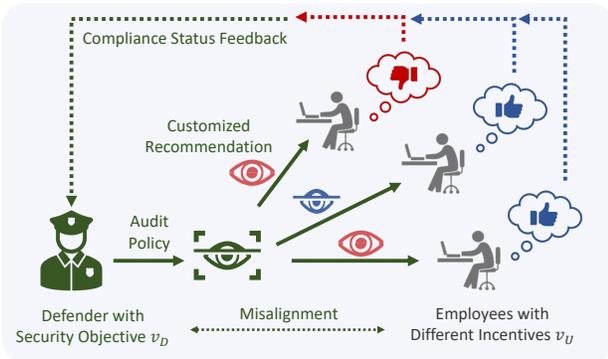


Fig. 2: An illustration of the ZETAR feedback system: the defender of a corporate network audits insiders' compliance status and provides customized recommendations to insiders based on the learning of their incentives. ZETAR reduces the incentive misalignment between insiders and the defender.

Finally, since insiders' incentives are not directly *observable*, we develop a feedback process for the defender to learn the insiders' incentives based on their compliance status, i.e., their behaviors under a selected recommendation mechanism, as shown in Fig. 2. Through a thorough theoretical characterization of the incentive design problem, we further identify the *policy separability principle* and the *convexity* of the feasible

region, which enable us to develop efficient incentive learning algorithms that guarantee to converge in finite steps.

A. Summary of Contribution

We summarize the contribution of this paper as follows.

- **Modeling:** By integrating the social solution of strategic recommendations with the technical solution of audits, we develop a social-technical paradigm called ZETAR that can reduce the compliance gap resulting from the incentive misalignment between the insiders and the organization (represented by the defender).
- **Concept and Metrics:** We formally define abstracted concepts (e.g., compliance, trustworthiness, and satisfaction) to characterize their interrelationships and furnish transferable metrics. Additionally, we give a formal delineation of an insider's incentive, categorizing them into amenable, malicious, and self-interested groups.
- **Computation and Analysis:** We formulate the design of ZETAR into a mathematical programming problem and simplify the computation by recognizing that Completely Trustworthy (CT) recommendation policies are sufficient for the optimal compliance improvement. The analysis of the problem enriches both the theory of compliance and incentive design. It also offers security insights and guidelines, including principles of information disclosure to insiders with different incentives.
- **Algorithm Design:** Compared to classical feedback learning methods that are universal yet inefficient, we develop efficient feedback algorithms with a binary search procedure that adequately exploit the structure of the problem. The algorithm itself further contributes to the field of learning within the Bayesian persuasion framework [6].
- **Application and Validation:** We present a case study to corroborate the effectiveness of ZETAR in improving compliance for insiders with different risk and compliance attitudes. We decompose an insider's incentives into extrinsic and intrinsic ones. The results show that ZETAR can well adapt to different types of insiders and achieve a structural improvement of compliance for risk-averse insiders. Under binary action sets, we identify the *belief thresholds* of these insiders to determine whether to take compliant or non-compliant actions.

B. Notations and Organization of the Paper

We use the pronoun 'he' for an insider and 'she' for the defender throughout this paper. Calligraphic letter \mathcal{Y} defines a set, and $\Delta\mathcal{Y}$ represents the set of probability distributions over set \mathcal{Y} . Superscripts and subscripts represent elements and different categories, respectively. The rest of the paper is organized as follows. We present the system model and computational framework of ZETAR in Sections III and IV, respectively. Section V characterizes trustworthiness and compliance. These characterizations lead to efficient learning algorithms in Section VI when insiders' incentives are unknown to the defender. Section VII presents a case study, and Section VIII concludes the paper.

II. RELATED WORKS

A. Insider Threat Mitigation

Insider threats are usually classified into unintentional or intentional ones. For intentional insider threats, the authors in [3]–[5] have recognized incentives as a leading factor and incentive designs as a class of promising mitigation strategies. In their recent study [7], the authors employ defensive deception as a strategy to differentiate between non-compliant insiders and attacks, thereby mitigating insider threats.

For unintentional insider threats, the authors in [8], [9] have identified three contributing factors (i.e., organizational, human, and demographic factors) and a set of proactive mitigation strategies (e.g., awareness training, relieving workload pressure, and security tools to help overcome user errors). Many unintentional insider threat incidents result from various human cognitive vulnerabilities, such as limited rationality and attention [10]. For example, most employees have the security knowledge to recognize a phishing email yet still fall victim to it due to a lack of attention [11]. Recent works [12], [13] have attempted to mitigate the above attentional vulnerability by integrating real-time human biometric data (e.g., eye-tracking data and EEG) with AI and learning technologies.

B. Security Policy Compliance

The existing research on security policy compliance has largely fallen into two distinct categories. The first category exploits technical methods, including deep learning [14], graph-based approaches [15], and game theory [16], to detect and manage policy violations. The second category focuses on human and social aspects to identify the critical factors for human compliance decisions (see, e.g., [17]). While both categories lay solid foundations for security policy compliance, they fall short in offering a holistic design of technical (e.g., audit and access control) and social (e.g., security policies and positive organizational culture) solutions [18]–[20]. ZETAR provides a unique, quantitative, and automated framework to provide strategic and customized recommendation policies to elicit compliant behaviors from insiders.

C. Incentive Mechanisms for Cyber-Physical Security

There is a rich literature on designing incentive mechanisms to enhance Cyber-Physical System (CPS) security [21], [22]. Informational control is relatively less explored compared to the classical design of payment and allocation rules [23]. It provides an affordable, scalable, flexible and complementary way to change agents' beliefs for compliance. In the content of this paper, it is convenient to dynamically tailor the recommendation mechanism, operating at the information level, to insiders with different incentives. However, it is much more costly to customize or change the audit mechanism, which needs actual implementation.

Among the recent works that focus on the strategical design and control of information [24]–[26], the defender often keeps their strategies *covert* to influence the agents' reasoning. In contrast, ZETAR employs a *transparent* and *overt* recommendation strategy to align with insiders' incentives, which can

potentially foster a culture of trust between insiders and the organization.

Uncertainties in incentive designs are challenging to deal with. Previous works have taken several approaches to address this issue, including robust methods [27], Bayesian methods [28], and learning methods [29]. In this work, ZETAR leverages the feedback of insiders' compliance status and the structures of the solution to develop efficient incentive learning algorithms that are provably convergent in finite steps.

III. SYSTEM MODEL OF ZETAR

As illustrated in Fig. 2, ZETAR provides customized recommendation designs for insiders with different incentives, based on the same audit policy. Each design involves two players, the defender D and an insider U . The defender can assess the organization's security posture (explained in Section III-A) and audit insiders' behaviors either by himself or through a third-party service provider (detailed in Section III-B). The defender receives audit outcomes detailing each insider's compliance status and enhances compliance through effective incentive management and strategic recommendations.

A. An Organization's Security Posture

Security Posture (SP) reflects an enterprise's overall cybersecurity strength and capacities to deter, detect, and respond to the dynamic threat landscape [30]. Based on different scoring and categorization methodologies [31], [32], SP can be classified into finite categories (e.g., high-risk SP and low-risk SP). In this work, we consider a finite number of J SP categories that compose the set $\mathcal{Y} := \{y^j\}_{j \in \mathcal{J}}$, where $\mathcal{J} := \{1, \dots, J\}$.

The current SP can be assessed based on penetration tests, honeypots, and alert analysis [33]. Since an organization's SP changes probabilistically based on the dynamic behaviors of attackers, users, and defenders, we let $b_Y(y^j) \in [0, 1]$ denote the probability of the organization to be in the state of SP $y^j \in \mathcal{Y}, \forall j \in \mathcal{J}$. With a slight abuse of notation, we define $b_Y \in \Delta\mathcal{Y}$ as the probability distribution over \mathcal{Y} .

B. Zero-Trust Audit Policy

The defender of an organization follows prescribed security rules to improve the organization's cyber hygiene. These rules can be set and audited by regulatory agencies, cyber insurance providers, or the organization itself. In accordance with the zero-trust security principle (e.g., see [34]), every insider within the organization is subject to audit and not inherently trusted.

Consider a finite set of I Audit Schemes (ASs), denoted by \mathcal{X} . Each AS contains the entire audit procedure. For example, for a given AS $x \in \mathcal{X}$, the audit involves the steps of (1) monitoring and checking the insider's behaviors, (2) assigning a compliance score to the insider, and (3) informing (the defender) of the compliance score and action. A different AS $x' \in \mathcal{X}, x' \neq x$, can vary in the monitoring or scoring scheme.

The ASs are prescribed based on the SP of the organization. Let $\psi \in \Psi: \mathcal{Y} \mapsto \Delta\mathcal{X}$ denote the audit policy, which probabilistically determines an AS $x \in \mathcal{X}$, where $|\mathcal{X}| = I$. The

probability of choosing $x \in \mathcal{X}$ given the SP $y \in \mathcal{Y}$ is thus given by $\psi(x|y) \in [0, 1]$. The outcome of the audit scheme is used by the defender to create penalties or rewards for the insiders to shape their incentives and elicit compliant behaviors. Hence, the incentives of the insiders and the security objective of the defender are naturally dependent on the prescribed audit scheme. They will be further elaborated on in Section III-C.

We characterize the system model by system-level concepts, including SP, audit policy, and AS, that are designed to be versatile, allowing for further specification to cater to diverse scenarios of insider threat mitigation. We provide the following example to offer intuitive insights into the above mathematical formulation and demonstrate the practical applicability of our system model. The example typifies the system model's use in the stochastic audit of essential security rules.

Example 1 (Stochastic Audits of Critical Security Rules).

Consider an organization that needs to comply with a finite set of H critical security rules, denoted by $\mathcal{H} := \{1, \dots, H\}$, set by a U.S. regulatory agency. The rules entail proper behaviors for remote access, user accounts, and backups [35]. The compliance of an insider is monitored by checking each rule. Its outcome, denoted by o^h , also known as the compliance status concerning rule $h \in \mathcal{H}$, is either full, partial, or no compliance, denoted by ι_f , ι_p , and ι_n , respectively. By lumping the outcomes into a vector, we let $a = (o^1, \dots, o^H) \in \mathcal{A} := \prod_{h \in \mathcal{H}} \mathcal{O}^h$, where $\mathcal{O}^h = \{\iota_f, \iota_p, \iota_n\}$, be the consolidated compliance status of an insider. An insider can choose his consolidated compliance status $a \in \mathcal{A}$ based on his incentives. Let $\mathcal{X} = \{x^1, \dots, x^{H+1}\}$ be the set of $I = H + 1$ ASs. Each AS follows the same procedure of checking the compliance of the H rules to report an insider's compliance status but differs in assessing compliance scores. AS $x^h \in \mathcal{X}$, $h = 1, \dots, H$, yields a compliance score $r^h \in \mathbb{R}$ solely based on the outcome $o^h \in \mathcal{O}^h$, i.e., $r^h = g^h(o^h)$, where $g^h : \mathcal{O}^h \rightarrow \mathbb{R}$ is the scoring function associated with AS x^h . AS $x^{H+1} \in \mathcal{X}$ uses the outcomes associated with all the rules for the assessment, i.e., $r^{H+1} = g^{H+1}(a)$, where $g^{H+1} : \mathcal{A} \rightarrow \mathbb{R}$ is the scoring function associated with AS x^{H+1} . It is clear that x^{H+1} is the most stringent AS among all. The score is used as the criterion to penalize insiders and thus affects their incentives that will be formally defined in Section III-C.

In Example 1, the audit policy $\psi \in \Psi$ is chosen based on a predetermined level of tolerance. A proper level of tolerance trades off between the organization's security and the compliance cost resulting from the overhead and the lack of flexibility [3]. An appropriate choice of tolerance depends on the SP; e.g., an audit policy can prescribe the stringent audit $x^{H+1} \in \mathcal{X}$ at a higher rate under high-risk SP than low-risk SP. We assume that the audit policy ψ set by the organization or regulatory agencies remains the same for a sufficiently long time, making the policy more implementable and agreeable to insiders over the entire corporate network [4].

Let \mathcal{A} denote the set (with cardinality K) of an insider's actions. In Example 1, an action $a \in \mathcal{A}$ is referred to as the rule compliance profile, i.e., $a = (o^1, \dots, o^H)$, which is a result of the insiders' behaviors, including keystrokes, full application contents (e.g., email, chat, data import, and data export), and

screen captures [36]. In the case where there is one rule, i.e., $H = 1$, \mathcal{A} is reduced to an action set that comprises three actions: full, partial, and no compliance. The insider's actions are monitored by the AS, and the defender is informed of the insider's compliance status to nudge compliant behaviors. Note that ZETAR does not aim to design insiders' incentives to prevent all non-compliant behaviors, but focuses on the actions that can be audited with full fidelity and social acceptance. For instance, audits should not encompass sensitive behavioral data, such as the duration spent in restrooms. Consequently, \mathcal{A} encompasses only those behaviors whose compliance status can be comprehensively audited without infringing on privacy norms or regulations.

C. Utilities of the Defender and Insiders

In the past five years, financially motivated insider threats have continued to be the most common motive of threat actors [1]. We define utility functions $v_p : \mathcal{Y} \times \mathcal{X} \times \mathcal{A} \mapsto \mathbb{R}$ for $p \in \{U, D\}$ to capture an insider's incentive and the defender's security objective, respectively. The defender's utility $v_D(y, x, a)$ assesses the impact of an insider's action $a \in \mathcal{A}$ on network security under the SP $y \in \mathcal{Y}$ and AS $x \in \mathcal{X}$. Since the impact is assessed subjectively by the defender, v_D represents the defender's security objective. For example, under life-critical scenarios with zero tolerance to non-compliance, the defender can assign $v_D(y, x, a^{ic}) = -\infty, \forall y \in \mathcal{Y}, x \in \mathcal{X}$.

An insider's utility $v_U(y, x, a)$ models his extrinsic and intrinsic incentives to take action $a \in \mathcal{A}$ under SP $y \in \mathcal{Y}$ and AS $x \in \mathcal{X}$. On the one hand, v_U can incorporate monetary incentives (through reward and recognition) and disincentives (through penalty and punishment) from the defender. On the other hand, v_U can represent an insider's proclivity for compliant behaviors. The utility function may also capture other factors, including different risk attitudes. Readers can refer to Section VII-A2 and VII-A1 for an example of v_D and v_U , respectively.

The utility functions aptly capture the essence of the incentive design problem in Section III-D. They also provide the proper level of abstraction for incentive modeling and the derivation of theoretical insights. The detailed form of the utility functions v_U and v_D is beyond the scope of this paper.

D. Strategic Recommendations for Customized Compliance

Following Section III-B, the audit policy ψ remains unchanged once determined. Since it is challenging for a fixed audit policy to achieve optimal inspection outcomes for insiders with different compliance requirements and incentives (as will be further elaborated in Section III-D2), the defender designs a customized incentive mechanism, encompassing a recommendation policy $\pi \in \Pi$ that results in a recommendation $s \in \mathcal{S}$, as shown in the third stage of Fig. 3.

1) *Information Structure and Timeline:* As stated in [3], transparent criteria for organizational policies can create a culture of trust and consequently serve as a positive incentive to reduce non-compliance. Thus, we assume that the sets $\mathcal{Y}, \mathcal{X}, \mathcal{S}, \mathcal{A}$, the prior statistics $b_Y \in \Delta \mathcal{Y}$, the audit policy $\psi \in \Psi$, and the recommendation policy $\pi \in \Pi$ are common

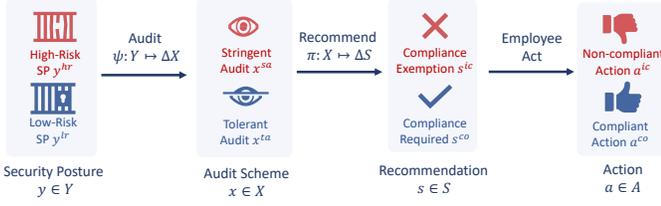


Fig. 3: The timeline of ZETAR to enhance insiders' compliance in corporate networks. The defender is informed of the SP and the audit outcomes of all insiders' behaviors. The defender designs a recommendation policy $\pi \in \Pi$ to improve compliance.

knowledge. Since the organization's SP changes randomly as shown in Section III-A, the SP is assessed repeatedly on a weekly or monthly basis, and it is unknown to insiders.

Fig. 3 illustrates the timeline of ZETAR as follows. Given the current SP $y \in \mathcal{Y}$ and the audit policy $\psi \in \Psi$, the chosen AS $x \in \mathcal{X}$ is known to the defender yet remains unknown to the insiders. Before implementing the chosen AS x , the defender recommends an action based on x and the recommendation policy $\pi \in \Pi$. Then, the insider takes an action $a \in \mathcal{A}$ that is not necessarily the recommended one. Finally, the defender implements the chosen AS and penalizes insiders based on the audit outcome. Insiders observe the chosen AS after it is implemented. After the zero-trust audit, the insiders' actions become known to the defender.

2) *Insider's Initial Compliance:* Without the recommendation mechanism, an insider takes an action $a_0 \in \mathcal{A}$ to maximize his expected utility concerning the prior statistics $b_Y \in \Delta \mathcal{Y}$ and $\psi \in \Psi$, i.e., $a_0 \in \arg \max_{a \in \mathcal{A}} \sum_{y \in \mathcal{Y}} b_Y(y) \sum_{x \in \mathcal{X}} \psi(x|y) v_U(y, x, a)$. Due to the misalignment between an insider's incentive v_U and the defender's security objective v_D , the insider's initial compliance status represented by $a_0 \in \mathcal{A}$ may negatively affect corporate security. For example, a self-interested insider tends to break the security rules for convenience if the audit policy ψ chooses a stringent audit (e.g., $x^{H+1} \in \mathcal{X}$ in Example 1) less frequently.

3) *Recommendation Mechanism:* To align insiders' incentives with the defender's security objective, the defender can recommend an action to an insider. Thus, set $\mathcal{S} := \{s^k\}_{k \in \mathcal{K}}$ has the same cardinality with \mathcal{A} and represents the finite set of K recommendations where $s^k \in \mathcal{S}$ recommends the insider to take action $a^k \in \mathcal{A}$. The defender recommends the action according to a stochastic recommendation policy $\pi \in \Pi: \mathcal{X} \mapsto \Delta \mathcal{S}$; i.e., given the chosen AS $x \in \mathcal{X}$, the defender chooses recommendation $s \in \mathcal{S}$ with probability $\pi(s|x)$. As will be shown in Section III-D4, by strategically choosing the recommendation policy, the defender can manipulate an insider's belief of the current SP and the chosen AS, thus affecting his perception of the expected utility and enhancing compliance.

4) *Insider's Belief Update and Best-Response Action:* The received recommendation reveals the defender's knowledge of the SP and the chosen AS. An insider can form and update a belief of the unknowns by observing the recommendations. Denote $b_{Y,X} \in \mathcal{B}_{Y,X} \subseteq \Delta(\mathcal{X} \times \mathcal{Y})$ as the joint prior distribution of the current SP and the chosen AS, i.e., $b_{Y,X}(y, x) := b_Y(y) \psi(x|y)$, $\forall x \in \mathcal{X}, y \in \mathcal{Y}$. Analogously,

we define $b_X(x) := \sum_{y' \in \mathcal{Y}} b_{Y,X}(y', x)$ as the marginal prior probability of AS $x \in \mathcal{X}$, $b_{Y|X}(y|x) := b_{Y,X}(y, x)/b_X(x)$ as the conditional prior probability of SP $y \in \mathcal{Y}$ under AS $x \in \mathcal{X}$, and $b_S^\pi(s) := \sum_{x' \in \mathcal{X}} b_X(x') \pi(s|x')$ as the probability of recommendation $s \in \mathcal{S}$ under $\pi \in \Pi$, where $b_X \in \mathcal{B}_X \subseteq \Delta \mathcal{X}$, $b_{Y|X} \in \mathcal{B}_{Y|X}$, and $b_S^\pi \in \Delta \mathcal{S}$.

Following the requirement of transparent criteria in Section III-D1, the recommendation policy $\pi \in \Pi$ is assumed to be common knowledge. The assumption can be justified by the fact that an insider can learn the recommendation policy $\pi \in \Pi$ based on the repeated observations of the recommendation policy input (i.e., AS $x \in \mathcal{X}$) and the policy output (i.e., recommendation $s \in \mathcal{S}$) after they are implemented. Thus, for rational insiders who adopt Bayesian rules to update their beliefs, each recommendation $s \in \mathcal{S}$ under recommendation policy $\pi \in \Pi$ results in posterior belief $b_{Y,X}^\pi(y, x|s) \in \mathcal{B}_{Y,X}^\pi \subseteq \Delta(\mathcal{X} \times \mathcal{Y})$, i.e.,

$$b_{Y,X}^\pi(y, x|s) = \frac{b_{Y,X}(y, x) \pi(s|x)}{\sum_{x' \in \mathcal{X}} b_X(x') \pi(s|x')}, \forall x \in \mathcal{X}, y \in \mathcal{Y}. \quad (1)$$

Then, we can obtain the insider's marginal posterior belief of AS $x \in \mathcal{X}$, his marginal posterior belief of SP $y \in \mathcal{Y}$, and the associated conditional posterior belief under recommendation $s \in \mathcal{S}$ as $b_X^\pi(x|s) := \sum_{y \in \mathcal{Y}} b_{Y,X}^\pi(y, x|s) = \frac{b_X(x) \pi(s|x)}{b_S^\pi(s)} \in \mathcal{B}_X^\pi \subseteq \Delta \mathcal{X}$, $b_Y^\pi(y|s) := \sum_{x \in \mathcal{X}} b_{Y,X}^\pi(y, x|s) \in \Delta \mathcal{Y}^\pi \subseteq \Delta \mathcal{Y}$, and $b_{Y|X}^\pi(y|x, s) := b_{Y,X}^\pi(y, x|s)/b_X^\pi(x|s)$, respectively. Since $b_{Y|X}^\pi(y|x, s) = b_{Y|X}(y|x)$, $\forall s \in \mathcal{S}$, these recommendations under policy $\pi \in \Pi$ have no impact on the conditional probability $b_{Y|X}^\pi$. However, as it does not hold in general that $b_{Y,X}^\pi = b_{Y,X}$, $b_X^\pi = b_X$, $b_Y^\pi = b_Y$, $\forall s \in \mathcal{S}$, the recommendation mechanism (i.e., $\pi \in \Pi$ and $s \in \mathcal{S}$) can change the insiders' marginal beliefs of the current SP and the implemented AS as well as their joint beliefs. We summarize the above observations in Lemma 1.

Lemma 1 (Invariance of Conditional Belief). *A recommendation policy $\pi \in \Pi$ has no impact on $b_{Y|X}^\pi$.*

With a recommendation policy $\pi \in \Pi$, the insider takes a best-response action denoted by $a_{\pi, s}^* \in \mathcal{A}$ to maximize his posterior utility under recommendation $s \in \mathcal{S}$, i.e.,

$$a_{\pi, s}^* \in \arg \max_{a \in \mathcal{A}} \mathbb{E}_{y, x \sim b_{Y,X}^\pi(\cdot|s)} [v_U(y, x, a)]. \quad (2)$$

Letting $\bar{v}_p(x, a) := \sum_{y \in \mathcal{Y}} b_{Y|X}(y|x) v_p(y, x, a)$, $\forall x \in \mathcal{X}$ for $p \in \{U, D\}$ be an insider's expected incentive and the defender's expected security objective, respectively, we obtain

$$\mathbb{E}_{y, x \sim b_{Y,X}^\pi(\cdot|s)} [v_p(y, x, a)] = \sum_{x \in \mathcal{X}} b_X^\pi(x|s) \bar{v}_p(x, a), \forall s \in \mathcal{S}. \quad (3)$$

We refer to $a_{\pi, s}^* \in \mathcal{A}$ as an action induced by recommendation policy $\pi \in \Pi$ under recommendation $s \in \mathcal{S}$, which is in general different from the insider's initial compliance status $a_0 \in \mathcal{A}$ in Section III-D2. For a given π , not all recommendations induce a compliant action. However, by strategically choosing the recommendation policy, the defender can improve compliance on average. We formally quantify the improvement of compliance and its average impact on the corporate security in Section III-D6.

5) *Trustworthiness of the Recommendation Scheme*: Following Section III-D4, the defender's recommendation $s \in \mathcal{S}$ from a recommendation policy $\pi \in \Pi$ may not be trusted by an insider; i.e., the recommended action is not a best-response action. We formalize the definitions of trustworthy recommendations and trustworthy recommendation policies in Definitions 1 and 2, respectively.

Definition 1 (Trustworthy Recommendations). A recommendation $s^k \in \mathcal{S}, k \in \mathcal{K}$, under a recommendation policy $\pi \in \Pi$ is trustworthy (resp. untrustworthy); i.e., the policy π is trusted by an insider with an incentive \bar{v}_U , if the induced action follows (resp. does not follow) the recommended action $a^k \in \mathcal{A}$, i.e., $a^k \in$ (resp. \notin) $\arg \max_{a \in \mathcal{A}} \mathbb{E}_{x \sim b_X^{\pi}(\cdot|s)}[\bar{v}_U(x, a)]$.

Remark 1 (Compliance and Trustworthiness). Following Definition 1, an insider complies with a recommendation (i.e., takes the recommended action) only if it is trustworthy.

Definition 2 (Trustworthy Recommendation Policies). Recommendation policies under which recommendation $s^k \in \mathcal{S}, k \in \mathcal{K}$, is trustworthy (resp. untrustworthy) formulate the k -th Partially Trustworthy (PT) (resp. Partially Untrustworthy (PU)) policy set $\Pi_{pt}^k \subseteq \Pi$ (resp. $\Pi_{pu}^k \subseteq \Pi$). A recommendation policy $\pi \in \Pi$ is Completely Trustworthy (CT) (resp. Completely Untrustworthy (CU)) if all recommendations under π are trustworthy (resp. untrustworthy). All CT (resp. CU) recommendation policies formulate the CT (resp. CU) policy set $\Pi_{ct} := \bigcap_{k=1}^K \Pi_{pt}^k$ (resp. $\Pi_{cu} := \bigcap_{k=1}^K \Pi_{pu}^k$).

Different recommendation policies reveal varied amounts of information about the AS and the SP, which consequently affect the insider's compliance status. Two extreme cases are defined in Definition 3. Let the optimal action of an insider U or the defender D at AS $x \in \mathcal{X}$ and SP $y \in \mathcal{Y}$ be given by $\tilde{a}_p^{max}(y, x) \in \arg \max_{a \in \mathcal{A}} v_p(y, x, a)$. Analogously, let $a_p^{max}(x) \in \arg \max_{a \in \mathcal{A}} \bar{v}_p(x, a)$ for all $x \in \mathcal{X}$ and $p \in \{U, D\}$. A zero-information recommendation policy, denoted by $\pi_z \in \Pi$, recommends the same actions as an insider's initial compliance status in Section III-D2 regardless of the chosen AS. Hence π_z does not change the insider's belief, i.e., $b_X^{\pi_z}(x|s) = b_X(x), \forall s \in \mathcal{S}, \forall x \in \mathcal{X}$, and does not bring new information to the insider. Meanwhile, a full-information recommendation policy denoted by $\pi_f \in \Pi$ recommends optimal action $a_U^{max}(x)$ under the chosen AS $x \in \mathcal{X}$. Remark 2 shows that it is feasible for the defender to implement CT recommendation policies regardless of ZETAR settings in Sections III-A to III-C.

Definition 3 (Zero- and Full-Information Recommendation Policy). A recommendation policy $\pi_z \in \Pi$ contains zero information if $\pi_z(s^k|x) = \mathbf{1}_{\{a^k=a_0\}}, \forall k \in \mathcal{K}, \forall x \in \mathcal{X}$. A recommendation policy $\pi_f \in \Pi$ contains full information if $\pi_f(s^k|x) = \mathbf{1}_{\{a^k=a_U^{max}(x)\}}, \forall k \in \mathcal{K}, \forall x \in \mathcal{X}$.

Remark 2 (Feasibility). Following Definition 3, zero- and full-information recommendation policies are CT, i.e., $\pi_z, \pi_f \in \Pi_{ct}$. Thus, Π_{ct} is nonempty regardless of ZETAR settings.

6) *Defender's Optimal Recommendation Policy*: Following (2) and (3), an insider's expected utility defined in (4) represents the insider's Acquired Satisfaction Level (ASaL) under

recommendation policy $\pi \in \Pi$.

$$J_U(\pi, b_X, \bar{v}_U) := \sum_{s \in \mathcal{S}} b_S^{\pi}(s) \mathbb{E}_{y, x \sim b_{Y, X}^{\pi}(\cdot|s)}[v_U(y, x, a_{\pi, s}^*)]. \quad (4)$$

Since an insider's action induced by zero-information policy π_z is his initial-compliance action $a_0 \in \mathcal{A}$, $J_U(\pi, b_X, \bar{v}_U)$ represents the insider's Innate Satisfaction Level (ISaL). To capture the average impact of an insider's compliance status on corporate security under different recommendations, we define the defender's Acquired Security Level (ASeL) under recommendation policy $\pi \in \Pi$ as

$$\begin{aligned} \check{J}_D(\pi, b_{Y, X}, v_D, v_U) &:= \mathbb{E}_{y, x \sim b_{Y, X}(\cdot)}[\mathbb{E}_{s \sim \pi(\cdot|x)}[v_D(y, x, a_{\pi, s}^*)]] \\ &= \sum_{x \in \mathcal{X}} b_X(x) \sum_{s \in \mathcal{S}} \pi(s|x) \bar{v}_D(x, a_{\pi, s}^*) := J_D(\pi, b_X, \bar{v}_D, \bar{v}_U). \end{aligned} \quad (5)$$

Since an insider's best-response action $a_{\pi_z, s}^* \in \mathcal{A}$ remains the same as $a_0 \in \mathcal{A}$ in Section III-D2 under all recommendations $s \in \mathcal{S}$, a zero-information recommendation policy $\pi_z \in \Pi_{ct}$ has no impact on the insider's compliance. Hence $J_D(\pi_z, b_X, \bar{v}_D, \bar{v}_U)$ quantifies the impact of an insider's initial compliance status and represents the defender's Initial Security Level (ISeL). The difference in the defender's security level $J_D^{acel}(\pi, b_X, \bar{v}_D, \bar{v}_U) := J_D(\pi, b_X, \bar{v}_D, \bar{v}_U) - J_D(\pi_z, b_X, \bar{v}_D, \bar{v}_U)$ measures the average impact of the insider's compliance status changes (under recommendation policy $\pi \in \Pi$) on the corporate security, and we refer to J_D^{acel} as the Average Compliance Enhancement Level (ACEL) in Definition 4.

Definition 4 (Average Compliance Enhancement Level). For an insider with incentive \bar{v}_U and the defender with security objective \bar{v}_D , we define $J_D^{acel}(\pi, b_X, \bar{v}_D, \bar{v}_U) \in \mathbb{R}$ as the Average Compliance Enhancement Level (ACEL) under the prior statistic $b_X \in \mathcal{B}_X$ defined in Section III-D4 and recommendation policy $\pi \in \Pi$ defined in Section III-D3.

The defender's goal is to design the optimal recommendation policy $\pi^* \in \Pi$ that maximizes the ACEL, where $J_D^{acel, *}$ denotes the optimal ACEL, i.e., $J_D^{acel, *}(b_X, \bar{v}_D, \bar{v}_U) := J_D^{acel}(\pi^*, b_X, \bar{v}_D, \bar{v}_U) = \max_{\pi \in \Pi} J_D^{acel}(\pi, b_X, \bar{v}_D, \bar{v}_U) \geq 0$. The optimal ACEL gauges the maximum improvement of an insider's compliance. Thus, its value is proportional to the insider's persuadability under a recommendation scheme. On the other hand, the ISeL quantifies the defender's expected utility in the presence of insider behaviors without any incentive mechanism. Thus, its value is proportional to the insider's initial compliance. These metrics are useful to develop scoring metrics to quantitatively categorize insiders, as shown in Remark 3.

Remark 3 (Scoring Metrics). The values of ISeL $J_D(\pi_z, b_X, \bar{v}_D, \bar{v}_U)$ and the optimal ACEL $J_D^{acel, *}(b_X, \bar{v}_D, \bar{v}_U)$ measure how compliant and persuadable, respectively, an insider with incentive \bar{v}_U is under security objective \bar{v}_D .

IV. COMPUTATIONAL FRAMEWORK OF ZETAR

In this section, we formulate the design of ZETAR into mathematical programming problems, where the defender has complete information of an insider's incentive \bar{v}_U .

A. Level of Recommendation Customization

As illustrated in Section III-B and III-D and also in Fig. 2, the defender determines a unified audit policy to inspect all insiders' behaviors yet designs customized recommendation policies. Since the difference in these recommendation policies can lead to the perceptions of unfairness and distrust [4], the defender needs to strike a balance between the optimal ACEL and the Level of Recommendation Customization (LoRC). We let $\eta \in \mathbb{R}^+$ be the defender's LoRC, $\pi_d \in \Pi$ be a default recommendation policy, and the KL divergence $KL(\pi || \pi_d) := \sum_{k \in \mathcal{K}, x \in \mathcal{X}} \pi(s^k | x) \log \frac{\pi(s^k | x)}{\pi_d(s^k | x)}$ be the measure of policy difference, respectively. If $\pi_d(s^k | x) = 0$, then $\pi(s^k | x) = 0$ by default, and $\pi(s^k | x) \log \frac{\pi(s^k | x)}{\pi_d(s^k | x)} = 0$ as $\lim_{z \rightarrow 0^+} z \log z = 0$.

B. Primal Mathematical Programming

Without loss of generality, the defender can narrow the policy search space to $\Pi_{ct} \subseteq \Pi$ to achieve the optimal ACEL [6], i.e., $J_D^{acel,*}(b_X, \bar{v}_D, \bar{v}_U) = \max_{\pi \in \Pi_{ct}} J_D^{acel}(\pi, b_X, \bar{v}_D, \bar{v}_U)$. Under a CT recommendation policy, the insider complies to the recommendation and chooses $a^k \in \mathcal{A}$ when the recommendation is $s^k \in \mathcal{S}, \forall k \in \mathcal{K}$. Thus, $\max_{\pi \in \Pi_{ct}} J_D^{acel}(\pi, b_X, \bar{v}_D, \bar{v}_U) = \max_{\pi \in \Pi_{ct}} \sum_{x \in \mathcal{X}} b_X(x) \sum_{k \in \mathcal{K}} \pi(s^k | x) \bar{v}_D(x, a^k)$. For a LoRC η , we formulate the following convex program denoted by P_η .

$$[P_\eta]: r_\eta = \max_{\pi \in \Pi} \sum_{x \in \mathcal{X}} b_X(x) \sum_{k \in \mathcal{K}} \pi(s^k | x) \bar{v}_D(x, a^k) - \frac{KL(\pi || \pi_d)}{\eta}$$

- (a). $\pi(s^k | x) \geq 0, \forall k \in \mathcal{K}, \forall x \in \mathcal{X}$,
- (b). $\sum_{k \in \mathcal{K}} \pi(s^k | x) = 1, \forall x \in \mathcal{X}$,
- (c). $\sum_{x \in \mathcal{X}} b_X(x) \pi(s^k | x) [\bar{v}_U(x, a^k) - \bar{v}_U(x, a^l)] \geq 0, \forall k, l \in \mathcal{K}$.

Let $\pi_\eta^* \in \Pi_{ct}$ and r_η be the maximizer and the optimal value of P_η , respectively, for all $\eta \in \mathbb{R}^+$. Constraints (a), (b) explicitly describe the set Π , and constraint (c) limits the recommendation policy to be CT defined in Definition 2. All recommendation policies that satisfy constraints (a), (b), (c) compose the set $\Pi_{ct} \subseteq \Pi$. Due to the feasibility of CT policies in Remark 2 and the boundedness of v_D , the program P_η is feasible and bounded for all $\eta \in \mathbb{R}^+$. When the defender aims to design CT recommendation policies closest to the default policy $\pi_d \in \Pi$ (i.e., $\eta \rightarrow 0^+$), then $\pi_0^* = \pi_d$ if and only if $\pi_d \in \Pi_{ct}$. As the LoRC η increases, the defender focuses more on compliance enhancement, and the optimizer of P_∞ coincides with π^* that achieves the optimal ACEL $J_D^{acel,*}$, i.e., $\pi_\infty^* = \pi^*$. By specifying $a^l \in \mathcal{A}$ in constraint (c) of P_η as the initial-compliance action $a_0 \in \mathcal{A}$, we prove that CT policies never decrease an insider's satisfaction level in Proposition 1.

Proposition 1 (Trustworthiness Promotes Satisfaction). *An insider's ASaL $J_U(\pi, b_X, \bar{v}_U)$ is not lower than his ISaL $J_U(\pi_z, b_X, \bar{v}_U)$ for all $\pi \in \Pi_{ct}$ and $b_X \in \mathcal{B}_X$.*

Proof. An insider's ASaL in (4) under a CT recommendation policy $\pi \in \Pi_{ct}$ can be represented as $J_U(\pi, b_X, \bar{v}_U) = \sum_{s \in \mathcal{S}} b_S^T(s) \cdot \max_{a \in \mathcal{A}} \sum_{x \in \mathcal{X}} b_X^\pi(x|s) \bar{v}_U(x, a) = \sum_{x \in \mathcal{X}} b_X(x) \sum_{k \in \mathcal{K}} \pi(s^k | x) \bar{v}_U(x, a^k)$. Based on constraint (c) of P_η , $\sum_{x \in \mathcal{X}} b_X(x) \pi(s^k | x) [\bar{v}_U(x, a^k) - \bar{v}_U(x, a_0)] \geq 0$ for all $k \in \mathcal{K}$

and $\pi \in \Pi_{ct}$. Hence, $J_U(\pi, b_X, \bar{v}_U) \geq \sum_{x \in \mathcal{X}} b_X(x) \bar{v}_U(x, a_0) = \max_{a \in \mathcal{A}} \sum_{x \in \mathcal{X}} b(x) \bar{v}_U(x, a) = J_U(\pi_z, b_X, \bar{v}_U)$. \square

Remark 4 (Win-Win Situation). *Proposition 1 shows that an insider's ASaL is not lower than his ISaL if a recommendation policy is CT. Based on Remark 2, the defender's ASaL is not lower than her ISEL under the optimal recommendation policy, i.e., $J_D^{acel,*}(b_X, \bar{v}_D, \bar{v}_U) \geq 0$. Thus, the optimal policy achieves a win-win situation between the defender and insiders by promoting cyber hygiene and insiders' satisfaction.*

C. Dual Mathematical Programming

Let $\alpha_\eta(s^k, x) \geq 0$, $\beta_\eta(x) \in \mathbb{R}$, and $\lambda_\eta(s^k, a^l) \geq 0$ denote the dual variables of the constraints (a), (b), and (c) in P_η , respectively. Define shorthand notation $\bar{\beta}_\eta(s^k, x, \lambda_\eta) := \bar{v}_D(x, a^k) + \sum_{a^l \in \mathcal{A}} \lambda_\eta(s^k, a^l) [\bar{v}_U(x, a^k) - \bar{v}_U(x, a^l)]$, where $\lambda_\eta(s^l, a^l), \forall l \in \mathcal{K}$, can take any finite values. The dual problem is denoted as D_η . The strong duality proved in Proposition 2 yields the bounds for the optimal value r_η of the primal problem P_η in Proposition 3. Define $\alpha_\eta^*(s^k, x)$, $\beta_\eta^*(x)$, and $\lambda_\eta^*(s^k, a^l)$ as the optimal dual variables and the shorthand notation $\underline{r} := \sum_{x \in \mathcal{X}} [\max_{k \in \mathcal{K}} b_X(x) \bar{\beta}_\eta(s^k, x, \lambda_\eta) + \log(\pi_d(s^k | x)) / \eta]$.

$$[D_\eta]: \min_{\substack{\beta_\eta(x) \in \mathbb{R}, x \in \mathcal{X}, \lambda_\eta(s^k, a^l) \in \mathbb{R}^{0+}, k, l \in \mathcal{K}}} \sum_{x \in \mathcal{X}} [\beta_\eta(x) + \frac{1}{\eta}]$$

- (a). $\sum_{x \in \mathcal{X}} [\bar{v}_U(x, a^k) - \bar{v}_U(x, a^l)] b_X(x) \pi_d(s^k | x) \cdot e^{\eta [b_X(x) \bar{\beta}_\eta(s^k, x, \lambda_\eta) - \beta_\eta(x)]} \geq 0, \forall k, l \in \mathcal{K}$,
- (b). $\sum_{k \in \mathcal{K}} \pi_d(s^k | x) e^{\eta [b_X(x) \bar{\beta}_\eta(s^k, x, \lambda_\eta) - \beta_\eta(x)] - 1} = 1, \forall x \in \mathcal{X}$.

Proposition 2 (Strong Duality). *For all $\eta \in \mathbb{R}^+$, D_η is the dual problem of P_η , and the optimal value of D_η is r_η .*

Proof. Since all constraints in P_η are linear, Slater's condition reduces to the feasibility of D_η [37], and strong duality holds. Thus, P_η and D_η achieve the same optimal value. Setting the gradient of the Lagrangian function of P_η concerning π to 0 yields $\frac{1}{\eta} (\log \frac{\pi(s^k | x)}{\pi_d(s^k | x)} + 1) = b_X(x) \bar{v}_D(x, a^k) + \alpha_\eta(s^k, x) - \beta_\eta(x) + \sum_{l \in \mathcal{K}} \lambda_\eta(s^k, a^l) b_X(x) [\bar{v}_U(x, a^k) - \bar{v}_U(x, a^l)]$, for all $k \in \mathcal{K}, x \in \mathcal{X}$, which leads to

$$\pi_\eta^*(s^k | x) = \pi_d(s^k | x) \cdot e^{\eta [b_X(x) \bar{\beta}_\eta(s^k, x, \lambda_\eta) + \alpha_\eta(s^k, x) - \beta_\eta(x)] - 1}. \quad (6)$$

Since $\pi_\eta^*(s^k | x)$ in (6) is non-negative for all $k \in \mathcal{K}, x \in \mathcal{X}$, constraint (a) of P_η holds. Moreover, the complementary slackness implies the optimal dual variables $\alpha_\eta^*(s^k, x) = 0, \forall k \in \mathcal{K}, x \in \mathcal{X}$. Plugging $\pi_\eta^*(s^k | x)$ in (6) into constraints (b) and (c) of P_η leads to constraints (a) and (b) of D_η , respectively. Then, by strong duality, D_η minimizes the Lagrangian function $L(\pi_\eta^*, \alpha_\eta^*, \beta_\eta, \lambda_\eta) = \sum_{x \in \mathcal{X}} [\beta_\eta(x) + 1/\eta]$ over dual variables $\beta_\eta(x) \in \mathbb{R}, \lambda_\eta(s^k, a^l) \in \mathbb{R}^{0+}, \forall k, l \in \mathcal{K}, x \in \mathcal{X}$. \square

Proposition 3 (Bounds of the Optimal Value). *The lower and upper bounds of r_η are \underline{r} and $\underline{r} + \log(K)/\eta$, respectively.*

Proof. Constraint (b) in D_η is equivalent to the log-sum-exp expression: $\beta_\eta(x) = \frac{1}{\eta} \log(\sum_{k \in \mathcal{K}} \pi_d(s^k | x) e^{\eta [b_X(x) \bar{\beta}_\eta(s^k, x, \lambda_\eta) - 1]})$. Thus, $\max_{k \in \mathcal{K}} \eta b_X(x) \bar{\beta}_\eta(s^k, x, \lambda_\eta) - 1 + \log(\pi_d(s^k | x)) \leq$

$\eta\beta_\eta(x) \leq \max_{k \in \mathcal{K}} \eta b_X(x) \bar{\beta}_\eta(s^k, x, \lambda_\eta) - 1 + \log(\pi_d(s^k|x)) + \log(K)$ for all $x \in \mathcal{X}$. Since strong duality holds, we obtain the bounds for r_η in P_η . \square

Following (6) and Proposition 3, the optimal policy π_η^* has the closed-form expression in (7) concerning the optimal dual variables $\lambda_\eta^*(s^k, a^l) \in \mathbb{R}^{0+}$, $l, k \in \mathcal{K}$, and the default recommendation policy $\pi_d \in \Pi$; i.e., for all $x \in \mathcal{X}$, $s^k \in \mathcal{S}$, $k \in \mathcal{K}$,

$$\pi_\eta^*(s^k|x) = \frac{\pi_d(s^k|x) \cdot e^{\eta b_X(x) \bar{\beta}_\eta(s^k, x, \lambda_\eta^*)}}{\sum_{k \in \mathcal{K}} \pi_d(s^k|x) \cdot e^{\eta b_X(x) \bar{\beta}_\eta(s^k, x, \lambda_\eta^*)}}. \quad (7)$$

D. Interpretation of ZETAR from Insiders' Perspectives

When ZETAR designs a fully customized recommendation policy (i.e., LoRC η goes to infinity), then the dual problem D_∞ is a linear program as shown in Proposition 4. Define $\hat{\beta}_\infty(x) := \beta_\infty(x)/b_X(x)$ where $\hat{\beta}_\infty(x) = 0$ if $b_X(x) = 0$.

Proposition 4. *When LoRC η goes to infinity, the dual problem D_∞ degenerates to the following linear program:*

$$\begin{aligned} [D_\infty]: \quad & \min_{\{\hat{\beta}_\infty(x) \in \mathbb{R}\}_{x \in \mathcal{X}}, \{\lambda_\infty(s^k, a^l) \in \mathbb{R}^{0+}\}_{k, l \in \mathcal{K}}} \sum_{x \in \mathcal{X}} b_X(x) \hat{\beta}_\infty(x) \\ \text{s.t.} \quad & \hat{\beta}_\infty(x) \geq \bar{\beta}_\infty(s^k, x, \lambda_\infty), \forall k \in \mathcal{K}, \forall x \in \mathcal{X}. \end{aligned}$$

Proof. When $\eta \rightarrow \infty$, the upper and lower bounds for $\beta_\eta(x)$ in Proposition 3 attain the same value, which implies $\beta_\eta(x) = \max_{k \in \mathcal{K}} \eta b_X(x) \bar{\beta}_\eta(s^k, x, \lambda_\eta)$. Thus, constraint (a) of D_η is feasible. Constraint (b) and the objective function of the convex program D_η are equivalent to the constraint and the objective function of the linear program D_∞ , respectively. \square

The dual problem D_∞ provides an interpretation of ZETAR with fully customized recommendation policies from an insider's perspective; i.e., each insider aims to minimize his effort to satisfy the security objective of the corporate network. Variable $\lambda_\infty(s^k, a^l)$ represents the insider's frequency to take action $a^l \in \mathcal{A}$ under recommendation $s^k \in \mathcal{S}$. The variable $\bar{\beta}_\infty(s^k, x, \lambda_\infty)$ represents the mixed security objective of the corporate network under AS $x \in \mathcal{X}$ and recommendation $s^k \in \mathcal{S}$, which involves the sum of the defender's utility \bar{v}_D and the insider's expected utility, i.e., $\sum_{a^l \in \mathcal{A}} \lambda_\infty(s^k, a^l) [\bar{v}_U(x, a^k) - \bar{v}_U(x, a^l)]$. The variable $\hat{\beta}_\infty(x)$ represents the insider's effort at AS $x \in \mathcal{X}$, and the effort is required to satisfy the security objective at each AS for all recommendations. An insider who prioritizes convenience over security chooses the rate of actions to minimize his expected effort $\sum_{x \in \mathcal{X}} b_X(x) \hat{\beta}_\infty(x)$.

V. CHARACTERIZATION OF TRUST AND COMPLIANCE

Section IV provides a unified computational framework to design the optimal CT recommendation policy under any LoRC. In this section, we consider fully customized recommendation policies, i.e., $\eta = \infty$. We characterize the invariance of an insider's compliance status and the defender's optimal recommendation policy under linear utility transformations in Section V-A. In Section V-B, we provide a geometric characterization of the CT policy set based solely on an insider's incentive v_U . The characterizations are useful to develop efficient algorithms in Section VI when insiders'

incentives are unknown. In Section V-C, we characterize the optimal ACEL under different levels of misalignment between the defender's security objective v_D and an insider's incentive v_U .

A. Impact of Linear Utility Transformations

We define the linear utility transformation for the defender and an insider in Definition 5. Following Remark 1, if a recommendation $s \in \mathcal{S}$ is trustworthy (or untrustworthy) to both two insiders, then they have the same compliant status under s . Lemma 2 illustrates the preservation of an insider's compliance status under linear transformations of v_U . The proof directly follows from Definition 1.

Definition 5 (Linear Utility Transformation). *Define the linear transformation of a player's utility with a scaling factor $\rho_p^{sa} \in \mathbb{R}$ and translation factors $[\rho_p^{tr}(y, x) \in \mathbb{R}]_{x \in \mathcal{X}, y \in \mathcal{Y}}$ as $v_p^{tr}(y, x, a) := \rho_p^{sa} v_p(y, x, a) + \rho_p^{tr}(y, x)$ for all $x \in \mathcal{X}$, $y \in \mathcal{Y}$, $a \in \mathcal{A}$, $p \in \{D, U\}$.*

Lemma 2 (Preservation of Compliance Status). *Interacting with the same defender, two insiders with incentives v_U and v_U^tr , respectively, have the same compliance status for all recommendation $s \in \mathcal{S}$ under any recommendation policy $\pi \in \Pi$. Moreover, the defender applies the same optimal recommendation policy to both insiders.*

Lemma 3 characterizes ZETAR from the perspective of linear systems; i.e., a linear transformation of v_D results in a linear transformation of the defender's ASeL in (5) and the ACEL in Definition 4 for any recommendation policy $\pi \in \Pi$. The proof directly follows from (5) and the fact that $\max_{\pi \in \Pi} J_D(\pi, b_X, \bar{v}_D^tr, \bar{v}_U) = \max_{\pi \in \Pi} J_D(\pi, b_X, \bar{v}_D, \bar{v}_U)$.

Lemma 3 (Preservation of Linearity). *Interacting with the same insider, the ASeL of two defenders with security objectives v_D and v_D^tr are linearly dependent, i.e., $J_D(\pi, b_X, \bar{v}_D^tr, \bar{v}_U) = \rho_D^{sa} J_D(\pi, b_X, \bar{v}_D, \bar{v}_U) + \sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} b_{Y,X}(y, x) \rho_D^{tr}(y, x)$, for all $\pi \in \Pi$. Moreover, the two defenders use the same optimal recommendation policy.*

Remark 5 (Policy Invariance). *Lemmas 2 and 3 show that linear utility transformation does not affect the optimal recommendation policy. The structures of an insider's incentive and the defender's security objective play more critical roles in compliance status and ASeL than their absolute values.*

B. Geometric Characterization of CT Sets, ASaL, and ASeL

We define the following notations for the matrix representations of recommendation policies and utilities in Section V-B and VI. Define $\hat{v}_p^k := [b_X(x^1) \bar{v}_p(x^1, a^k), b_X(x^2) \bar{v}_p(x^2, a^k), \dots, b_X(x^I) \bar{v}_p(x^I, a^k)]^T \in \mathbb{R}^{1 \times I}$, $p \in \{D, U\}$, for all $k \in \mathcal{K}$. For each recommendation $s^k \in \mathcal{S}$, $k \in \mathcal{K}$, and the shorthand notation $\hat{\pi}^{k,i} := \pi(s^k|x^i)$, we can define an I -dimension vector $\hat{\pi}^k = [\hat{\pi}^{k,1}, \dots, \hat{\pi}^{k,I}] \in \hat{\Pi}^k$. By definition, $\sum_{k=1}^K \hat{\pi}^k = [1, 1, \dots, 1] \in \mathbb{R}^I$. Then, a recommendation policy $\pi \in \Pi$ has an equivalent matrix form as $\hat{\pi} := [\hat{\pi}^1, \dots, \hat{\pi}^K]^T \in \hat{\Pi}$. Analogously, the k -th PT, k -th PU, and CT recommendation policies in matrix forms compose sets $\hat{\Pi}_{pt}^k$, $\hat{\Pi}_{pu}^k$, and $\hat{\Pi}_{ct}$, respectively. In Proposition

5, we identify $\hat{\pi}^k \in \hat{\Pi}^k$ as the sufficient component of $\hat{\pi} \in \hat{\Pi}$ to determine the trustworthiness of recommendation $s^k \in \mathcal{S}$.

Proposition 5 (Minimal Sufficiency for Trustworthy Recommendations). *Policy vector $\hat{\pi}^k \in \hat{\Pi}^k$ is the minimal sufficient component of the policy matrix $\hat{\pi} \in \hat{\Pi}$ to determine the trustworthiness of recommendation $s^k \in \mathcal{S}$.*

Proof. Based on (2) and Definition 1, a recommendation $s^k \in \mathcal{S}, k \in \mathcal{K}$, is trustworthy if and only if $\hat{\pi}^k[\hat{v}_U^k - \hat{v}_U^l] \geq 0, \forall l \in \mathcal{K}$ (i.e., the matrix representation of constraint (c) in P_η). \square

Proposition 5 leads to the policy separability principle in Remark 6; i.e., the defender can design the k -th policy vector $\hat{\pi}^k \in \hat{\Pi}^k$ separately for all $k \in \mathcal{K}$ to learn the k -th PT policy set. The policy separability contributes to efficient CT policy set learning algorithms in Section VI. We characterize an insider's ASaL, the convexity of the CT policy set, and the defender's ASeL in Lemmas 4-6, respectively. Section VII-C2 illustrates these characterizations when $I = J = K = 2$.

Remark 6 (Policy Separability). *The defender can determine the k -th PT policy set, i.e., $\hat{\Pi}_{pt}^k$, independently from other PT policy sets $\hat{\Pi}_{pt}^{k'}, \forall k' \in \mathcal{K} \setminus \{k\}$, to determine CT policy set $\hat{\Pi}_{ct}$.*

Lemma 4 (PWL and Convex of ASaL). *For any recommendation policy $\hat{\pi} \in \hat{\Pi}$, an insider's ASaL $J_U(\pi, b_X, \bar{v}_U)$ is PieceWise Linear (PWL) and convex in $\hat{\pi}^k \in \hat{\Pi}^k, \forall k \in \mathcal{K}$.*

Proof. Following (4), we can represent an insider's ASaL as $J_U(\pi, b_X, \bar{v}_U) = \sum_{k \in \mathcal{K}} \max_{a \in \mathcal{A}} [\sum_{x \in \mathcal{X}} b_X(x) \pi(s^k | x) \bar{v}_U(x, a)]$. Since $\sum_{x \in \mathcal{X}} b_X(x) \pi(s^k | x) \bar{v}_U(x, a)$ is a linear function in $\hat{\pi}^k \in \hat{\Pi}^k, \forall k \in \mathcal{K}$, and $a \in \mathcal{A}$, the point-wise maximum of a group of linear functions in (4) leads to a PieceWise Linear (PWL) and convex function concerning $\hat{\pi}^k \in \hat{\Pi}^k, \forall k \in \mathcal{K}$. Then, the sum of a group of PWL and convex functions remains PWL and convex. \square

Denote $\mathcal{C}_I^k := \{\hat{\pi} \in \hat{\Pi} | \hat{\pi}^k[\hat{v}_U^l - \hat{v}_U^k] \geq 0, \forall l \in \mathcal{K}\}$ as the set of recommendation policies that induce action $a^l \in \mathcal{A}$ under recommendation $s^k \in \mathcal{S}$. Define $\mathcal{C}_{\{l_1, \dots, l_K\}} := \bigcap_{k=1}^K \mathcal{C}_I^k$ as the set of recommendation policies that induce action $a^k \in \mathcal{A}$ under recommendation $s^k \in \mathcal{S}$ for all $k \in \mathcal{K}$. Within each (possibly empty) set $\mathcal{C}_{\{l_1, \dots, l_K\}}, \forall l_1, \dots, l_K \in \mathcal{K}$, we can represent the defender's ASeL in (5) equivalently as the matrix form $\hat{J}_D(\hat{\pi}, \hat{v}_D, v_U) := \sum_{k \in \mathcal{K}} \hat{\pi}^k \hat{v}_D^k, \forall \hat{\pi} \in \mathcal{C}_{\{l_1, \dots, l_K\}}$.

Lemma 5. *The K^k sets $\mathcal{C}_{\{l_1, \dots, l_K\}}, \forall l_1, \dots, l_K \in \mathcal{K}$, are mutually exclusive and convex. The union of these sets composes the entire recommendation policy set, i.e., $\hat{\Pi} = \bigcup_{l_1, \dots, l_K \in \mathcal{K}} \mathcal{C}_{\{l_1, \dots, l_K\}}$. The k -th PT policy set $\mathcal{C}_I^k, \forall k \in \mathcal{K}$, and the CT policy set $\hat{\Pi}_{ct} = \mathcal{C}_{\{1, \dots, K\}} = \bigcap_{k=1}^K \mathcal{C}_I^k$ are convex.*

Proof. The convexity of set \mathcal{C}_I^k directly follows its definition. The properties of the mutual exclusiveness and the union directly come from the definition of $\mathcal{C}_{\{l_1, \dots, l_K\}}$. Definition 2 leads to $\hat{\Pi}_{ct} = \bigcap_{k=1}^K \mathcal{C}_I^k$. Since the intersection of any collection of convex sets is convex, sets $\mathcal{C}_{\{l_1, \dots, l_K\}}$ and $\hat{\Pi}_{ct}$ are convex. \square

Lemma 6 (PWL of ASeL). *For any recommendation policy $\hat{\pi} \in \hat{\Pi}$, the defender's ASeL $\hat{J}_D(\hat{\pi}, \hat{v}_D, v_U)$ is (possibly discontinuous) piecewise linear concerning $\hat{\pi}^k \in \hat{\Pi}^k, \forall k \in \mathcal{K}$.*

Proof. Based on Lemma 5, the entire recommendation policy set $\hat{\Pi}$ is divided into K^k mutually exclusive (possibly empty) sets determined by an insider's incentive v_U . Within each set $\mathcal{C}_{\{l_1, \dots, l_K\}}$, the defender's ASeL $\hat{J}_D(\hat{\pi}, \hat{v}_D, v_U)$ in matrix form is linear in $\hat{\pi}^k \in \hat{\Pi}^k, \forall k \in \mathcal{K}$. \square

C. Optimal ACEL under Incentive Misalignment

We first classify the insiders into three incentive categories in Definition 6 based on the alignment of their incentives with the defender's security objective. Denote $\chi(\mathcal{K}) := [\chi(1), \chi(2), \dots, \chi(K)]$ as a permutation of set \mathcal{K} , i.e., $\chi(k) \in \mathcal{K}, \forall k \in \mathcal{K}$, and $\chi(k) \neq \chi(k')$ if $k \neq k', \forall k, k' \in \mathcal{K}$.

Definition 6 (Incentive Categories). *Consider the defender with security objective v_D . An insider is categorized as amenable (resp. malicious) if he shares the same (resp. opposite) preference ranking with the defender concerning actions for each SP and AS; i.e., for any given $x \in \mathcal{X}, y \in \mathcal{Y}$, if $v_U(y, x, a^{\chi(1)}) \geq v_U(y, x, a^{\chi(2)}) \geq \dots \geq v_U(y, x, a^{\chi(K)})$, then $v_D(y, x, a^{\chi(1)}) \geq$ (resp. \leq) $v_D(y, x, a^{\chi(2)}) \geq$ (resp. \leq) $\dots \geq$ (resp. \leq) $v_D(y, x, a^{\chi(K)})$. An insider is self-interested if he is neither amenable nor malicious.*

An amenable insider has a strong sense of responsibility to enhance security and prioritizes security over convenience. A malicious insider, e.g., a disgruntled insider or an insider whose credentials have been stolen, can misbehave or sabotage corporate security on purpose. Self-interested insiders represent the majority of insiders who are willing to follow security rules when there is no conflict of interests. Following Definition 5 and Remark 5, linear transformations of a malicious, self-interested, or amenable insider's incentive do not change his incentive category. Lemma 7 characterizes the optimal recommendation policy and the ACEL when an insider's incentive and the defender's security objective are linearly dependent.

Lemma 7. *Consider linearly dependent incentives of an insider and the defender with a scaling factor $\rho_{D,U}^{sa} \in \mathbb{R}$ and translation factors $[\rho_{D,U}^{tr}(y, x) \in \mathbb{R}]_{y \in \mathcal{Y}, x \in \mathcal{X}}$, i.e., $v_D(y, x, a) = \rho_{D,U}^{sa} v_U(y, x, a) + \rho_{D,U}^{tr}(y, x)$ for all $y \in \mathcal{Y}, x \in \mathcal{X}, a \in \mathcal{A}$. Then, the following two statements hold.*

- 1) $J_D^{acel,*}(b_X, \bar{v}_D, \bar{v}_U) = 0, \forall b_X \in \mathcal{B}_X$, if and only if $\rho_{D,U}^{sa} \leq 0$. Zero-information recommendation policy $\pi_z \in \Pi_{ct}$ achieves the optimal ACEL.
- 2) $J_D^{acel}(\pi, b_X, \bar{v}_D, \bar{v}_U) \geq 0, \forall \pi \in \Pi, \forall b_X \in \mathcal{B}_X$, if and only if $\rho_{D,U}^{sa} > 0$. Full-information recommendation policy $\pi_f \in \Pi_{ct}$ achieves the optimal ACEL, and we have $J_D^{acel,*}(b_X, \bar{v}_D, \bar{v}_U) = \rho_{D,U}^{sa} \sum_{x \in \mathcal{X}} b_X(x) \max_{a \in \mathcal{A}} \bar{v}_U(x, a) - \rho_{D,U}^{sa} \max_{a \in \mathcal{A}} \sum_{x \in \mathcal{X}} b_X(x) \bar{v}_U(x, a)$.

Proof. Under $\pi_z \in \Pi_{ct}$ and the linear dependency condition, the defender's ASeL in (5) becomes $\hat{J}_D(\pi_z, b_{Y,X}, v_D, v_U) = \sum_{y \in \mathcal{Y}, x \in \mathcal{X}} b_{Y,X}(y, x) [\rho_{D,U}^{sa} v_U(y, x, a_0) + \rho_{D,U}^{tr}(y, x)] = \rho_{D,U}^{sa} \max_{a \in \mathcal{A}} \sum_{y \in \mathcal{Y}, x \in \mathcal{X}} b_{Y,X}(y, x) v_U(y, x, a) + \sum_{y \in \mathcal{Y}, x \in \mathcal{X}} b_{Y,X}(y, x) \rho_{D,U}^{tr}(y, x)$. Based on the concavification technique in [6], $\hat{J}_D(\pi^*, b_{Y,X}, v_D, v_U)$ is the concave closure of $\hat{J}_D(\pi_z, b_{Y,X}, v_D, v_U)$ over $b_{Y,X} \in \mathcal{B}_{Y,X}$. Since $\max_{a \in \mathcal{A}} \sum_{y \in \mathcal{Y}} \sum_{x \in \mathcal{X}} b_{Y,X}(y, x) v_U(y, x, a)$ is PWL and convex

concerning $b_{Y,X}(y,x), \forall y \in \mathcal{Y}, x \in \mathcal{X}$, we obtain that $\tilde{J}_D(\pi_z, b_{Y,X}, v_D, v_U)$ is PWL and convex (resp. concave) in $b_{Y,X} \in \mathcal{B}_{Y,X}$ if and only if $\rho_{D,U}^{sa} > 0$ (resp. $\rho_{D,U}^{sa} \leq 0$). Then, the convex hull of a concave function is itself, and the optimal ACEL equals 0. Meanwhile, the convex hull of a convex function depends only on the vertices of the convex set $\mathcal{B}_{Y,X}$, i.e., $v_D(y,x, \tilde{a}^{max}(y,x)), \forall x \in \mathcal{X}, y \in \mathcal{Y}$. We arrive at the result: $\tilde{J}_D(\pi^*, b_{Y,X}, v_D, v_U) = \sum_{x \in \mathcal{X}} b_X(x) \bar{v}_D(x, a_U^{max}(x)) = \rho_{D,U}^{sa} \sum_{x \in \mathcal{X}} b_X(x) \max_{a \in \mathcal{A}} \bar{v}_U(x, a) + \sum_{y \in \mathcal{Y}, x \in \mathcal{X}} b_{Y,X}(y,x) \rho_{D,U}^{tr} v_U(y,x)$, under the optimal recommendation policy $\pi_f \in \Pi_{ct}$. \square

Remark 7. Since a recommendation policy $\pi \in \Pi$ has impact on $b_{Y,X}^r$ as shown in Lemma 1, the incentive \bar{v}_D is not a constant as b_Y changes. Thus, $\tilde{J}_D(\pi^*, b_{Y,X}, v_D, v_U)$ is linear in $b_{Y,X} \in \mathcal{B}_{Y,X}$ but not $b_X \in \mathcal{B}_X$ (or $b_Y \in \Delta \mathcal{Y}$) in general. If mapping $\Psi \in \Psi$ is non-stochastic, then ZETAR degenerates to the Bayesian persuasion model in [6], and $J_D(\pi^*, b_X, \bar{v}_D, \bar{v}_U)$ is linear in $b_X \in \mathcal{B}_X$ (or $b_Y \in \Delta \mathcal{Y}$).

According to Definition 6, an insider is amenable if $\rho_{D,U}^{sa} > 0$ and malicious if $\rho_{D,U}^{sa} \leq 0$. Therefore, Lemma 7 provides a closed-form solution of the optimal ACEL for malicious and amendable insiders. We extend the discussion on the optimal ACEL concerning amenable and malicious insiders in Proposition 6 and 7, respectively. For an amendable insider, Proposition 6 shows that within the entire action preference, the optimal action is the decisive factor.

Proposition 6. If the incentives of an insider and the defender share the same optimal action $\tilde{a}^{max}(y,x) \in \mathcal{A}$ for each AS $x \in \mathcal{X}$ and SP $y \in \mathcal{Y}$, then for all $b_{Y,X} \in \mathcal{B}_{Y,X}$, full-information recommendation policy $\pi_f \in \Pi_{ct}$ achieves the optimal ACEL, and

$$J_D^*(b_X, \bar{v}_D, \bar{v}_U) = J_D^*(b_X, \bar{v}_U, \bar{v}_U) - \sum_{x \in \mathcal{X}} b_X(x) \delta(x), \quad (8)$$

where $J_D^*(b_X, \bar{v}_U, \bar{v}_U) = \sum_{x \in \mathcal{X}} b_X(x) \max_{a \in \mathcal{A}} \bar{v}_U(x, a)$ and $\delta(x) := \bar{v}_U(x, a^{max}(x)) - \bar{v}_D(x, a^{max}(x)), \forall x \in \mathcal{X}$. Moreover, $J_D^{acel}(\pi, b_X, \bar{v}_D, \bar{v}_U) \geq 0, \forall \pi \in \Pi, b_X \in \mathcal{B}_X$.

Proof. Based on Lemma 7, if we construct $v_D^0 := v_U$, then $\tilde{J}_D(\pi_z, b_{Y,X}, v_D^0, v_U)$ is PWL and convex in $b_{Y,X} \in \mathcal{B}_{Y,X}$, and $\tilde{J}_D(\pi^*, b_{Y,X}, v_D^0, v_U)$ only depends on $v_D^0(y,x, \tilde{a}^{max}(y,x)), \forall x \in \mathcal{X}, y \in \mathcal{Y}$, for all $b_{Y,X} \in \mathcal{B}_{Y,X}$. Thus, we can construct v_D^1 from v_D^0 to make $\tilde{J}_D(\pi^*, b_{Y,X}, v_D^1, v_U) = \tilde{J}_D(\pi^*, b_{Y,X}, v_D^0, v_U)$ as long as $v_D^1(y,x, \tilde{a}^{max}(y,x)) = v_D^0(y,x, \tilde{a}^{max}(y,x)), \forall y \in \mathcal{Y}, x \in \mathcal{X}$.

If an insider with incentive v_U and the defender with security objective v_D prefer the same optimal action for each AS and SP, we can construct $\bar{v}_D^{eq}(x, a) := \bar{v}_D(x, a) + \delta(x)$ such that $\bar{v}_D^{eq}(x, a^{max}(x)) = \bar{v}_U(x, a^{max}(x)), \forall x \in \mathcal{X}$. Then, $J_D^*(b_X, \bar{v}_D^{eq}, \bar{v}_U) = J_D^*(b_X, \bar{v}_U, \bar{v}_U)$. Based on Lemma 3, $J_D^*(b_X, \bar{v}_D^{eq}, \bar{v}_U) = J_D^*(b_X, \bar{v}_D, \bar{v}_U) + \sum_{x \in \mathcal{X}} \delta(x)$, which leads to (8). Since $J_D(\pi, b_X, \bar{v}_D^{eq}, \bar{v}_U) \geq J_D(\pi_z, b_X, \bar{v}_D^{eq}, \bar{v}_U), \forall \pi \in \Pi, b_X \in \mathcal{B}_X$, based on Lemma 7, Lemma 3 yields $J_D(\pi, b_X, \bar{v}_D, \bar{v}_U) \geq J_D(\pi_z, b_X, \bar{v}_D, \bar{v}_U)$. \square

Remark 8 (Sufficiency under Aligned Action Preference). Proposition 6 shows that if an insider and the defender share the same optimal action $\tilde{a}^{max}(y,x) \in \mathcal{A}$ for each AS $x \in \mathcal{X}$ and SP $y \in \mathcal{Y}$, then $v_D(y,x, \tilde{a}^{max}(y,x)), \forall x \in \mathcal{X}, y \in \mathcal{Y}$, are

the minimal sufficient component of the defender's security objective v_D to determine the defender's optimal ASeL.

Remark 9 (Simplified ZETAR Problem). When $v_D = v_U$, the principal-agent problem $\tilde{J}_D(\pi^*, b_{Y,X}, v_U, v_U)$ is equivalent to a single-agent decision problem that directly solves $\sum_{x \in \mathcal{X}} b_X(x) \max_{a \in \mathcal{A}} \bar{v}_U(x, a)$. Thus, Proposition 6 contributes to an efficient computation of the defender's optimal ASeL when she shares the same \tilde{a}^{max} with an insider.

Remark 10 (Full Information Disclosure to Amendable Insiders). The defender should share full information (i.e., adopt $\pi_f \in \Pi_{ct}$) with amendable insiders. By synchronizing information with compliant insiders, the defender encourages amendable insiders to contribute to corporate security.

For malicious insiders, we first introduce a class of invariant perturbations of the defender's security objective that achieve the same optimal ACEL of $J_D^{acel,*}(b_X, \bar{v}_D, \bar{v}_U) = 0$ in Proposition 7. Define shorthand notation $a^{min}(y,x) \in \text{argmin}_{a \in \mathcal{A}} v_D(y,x,a)$ for all $x \in \mathcal{X}, y \in \mathcal{Y}$.

Proposition 7 (Compliance Equivalency under Security Objective Perturbations). We construct \bar{v}_D^{ip} as a copy of \bar{v}_D with the following revision: for each $x^i \in \mathcal{X}, i \in \mathcal{I}, y \in \mathcal{Y}$, if $a^{min}(y,x^i) \neq a^{min}(y,x^i)$, then $v_D^{ip}(y,x^j, a^{min}(y,x^i)) \leq v_D(y,x^j, a^{min}(y,x^i)), \forall j \in \mathcal{I} \setminus \{i\}$. If there exist $\rho_{D,U}^{sa} < 0$ and $\rho_{D,U}^{tr}(y,x) \in \mathbb{R}$ such that $v_D(y,x,a) = \rho_{D,U}^{sa} v_U(y,x,a) + \rho_{D,U}^{tr}(y,x)$ for all $y \in \mathcal{Y}, x \in \mathcal{X}, a \in \mathcal{A}$, then $J_D^*(b_X, \bar{v}_D^{ip}, \bar{v}_U) = J_D^*(b_X, \bar{v}_D, \bar{v}_U)$.

Proof. Lemma 7 shows that $\tilde{J}_D(\pi^*, b_{Y,X}, v_D, v_U)$ as the concave closure of $\tilde{J}_D(\pi_z, b_{Y,X}, v_D, v_U)$ is PWL and concave in $b_{Y,X} \in \mathcal{B}_{Y,X}$ if $\rho_{D,U}^{sa} < 0$. Based on the geometry, changing v_D to v_D^{ip} does not affect the concave closure (yet $\pi^* \in \Pi$ can change and does not contain zero information), i.e., $J_D^*(b_X, \bar{v}_D^{ip}, \bar{v}_U) = J_D^*(b_X, \bar{v}_D, \bar{v}_U)$. \square

Remark 10 provides the defender with the guidance of full-information disclosure to amendable insiders. Based on Lemma 7 and Proposition 6, it is natural to conjecture that the defender should disclose zero information to malicious insiders. However, it does not hold, and we present a counterexample in Proposition 7; i.e., although an insider with incentive v_U is malicious to both the defender with security objective v_D and the one with v_D^{ip} , zero information recommendation policy is not the optimal policy for the defender with v_D^{ip} . Thus, Proposition 7 leads to the strategic information disclosure guideline in Remark 11. It further shows that ZETAR can improve an insider's compliance even if he is malicious based on the incentive categorization in Definition 6.

Remark 11 (Strategic Information Disclosure to Malicious Insiders). The defender should disclose information strategically rather than hide information (i.e., adopting $\pi_z \in \Pi$) even when the insider is malicious and tends to take an action that results in the least utility to the defender.

VI. FEEDBACK DESIGN FOR UNKNOWN INCENTIVES

When the defender knows an insider's incentive v_U , we can use primal and dual convex programs in Section IV to compute

the optimal recommendation policy π_η^* for a given LoRC $\eta \in \mathbb{R}^{0+}$. In practice, however, insiders' incentives usually remain unknown to the defender, and the defender may not be able to formulate constraint (c) in P_η to determine the CT policy set. To this end, we provide a feedback design approach in Section VI for the defender to learn the optimal recommendation policy based on the insiders' responses to recommendations, as shown in Fig. 2. In the proposed learning algorithms, the defender needs no prior knowledge nor trust in an insider's incentives. The zero-trust audit of all insiders provides the defender with their behaviors to learn incentives.

A straightforward feedback learning paradigm optimizes the defender's ASeL $J_D(\pi, b_X, \bar{v}_D, \bar{v}_U)$ over all recommendation policies in set $\hat{\Pi}$ directly. For a new insider with an unknown incentive, the defender at stage $m \in \{1, 2, \dots\}$ recommends actions according to a recommendation policy $\hat{\pi}_m \in \hat{\Pi}$. Then, the defender observes the insider's responses to these recommendations and evaluates her ASeL. At stage $m + 1$, the defender uses her ASeL evaluation to update the recommendation policy from $\hat{\pi}_m \in \hat{\Pi}$ to $\hat{\pi}_{m+1} \in \hat{\Pi}$. The update rule depends on bespoke optimization methods (e.g., simulated annealing, Bayesian optimization, and reinforcement learning). The above learning paradigm is universal yet inefficient and does not guarantee global optimality. In Algorithms 1 and 2, we design efficient feedback learning algorithms by exploiting the ZETAR features characterized in Section V. In particular, the defender only learns the CT policy set $\hat{\Pi}_{cr}$ and then uses the primal convex program P_η in Section IV to compute the optimal recommendation policy $\hat{\pi}_\eta^*$ and the optimal ACEL $J_D^{acel,*}$. The defender can achieve it as she knows her security objective v_D to compute the objective function in P_η .

Based on Definition 2, we only need to learn all the PT policy sets $\hat{\Pi}_{pt}^k, \forall k \in \mathcal{K}$, to determine the CT policy set.

Following the matrix representation in Section V-B, the k -th row vector $\hat{\pi}^k \in \hat{\Pi}^k$ of a recommendation policy $\hat{\pi} \in \hat{\Pi}$ can be equivalently represented a point, denoted by (p_k^1, \dots, p_k^I) , in the unit hypercube of dimension I , where the coordinate $p_k^i = \hat{\pi}^{k,i} \in [0, 1], \forall k \in \mathcal{K}, i \in \mathcal{I}$. We refer to a point in the k -th hypercube as a k -th PT point if it represents the k -th row vector $\hat{\pi}^k$ of a k -th PT recommendation policy $\hat{\pi} \in \hat{\Pi}_{pt}^k$. Since the k -th row $\hat{\pi}^k$ of $\hat{\pi}$ is sufficient to determine whether $\hat{\pi}$ is PT based on Proposition 5, learning the k -th PT set $\hat{\Pi}_{pt}^k$ is equivalent to determining the region formulated by the k -th PT points. We refer to the region as the k -th PT region, which is a convex polytope in the k -th hypercube of dimension I based on Lemma 5. Since a convex polytope can be uniquely represented by its vertices, we develop the following two algorithms to obtain the vertex representation (V-representation) of these regions. Due to the policy separability principle in Remark 6, we can determine the V-representation of the k -th PT region independently for each $k \in \mathcal{K}$. For any point (p_k^1, \dots, p_k^I) of the k -th hypercube, we define $\Omega(p_k^1, \dots, p_k^I) \subseteq \hat{\Pi}$ as the set of recommendation policies whose k -th row vectors satisfy $\hat{\pi}^k = [p_k^1, \dots, p_k^I]$. In Algorithm 1, we determine the whether the 2^I vertices of the k -th hypercube are k -th PT points. Let $V^k := \{(p_k^1, \dots, p_k^I) | p_k^i \in \{0, 1\}, \forall i \in \mathcal{I}\}$ be the set of these 2^I vertices. Among these 2^I vertices, the k -th PT ones compose

the k -th PT cube-vertex set denoted as $V_{pt}^k \subseteq V^k$.

Algorithm 1: Algorithm to learn the k -th PT cube-vertex set V_{pt}^k for a given insider.

- 1 **Initialize** the k -th PT cube-vertex set $V_{pt}^k \leftarrow \emptyset$;
 - 2 **foreach** vertex $(p_k^1, \dots, p_k^I) \in V^k$ **do**
 - 3 **while** s^k has not been recommended, i.e., $k' \neq k$ **do**
 - 4 Recommend $s^{k'} \in \mathcal{S}$ randomly based on a recommendation policy $\hat{\pi} \in \Omega(p_k^1, \dots, p_k^I)$;
 - 5 **if** recommendation s^k induces $a^k \in \mathcal{A}$ **then**
 $V_{pt}^k \leftarrow V_{pt}^k \cup \{(p_k^1, \dots, p_k^I)\}$;
 - 6 **Return** the k -th PT cube-vertex set V_{pt}^k ;
-

In Algorithm 2, we determine the vertex coordinates of the k -th PT region. As a convex polytope, the region contains a finite set of polytope-vertices defined as \bar{V}_{pt}^k . Since the k -th PT region is determined by a hyperplane in the k -th hypercube, its vertices are on the edges, and it contains all the elements in the k -th PT cube-vertex set V_{pt}^k as shown in the initialization step in line 7. Each cube-vertex $(p_k^1, \dots, p_k^I) \in V_{pt}^k$ has I neighboring cube-vertices, and the coordinate of its i -th neighboring cube-vertex is $(p_k^1, \dots, p_k^{i-1}, 1 - p_k^i, p_k^{i+1}, \dots, p_k^I)$. After we select a k -th PT cube-vertex in line 8, we search over its I neighboring cube-vertices in line 9. If the neighboring vertex is also k -th PT, then the points on the edge of these two cube-vertices are both k -th PT. If the neighboring vertex is not k -th PT as shown in line 10, then there is an additional polytope-vertex on the edge of these two cube-vertices. As shown in lines 11 – 17, we use the binary search to learn the coordinate of this additional polytope-vertex and add it to the k -th polytope-vertex set \bar{V}_{pt}^k in line 18. In particular, the binary search adopts an accuracy $\varepsilon > 0$ used in the stopping criteria shown in line 12. For the worst case where a polytope-vertex is close to a cube-vertex, we need $N \in \mathbb{Z}^+$ iterations to reach the stop criteria, i.e., $(1/2)^N \leq \varepsilon$, which leads to $N \geq \log_2(1/\varepsilon)$. Since an I -dimensional hypercube has $2^{n-1}n$ edges, Algorithm 2 is guaranteed to stop within $2^{n-1}n \log_2(1/\varepsilon)$ steps.

After we obtain the V-representation of the k -th PT policy set, i.e., \bar{V}_{pt}^k , for each $k \in \mathcal{K}$, we can use facet enumeration methods (e.g., [38]) to obtain the half-space representation (H-representation) that can be directly used to construct the constraints in the primal convex program $P_\eta, \forall \eta \in \mathbb{R}^+$, in $\hat{\pi} \in \hat{\Pi}$. We provide a graphical illustration in Section VII-B when $I = J = K = 2$.

VII. CASE STUDY

In this section, we illustrate the design of ZETAR in Fig. 2 under fully customized recommendation policies (i.e., $\eta = \infty$) to improve compliance for insiders with different incentives.

A. Model Description

Following Fig. 3, we consider the binary SP, i.e., $\mathcal{Y} = \{y^{hr}, y^{lr}\}$, where y^{hr} and y^{lr} represent the high-risk SP and the low-risk SP, respectively. For illustration purposes, we consider binary audit schemes, i.e., $\mathcal{X} = \{x^{sa}, x^{ta}\}$, where x^{sa} and

Algorithm 2: Algorithm to learn the polytope-vertex set \bar{V}_{pt}^k for a given insider.

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7 Initialize  $\bar{V}_{pt}^k \leftarrow V_{pt}^k$ , and accuracy  $\varepsilon > 0$ ;
8 foreach  $k$ -th PT vertex  $(p_k^1, \dots, p_k^I) \in V_{pt}^k$  do
9   for  $i \leftarrow 1$  to  $I$  do
10    if  $(p_k^1, \dots, p_k^{i-1}, 1 - p_k^i, p_k^{i+1}, \dots, p_k^I) \notin V_{pt}^k$  then
11       $lb \leftarrow 0$  and  $ub \leftarrow 1$ ;
12      while  $ub - lb > \varepsilon$  do
13        Recommend  $s \in \mathcal{S}$  randomly based on
14         $\hat{\pi} \in \Omega(p_k^1, \dots, p_k^{i-1}, \frac{lb+ub}{2}, p_k^{i+1}, \dots, p_k^I)$ ;
15        if  $s = s^k$  and  $p_k^i = 0$  then
16          if insider takes action  $a^k \in \mathcal{A}$  then
17             $lb = \frac{lb+ub}{2}$  else  $ub = \frac{lb+ub}{2}$ ;
18          else  $s = s^k$  and  $p_k^i = 1$ 
19            if insider takes action  $a^k \in \mathcal{A}$  then
20               $ub = \frac{lb+ub}{2}$  else  $lb = \frac{lb+ub}{2}$ ;
21         $\bar{V}_{pt}^k \leftarrow \bar{V}_{pt}^k \cup \{(p_k^1, \dots, p_k^{i-1}, \frac{lb+ub}{2}, p_k^{i+1}, \dots, p_k^I)\}$ ;
19 Return the  $k$ -th PT polytope-vertex set  $\bar{V}_{pt}^k$ ;

```

x^{ta} represent stringent audit and tolerant audit, respectively. The insider's behaviors are categorized into binary actions, i.e., $\mathcal{A} = \{a^{ic}, a^{co}\}$, where a^{ic} and a^{co} represent non-compliant and compliant behaviors, respectively. Since insiders have different risk attitudes toward gains and losses, we introduce a risk perception function κ^γ with parameter $\gamma := [\gamma_a, \gamma_s]$, where $\kappa^\gamma(v) := v^\gamma, v \geq 0$, and $\kappa^\gamma(v) := -\gamma_s(-v)^\gamma, v < 0$, based on Cumulative Prospect Theory (CPT) [39].

1) *Insider's Intrinsic and Extrinsic Incentives:* As shown in Table I, we separate an insider's incentive v_U^Y under κ^γ into intrinsic incentive $v_{U,I}$ and extrinsic incentive $v_{U,E}^Y$.

$v_{U,E}^Y$	x^{sa}	x^{ta}
a^{ic}	$\kappa^\gamma(-c_D^{ic})$	0
a^{co}	$\kappa^\gamma(r_D^{co}) - c_U^{co}$	$-c_U^{co}$

(a) Extrinsic incentive.

$v_{U,I}$	y^{hr}	y^{lr}
a^{ic}	c_U^{hr}	c_U^{lr}
a^{co}	r_U^{hr}	r_U^{lr}

(b) Intrinsic incentive.

TABLE I: Insider's utility $v_U^Y = v_{U,I} + v_{U,E}^Y$.

The extrinsic incentive in Table I(a) is independent of SP and captures the impact of AS on compliance. Compliant action $a^{co} \in \mathcal{A}$ introduces a compliance cost $c_U^{co} \in \mathbb{R}^+$ to an insider regardless of the AS. For example, an insider compliant with the air-gap rule has to spend additional time and effort to transfer data using a CD rather than a USB. Under AS $x^{sa} \in \mathcal{X}$, the defender introduces a reward $r_D^{co} \in \mathbb{R}^+$ and a penalty $c_D^{ic} \in \mathbb{R}^+$ to compliant action a^{co} and non-compliant action a^{ic} , respectively. We assume that the tolerant audit scheme x^{ta} introduces a reward and penalty of 0 to a^{co} and a^{ic} , respectively. The intrinsic incentive in Table I(b) is independent of AS and captures an insider's internal inclination to comply under different SP realizations. Under high-risk SP y^{hr} (resp. low-risk SP y^{lr}), an insider receives an intrinsic penalty (e.g., the guilty of misconduct) denoted by c_U^{hr} (resp. c_U^{lr}) to take non-compliant action a^{ic} and an intrinsic reward (e.g., the gratification of being compliance-

seeking) denoted by r_U^{hr} (resp. r_U^{lr}) to take compliant action a^{co} . Based on Lemma 2, we can choose $\rho_U^{tr}(y^{hr}, x) = -r_U^{hr}$ and $\rho_U^{tr}(y^{lr}, x) = -r_U^{lr}$ for all $x \in \mathcal{X}$ without affecting the insider's compliance and the optimal recommendation policy $\pi^* \in \Pi$. Thus, without loss of generality, we calibrate $r_U^{hr} = r_U^{lr} = 0$ and $c_U^{hr}, c_U^{lr} \in \mathbb{R}$ and characterize the following three compliance attitudes of insiders in Definition 7.

Definition 7 (Compliance Attitudes). An insider is said to be compliance-seeking, compliance-averse, and compliance-neutral if both c_U^{hr} and c_U^{lr} are positive, negative, and zero, respectively.

2) *Defender's Security Objective:* Table II illustrates the defender's security objective v_D . Following Section III-B, stringent audit increases insiders' pressures and reduces their working efficiency. We capture the efficiency reduction with a cost $c_D^{ca} \in \mathbb{R}^+$. When an insider takes a non-compliant action a^{ic} , the stringent audit x^{sa} requires an immediate correction from the insider to patch the induced vulnerability, which yields a reward of $r_D^{ca} \in \mathbb{R}^+$ in Table II regardless of the SP realizations. Meanwhile, the tolerant audit x^{ta} introduces no cost of efficiency reduction but additional risks of insider threats captured by the cost $c_D^{la} \in \mathbb{R}^+$ in Table II(a) and $c_D^{lr} \in \mathbb{R}^+$ in Table II(b) under high-risk SP y^{hr} and low-risk SP y^{lr} , respectively. When an insider takes a compliant action a^{co} , the risk of insider threats is reduced to a minimum and is represented as the defender's payoff $r_D^{sa} \in \mathbb{R}$.

v_D	x^{sa}	x^{ta}
a^{ic}	$r_D^{ca} - c_D^{ca}$	$-c_D^{hr}$
a^{co}	$-c_D^{ca}$	r_D^{sa}

(a) v_D at high-risk SP.

v_D	x^{sa}	x^{ta}
a^{ic}	$r_D^{ca} - c_D^{ca}$	$-c_D^{lr}$
a^{co}	$-c_D^{ca}$	r_D^{sa}

(b) v_D at low-risk SP.TABLE II: Defender's utility v_D at two SP states.

B. Graphical Illustration of Learning Algorithms

In this case study, the defender has no prior knowledge of an insider's risk and compliance attitudes. Moreover, the defender assigns no prior trust to the insiders and applies the algorithms in Section VI to learn their incentives. Fig. 4a and Fig. 4b illustrate the Algorithms under compliance-seeking and compliance-averse insiders, respectively. Since $K = 2$, the recommendation policy $\hat{\pi} \in \hat{\Pi}$ can be equivalently represented as a point (p^1, p^2) in the unit hypercube of dimension $I = 2$ (i.e., a unit square), where $p^1 = \pi(s^{ic}|x^{sa}), p^2 = \pi(s^{ic}|x^{ta})$ as shown in Section VI. In the hypercube space illustrated by Fig. 4, the green and blue regions represent the CT and CU policy sets, respectively.

Algorithm 1 determines whether the four vertices of the hypercube are the 1-st PT or not, which are illustrated by the blue upward and red downward triangles, respectively, in Fig. 4. Algorithm 2 further determines the additional polytope-vertex (represented by the blue circle in Fig. 4) of the 1-st PT polytope in green. From each blue triangle (line 8), if a neighboring cube-vertex (line 9) is also a blue triangle, then no additional polytope-vertices are needed to determine the green region (line 10). If the neighboring cube-vertex is red, then binary search is applied to determine the additional

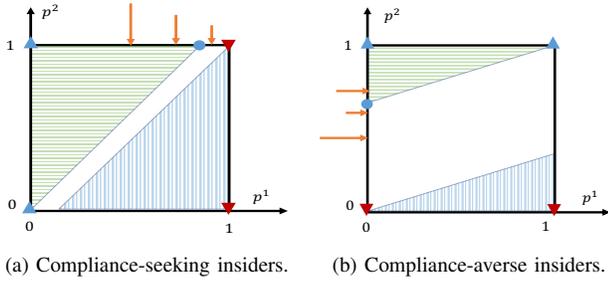


Fig. 4: The blue upward and the red downward triangles represent the CT and CU recommendations policies, respectively. The green (resp. blue) region with horizontal (resp. vertical) lines represents the CT (resp. CU) policy sets, respectively. The orange lines show the steps of the binary search in Algorithm 2.

polytope-vertex. In Fig. 4a (resp. Fig. 4b), from the blue cube-vertex $(0, 1)$, the red neighboring cube-vertex is $(1, 0)$ (resp. $(0, 0)$), and the binary search adopts line 15 (resp. line 17). We use the orange lines in Fig. 4b to illustrate the binary search process, i.e., line 11 to 17 in Algorithm 2. The first step of the binary search (represented by the longest orange line) evaluates the recommendation policy represented by the point $(0, 1/2)$, and the policy is not the 1-st PT. Thus, we update the lower bound lb based on the *else* condition in line 16 of Algorithm 2. The second step (represented by the second-longest orange line) evaluates the recommendation policy represented by the point $(0, 3/4)$, and the policy is the 1-st PT. Thus, we update the upper bound ub based on the *then* condition in line 14. The third step (represented by the third-longest orange line) evaluates the recommendation policy represented by the point $(0, 5/8)$, and the policy is not the 1-st PT. Thus, we update the lower bound again. We repeat the above process of binary search until $ub - lb \leq \epsilon$ as shown in line 12, and we find the additional polytope vertex represented by the blue circle in Fig. 4b. After we obtain all the vertices of the polytope that represent the CT policy set, we can use facet enumeration methods to obtain the H -representation and construct the constraints of P_η concerning $p^1, p^2 \in [0, 1]$. For example, if the coordinate of the blue circle in Fig. 4b is $(0, w)$, $w \in [0, 1]$, then the constraint is $p^2 \geq (1 - w)p^1 + w$.

C. Numerical Results

We choose $\psi(x^{sa}|y^{hr}) = 0.8$ and $\psi(x^{sa}|y^{lr}) = 0.3$; i.e., the audit firm chooses a stringent audit with probability 0.8 and 0.3 under high-risk SP y^{hr} and low-risk SP y^{lr} , respectively.

1) *Compliance Threshold*: Following Section III-D2, we investigate the initial compliance of an insider with three compliance attitudes in Definition 7 and different risk perception parameters γ . Define $t_{ze} \in \mathbb{R}$ as the zero of the function $f(b_Y(y^{hr})) := \sum_{y \in \mathcal{Y}} b_Y(y) \sum_{x \in \mathcal{X}} \Psi(x|y)[v_U(y, x, a_1) - v_U(y, x, a_2)]$. Let $t_{bt} := \max\{\min\{t_{ze}, 1\}, 0\}$ be the belief threshold of an insider. For binary actions, an insider adopts a *threshold policy* where $a_0 = a^{co}$ if $b_Y(y^{hr}) \geq t_{bt}$ and $a_0 = a^{ic}$ if $b_Y(y^{hr}) < t_{bt}$. Fig. 5 illustrates the belief threshold versus the non-compliance penalty $c_D^{ic} \in \mathbb{R}^+$. The plots show that increasing penalty c_D^{ic} can make insiders more likely to take compliant action a^{co} (i.e., a smaller belief threshold). Fixing the penalty

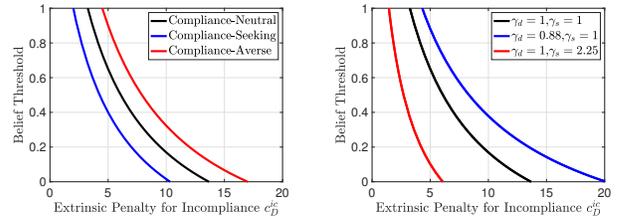


Fig. 5: Insiders' belief thresholds $t_{bt} \in [0, 1]$ to compliant actions versus the value of non-compliance penalty $c_D^{ic} \in \mathbb{R}^+$.

value, compliance-averse (resp. compliance-seeking) insiders are the least (resp. most) likely to comply, i.e., the largest (resp. smallest) belief thresholds, among insiders with three compliance attitudes, as shown in Fig. 5a. In Fig. 5b, a larger γ_s in red represents a higher degree of loss aversion, which makes an insider more likely to comply. A small γ_d in blue enhances the effect of diminishing sensitivity, which makes a large penalty less effective to induce compliant behaviors.

2) *Impacts of Recommendation Policies*: Here, we specify $b(y^{hr}) = 0.2$ and $c_D^{ic} = 10$ to inspect the impact of recommendation policies on an insider's behaviors. Fig. 6 illustrates the impact of different recommendation policies $\hat{\pi} \in \hat{\Pi}$ on an insider's posterior belief b_X^π under Bayesian belief update in Section III-D4. The posterior belief is independent of v_D, v_U, η and γ . The plot illustrates the Bayesian plausibility [6] where $\sum_{s \in \mathcal{S}} b_S^\pi(s) b_X^\pi(x|s) = b_X(x), \forall x \in \mathcal{X}, \pi \in \Pi$. Fig.

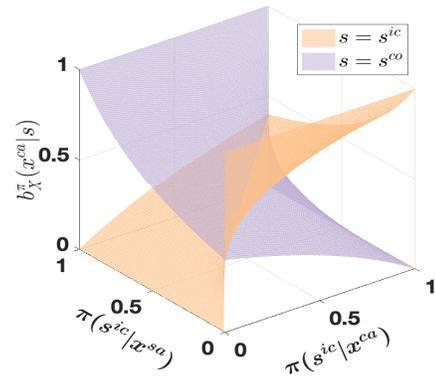


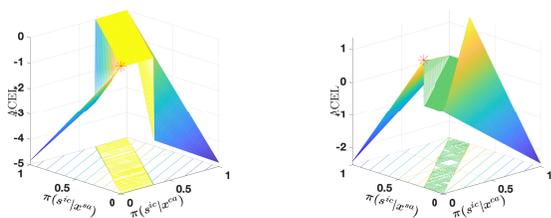
Fig. 6: An insider's posterior belief $b_X^\pi(x^{sa}|s)$ under recommendation $s = s^{ic}$ and $s = s^{co}$ in brown and pink, respectively, vs. $\pi(s^{ic}|x^{sa}) \in [0, 1]$ in x -axis and $\pi(s^{ic}|x^{ca}) \in [0, 1]$ in y -axis.

7 illustrates the impact of different recommendation policies $\hat{\pi} \in \hat{\Pi}$ on the ACEL under insiders with two compliance attitudes, which corroborate the PWL property in Lemma 6. Different compliance attitudes only affect the policy set partition denoted by $\mathcal{C}_i^k, \forall i, k \in \{ic, co\}$, following Section V-B. In Fig. 7a, the policy sets (also illustrated in Fig. 4a) illustrated by the contour plots on the xy -plane are sets $\mathcal{C}_{ic,co}$, $\mathcal{C}_{co,co}$, and $\mathcal{C}_{co,ic}$, respectively, from left to right. In Fig. 7b, the policy sets (also illustrated in Fig. 4b) illustrated by the contour plots on the xy -plane are sets $\mathcal{C}_{ic,co}$, $\mathcal{C}_{ic,ic}$, and $\mathcal{C}_{co,ic}$, respectively, from left to right. These policy sets are convex

as shown in Lemma 5. The sets $\mathcal{C}_{ic,co}$ and $\mathcal{C}_{co,ic}$ are CT and CU, respectively.

Fig. 7 illustrates that an improper recommendation policy may lead to a negative ACEL, but the optimal ACEL represented by the red star is always non-negative, as shown in Section III-D6. For compliance-seeking insiders, the defender's ISeL $J_D(\pi_z, b_X, \bar{v}_D, \bar{v}_U)$ and the optimal ASEL $J_D(\pi^*, b_X, \bar{v}_D, \bar{v}_U)$ are both 1.8. For compliance-averse insiders, the defender's ISeL $J_D(\pi_z, b_X, \bar{v}_D, \bar{v}_U)$ and the optimal ASEL $J_D(\pi^*, b_X, \bar{v}_D, \bar{v}_U)$ are -0.64 and 0.73 , respectively.

Remark 12 (Adaptivity and Structural Improvement). *The above results show that ZETAR can well adapt to insiders with different compliance attitudes and achieve a structural improvement of compliance (from a negative ISeL to a positive ASEL) for compliance-averse insiders.*



(a) Compliance-seeking insiders. (b) Compliance-averse insiders.

Fig. 7: ACEL $J_D^{acel}(\pi, b_X, \bar{v}_D, \bar{v}_U)$ versus $\pi(s^{ic}|x^{sa}) \in [0, 1]$ in x -axis and $\pi(s^{ic}|x^{ta}) \in [0, 1]$ in y -axis when $\gamma_d = \gamma_s = 1$.

3) *The Optimal ACEL:* We illustrate the impacts of the optimal recommendation policy π^* on the defender's and an insider's utilities under different likelihoods of the high-risk SP. In Fig. 8. Following Section VII-C1, the belief threshold $t_{bt} \in [0, 1]$, represented by the vertical dashed black lines, divides the entire prior belief region into the compliant region $b_Y(y^{hr}) \in [t_{bt}, 1]$ on the right and non-compliant region $b_Y(y^{hr}) \in [0, t_{bt}]$ on the left, where an insider takes a^{co} and a^{ic} , respectively. Under the compliant regions, an insider tends to take compliant actions, resulting in zero ACEL and zero-information recommendation policy $\pi^*(s^{ic}|x^{sa}) = \pi^*(s^{ic}|x^{ta}) = 0$. Under the non-compliant regions where an insider tends not to comply, the optimal recommendation policy induces positive ACEL. The defender's ISeL in compliant regions is larger than the one in non-compliant regions as shown by the blue lines in the two regions. As an insider changes from being compliance-averse to compliance-seeking, his ASaL in black decreases in the non-compliant region, the belief threshold reduces (also illustrated in Fig. 5), and the peak of the optimal ACEL increases. The orange and pink lines illustrate that a large ACEL results from a more distinguished recommendation policy, i.e., a larger difference between $\pi^*(s^{ic}|x^{sa})$ and $\pi^*(s^{ic}|x^{ta})$. Moreover, the defender can recommend compliant actions, i.e., s^{co} , with a high probability as an insider changes from compliance-averse to compliance-seeking. Despite the linearity of the defender's ISeL in blue, her optimal ASEL in red and the optimal ACEL in brown are nonlinear in b_Y , as shown in Remark 7. In Fig. 8, we further observe that an insider's ISaL coincides with his optimal ASaL, both

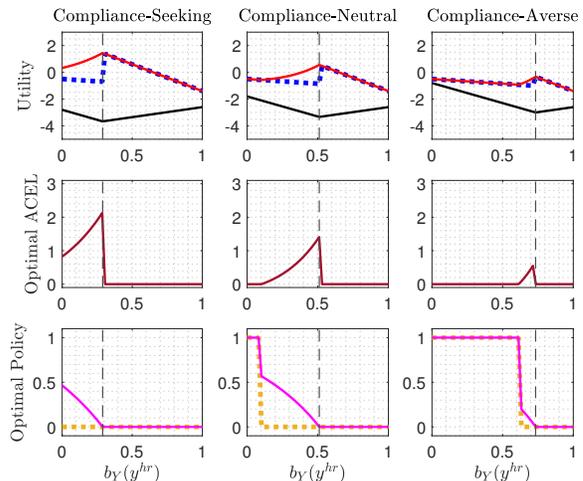


Fig. 8: Utilities, the optimal ACEL, and the optimal recommendation policies in the first, second, and third rows, respectively, versus prior statistic $b_Y(y^{hr}) \in [0, 1]$ concerning insiders with three compliance attitudes under $\gamma_s = \gamma_d = 1$. The defender's ISeL $J_D(\pi_z, b_X, \bar{v}_D, \bar{v}_U)$, her optimal ASEL $J_D(\pi^*, b_X, \bar{v}_D, \bar{v}_U)$, and an insider's optimal ASaL $J_U(\pi^*, b_X, \bar{v}_U)$ are in blue, red, and black, respectively. Two elements of the optimal recommendation policy, $\pi^*(s^{ic}|x^{sa})$ and $\pi^*(s^{ic}|x^{ta})$, are illustrated in orange and pink, respectively. The vertical dashed black lines represent the belief threshold $t_{bt} \in [0, 1]$.

represented by the black solid lines for all $b_Y(y^{hr}) \in [0, 1]$, which corroborates Proposition 1.

VIII. CONCLUSION

This work has developed ZETAR as a proactive framework to improve compliance of insiders with different incentives by zero-trust audits and recommendations. By a strategic and customized information disclosure of the audit scheme, the defender manages to influence an insider's incentives in favor of the corporate security objectives. We have formulated primal and dual convex problems with different levels of recommendation customization to provide a unified computational framework for ZETAR. We have shown its strong duality and degeneration to linear programs with fully customized recommendation policies. The dual problem has offered an interpretation of ZETAR from an insider's perspective; i.e., each insider aims to minimize his effort to satisfy the security objective of the corporate network.

We have characterized the structure of trustworthy recommendation policies and compliance status under malicious, self-interested, and amenable insiders. The characterizations have led to fundamental principles and information disclosure guidelines to insiders. Leveraging zero-trust design principles, we have assumed no trust and knowledge of the insider's incentives and developed efficient feedback algorithms to learn the insider's incentive based on the audit result of his behaviors. After identifying the policy separability principle and characterizing the Completely Trustworthy (CT) policy sets determined by the insider's incentive as convex polytopes, we have adopted a binary search algorithm to learn the vertices

of the polytope, which is guaranteed to achieve an accuracy of $\varepsilon > 0$ within $2^{n-1}n\log_2(1/\varepsilon)$ steps.

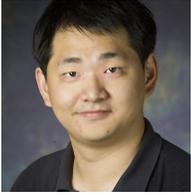
We have used a case study to corroborate that ZETAR enhances compliance for insiders with different extrinsic and intrinsic incentives. The results have shown that ZETAR can well adapt to insiders with different risk and compliance attitudes and structurally improve the defender's average security level when interacting with compliance-averse insiders. Under binary sets of actions and SP states, we have shown that insiders adopt a threshold policy with belief threshold $t_{bt} \in [0, 1]$ that divides the belief region into compliance region $b_Y(y^{hr}) \in [t_{bt}, 1]$ and non-compliant one $b_Y(y^{hr}) \in [0, t_{bt})$. Finally, CT recommendation policies have been shown to improve corporate network security without decreasing insiders' satisfaction level.

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