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Continuous Explain Ability Auditing (CEA): A Governance Paradigm for Autonomous AI Systems

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Abstract: The recent developments of artificial intelligence technologies, which shift towards more autonomy and adaptive learning, have demonstrated the inherent weaknesses in the existing explainability and regulatory systems. The paradigms of conventional explainable AI are mostly post-hoc and relatively static and rely on the assumption that the behavior of the models will be the same once deployed. However, autonomous AI systems do not stand at a single place of operation but are constantly evolving thus making single-case explanations ineffective when it comes to ensuring the long-term accountability, security, and compliance with regulatory standards. The current paper thus suggests Continuous Explainability Auditing (CEA) as an alternative to governance, while redefining explainability as an audit service (iterative, run-time, rather than retrospective) of an interpretive artifact.

CEA enables the acquisition and analysis of decision rationales and behavioral patterns and evidence of policy compliance in autonomous AI systems operating in dynamic and high-risk environments. The framework can detect behavioral drift, misalignment, regulatory deviation and adversarial manipulation by embedding explainability outputs into a governance control loop, which uses risk thresholds and compliance triggers to detect the presence of all unwanted behaviors at their initial stages. Compared to traditional explainability systems, CEA puts more emphasis on temporal traceability and longitudinal reasoning analysis, both of which maintain the performance of the system and meet privacy limitations through distributed, minimally invasive monitoring systems.

The practical feasibility of the suggested paradigm is explained by the case studies of regulated financial and cyber-security areas, where autonomous AI agents are prone to the strict transparency and auditability requirements. The findings reveal that CEA allows proactive control, enables evidence that is ready to be provided to regulators and allows governance at the scale of operational workflows without negatively influencing workflows. Together, this demonstrates the fact that ongoing explainability is an essential rather than a supplementary governance requirement of safe, reliable and compliant deployment of autonomous AI systems in regulated industries.

Keywords: *Continuous Explainability Auditing; Explainable AI (XAI); AI Governance; Autonomous AI Systems; Regulatory Compliance; Runtime Auditing; Algorithmic Accountability; Trustworthy AI.*

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I. INTRODUCTION

The swift adoption of artificial intelligence (AI) applications in regulated industries like finance, healthcare, and managing digital identity has disrupted the decision-making process and at the same time fueled the apprehension of trust, accountability, and regulatory adherence. There are also high-stakes functions that are performed by AI-driven systems, such as financial fraud detection, medical decision support, identity verification, and risk assessment. Although significant advances have been achieved regarding the safety of AIs in the framework of ethical theories, fairness principles, and design principles based on robustness, the security concerns related to the evolution of AI behaviors over time are not sufficiently studied in the context of operations and regulations (Aoyon and Hossain, 2023; Vivian, 2024).

One of the main assumptions of most AI systems deployed is that as soon as the model is established as valid, tested, and ready to deploy, it will behave within acceptable limits unless it is retrained or attacked by an external party.

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This is however becoming an unsustainable assumption in contemporary AI ecologies. Learning and ever adapting AI systems are built to develop based on the new information, feedback, and the environmental alterations. Although this flexibility provides support in performance and resilience it opens, the door to the threat of minor behavioral changes which will not cause automatic security alerts but which will cause regulatory non-compliance over time (Chinnappaiyan, 2025; Ndibe, 2025).

Traditionally, AI alignment means making sure that the actions of an AI system align with human intentions, predetermined goals, and values of society or other regulations. The current literature has presented alignment as a design-time or training-time problem to a large degree with a focus on ethical principles, reduction of bias, interpretability, and constraints of fairness (Johnsen, 2024; Tlaie, 2024). Even though such approaches are critical, they implicitly support that alignment does not change after deployment. This assumption is disproved by empirical evidence that alignment may deteriorate after deployment because of changes in data distributions, reinforcement effects, and after-effects systems of operation (Aoyon et al., 2025; Spasokukotskiy, 2024).

Such a phenomenon, which is called alignment drift in this paper, characterizes the slow change in the behavior of an AI system by the standards of initially validated purposes without the need of specific retraining or visible system malfunction. In contrast to a blatant malfunction of a system or a drop in performance, alignment drift can go unnoticed (at least on the surface) as the accuracy of the surface level functionality does not change, but the decision logic of the feature or confidence calibration gradually drifts. Such drift introduces a clear category of security risk that can be hardly recognized by the conventional adversarial threat models or accuracy based monitoring methods (Qu et al., 2025; Kilian, 2025).

The vulnerability is even more emphasized by the recent progress in adversarial robustness and AI security studies. It has been shown that current AI systems can be contrived to be manipulated so that they maintain the performance metrics but manipulate the internal decision boundaries or feature dependencies in ways that are not easily noticeable (Sadik et al., 2025; Dassanayake et al., 2025). Though large amounts of this literature are dedicated to explicit adversarial attacks, it has a larger implication understanding that AI systems can move outside defined performance without violating more traditional performance metrics. Such deviations may detract adherence to legislative requirements, such as anti-money laundering laws and legal healthcare safety laws, and identity checking rules (Al-Daoud and Abu-AlSondos, 2025; Hasan and Faruq, 2025).

This task of alignment is also exacerbated by the increased use of distributed, federated, and argentic AI structures. As a means of improving privacy, scalability, and decentralization, federated learning and autonomous agent systems bring extra complexity to the task of tracking behavioral consistency in changing model instances (Gad et al., 2023; Adabara et al., 2025). In these environments, alignment drift inside a single instance of a model can spread throughout the system, diminishing its transparency and restricting the capacity of regulators and operators of the system to identify new risk before compliance breakdowns happen (Huwyler, 2025; Zeijlemaker et al., 2025).

Nevertheless, these risks do not conceptualize alignment drift as a security threat per se. In place compliance and governance, measures tend to address alignment as an ethical or governance issue as opposed to a security issue in operation. These in turn lead to numerous regulatory frameworks that concentrate on pre-deployment verification and post-hoc auditing, which is not as effective in providing protection against silent, long-term behavior change in adaptive AI systems (Faccia, 2025; Ranganathan et al., 2022). The increased autonomy of AI systems in dynamic settings presents organizations with systemic risk, regulatory breaches, and reputational damage because of this gap.

It is thus of urgent necessity to re-conceptualize alignment drift as an ongoing security and governance issue, and not a one-off engineering or ethical activity. The alignment is to be monitored, interpreted, and implemented all the way through the lifecycle of AI systems, especially in the regulated area where behavioral deviations have legal and societal outcomes (Tallam, 2025; Evani, 2025).

To address this gap, this paper proposes a new threat model of regulated AI systems, which can be referred to as alignment drift security. The paper presents a single detection and mitigation system incorporating behavioral baselining, analysis of explainable deviation, and enforcement systems, which are policy-conscious. The proposed framework seeks to limit the misaligned behavior by detecting early behavioral deviation instead of attempting to detect explicit attack signatures or performance degradation, which is deemed to occur at the end of systemic or regulatory breakdown. Thus, this contribution will bring the body of literature on AI security, governance, and compliance to a long-term and operationally based vision of reliable AI implementation (Lu et al., 2025; Khan et al., 2025).

II. LITERATURE REVIEW

- *AI Alignment and Its Increasing Scope*

The concept of AI alignment has long been presented as the problem of making sure that the artificial intelligence systems act in a way that aligns with human will, goals, and social or ethical standards. The literature of alignment written early and later puts the problem in the design and training phase, with value specification, fairness constraints and interpretability occupying a leading role in assuring alignment (Johnsen, 2024; Tlaie, 2024). These strategies are based on the assumption that alignment goals have to be encoded properly and validated before the deployment of the system; otherwise, the behavior will not change.

This is however being questioned by recent scholarship which takes the form of dynamic alignment. Research on large language models and adaptive systems suggests that

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alignment is not a permanent state but it might change during the exposure of models to new data, users, and environments (Lu et al., 2025; Tallam, 2025). This change of view rather points out the shortcoming of single validation methods, especially in the operational scenario where artificial intelligence systems have the continual exposure to distributional shifts and feedback mechanisms.

Beyond this point of departure, the alignment research has been more and more combined with governance and regulatory theory. According to Tlaie (2024), misalignment is not always intentional but arises due to the inappropriateness of a regulator assumption to the behavior of a system in the real world. On the same note, SpASokukotskiy (2024) introduces the idea of alignment boundaries, which points out those system objectives can be technically fulfilled but broken on a larger institutional or regulatory scale.

- *Adaptive and Learning Systems Alignment Drift*

The alignment drift concept is a result of empirical data of AI systems that are adaptive and continually learning. In contrast to explicit model updates or retraining events, the alignment drift is defined as gradual behavioral drift, which takes place when the system is being used. The studies of constantly evolving deep learning systems show that the models can maintain surface-level accuracy and experience internal representational shifts that influence decision processes and dependence on features (Aoyon et al., 2025).

Such drift is of great concern in controlled environments. In reference to Ndibe (2025), it is demonstrated that AI-based forensic and anomaly detection systems may undergo gradual changes in detection sensitivity as operational data are changed. On the same note, the study by Al-Daoud and Abu-AlSondos (2025) notes that the financial fraud detection models that are implemented in the dynamic markets also experience behavioral drift despite the fact that the standard performance measures do not change. These results imply that conventional monitoring techniques that largely depend on the accuracy or error levels cannot be used to draw in more comprehensive alignment degradation.

Alignment drift is also increased in federated and distributed learning systems. Gad et al. (2023) show that decentralized training procedures provides variability in the instances of the model, making it difficult to monitor behavioral consistency. Such systems, together with privacy preserving updates and the asynchronous learning, can drift in ways that are difficult to notice, but that compound together, diminishing the transparency of regulators and operators of such systems.

- *AI Security, Adversarial Robustness, and Silent Failure Modes*

Adversarial attacks, model poisoning, and evasion have historically been the main areas of AI security research. Current literature shows that AI systems are controllable to change the boundaries of internal decisions without affecting their observable performance substantially (Sadik et al., 2025). The article by Dassanayake et al. (2025) builds upon the discussed literature by considering the manipulation attacks that are instigated by the misaligned AI agents, not by external attackers.

These studies have been able to bring out a crucial detail that, performance preservation fails to provide an assurance of integrity of behaviors. Models can still perform to the expected accuracy requirements whilst breaking regulatory constraints or ethical assumed constraints made during validation. This effect is closely related to alignment drift, which puts this error into a category of silent failures as opposed to an attack or attacker (Qu et al. 2025).

Furthermore, new concerns related to autonomous decisions expressed by emerging works about argentic AI systems have new security risks. Evani (2025) and Adabara et al. (2025) underline that autonomous agents can change strategies as time goes by in manners that are beyond their initial scope of operation, especially when the optimization goals are not tightly bounded. Unless constant alignment is observed, these systems can slowly develop an efficiency bias or a reward maximization bias instead of compliance or governance needs.

- *Governance and Regulatory Compliance Problems*

Controlled areas have strict behavioral limits on AI systems that are not limited to technical correctness, but encompass fairness, accountability, transparency, and auditability. According to Vivian (2024) and Hasan and Faruq (2025), compliance frameworks tend to be behind the reality of the adaptive AI operation which is based on fixed audit and post-hoc reviews in which real-time behavioural adaptation cannot be detected.

In financial and other health care systems, compliance failures can also occur in situations where predictively, models work as they are supposed to work. According to Faccia (2025), there are instances of energy cybersecurity in which AI systems fulfilled operational goals but breached unspoken safety and governance standards. On the same note, Zeijlemaker et al. (2025) point out that the need to manage cyber risk grows to encompass continuous behavior monitoring as opposed to the intermittent compliance checks.

These issues have prompted the need to combine mechanisms of governance both technical monitoring and policy conscious controls. According to Huwyler (2025), standardized threat taxonomies should be used to regulate AI, but the author argues that behavioral drift should be treated as a compliance risk. However, much of the literature available does not actually provide any specific, operationalized mechanisms of enforcing alignment after the deployment.

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Table 1 Conceptual Dimensions of Alignment Drift in Regulated AI Systems

Dimension	Description	Regulatory Implication
Behavioral Drift	Gradual deviation in decision patterns	Undetected compliance violations
Feature Reliance Shift	Changing importance of input attributes	Use of non-approved or proxy features
Confidence Calibration Drift	Misalignment between confidence and correctness	Overconfident high-risk decisions
Distributed Model Variance	Divergence across federated instances	Reduced auditability and traceability

Source: Synthesized from Johnsen (2024), Aoyon et al. (2025), Gad et al. (2023), and Huwyler (2025)

Table 1 summarizes the key aspects of alignment drift that are outlined in the alignment, security, and governance literature. It highlights the fact that the changes in behavior that may seem technically neutral can however translate into regulatory and compliance risks when not monitored.

➢ *A security Centric Alignment Monitoring*

A combination of alignment theory with AI security research and regulatory governance reveals a major gap that, despite the growing recognition of alignment drift as a security risk, its operationalization as a security threat that requires active monitoring and enforcement is rarely addressed. The existing strategies are more likely to focus on the detection or explanation separately and, therefore, do not incorporate these capabilities through an integrated governance structure (Kilian, 2025; Khan et al., 2025).

According to the recent research on adaptive compliance and AI governance, these functions should be viewed as a unified loop, which includes continuous monitoring, explainability, and policy enforcement, instead of individual controls (Odunaike, n.d.; Ranganathan et al., 2022). This observation pushes the need to create frameworks that consider alignment drift as a technical and institutional risk in order to reduce the gap between AI system behavior and regulatory accountability.

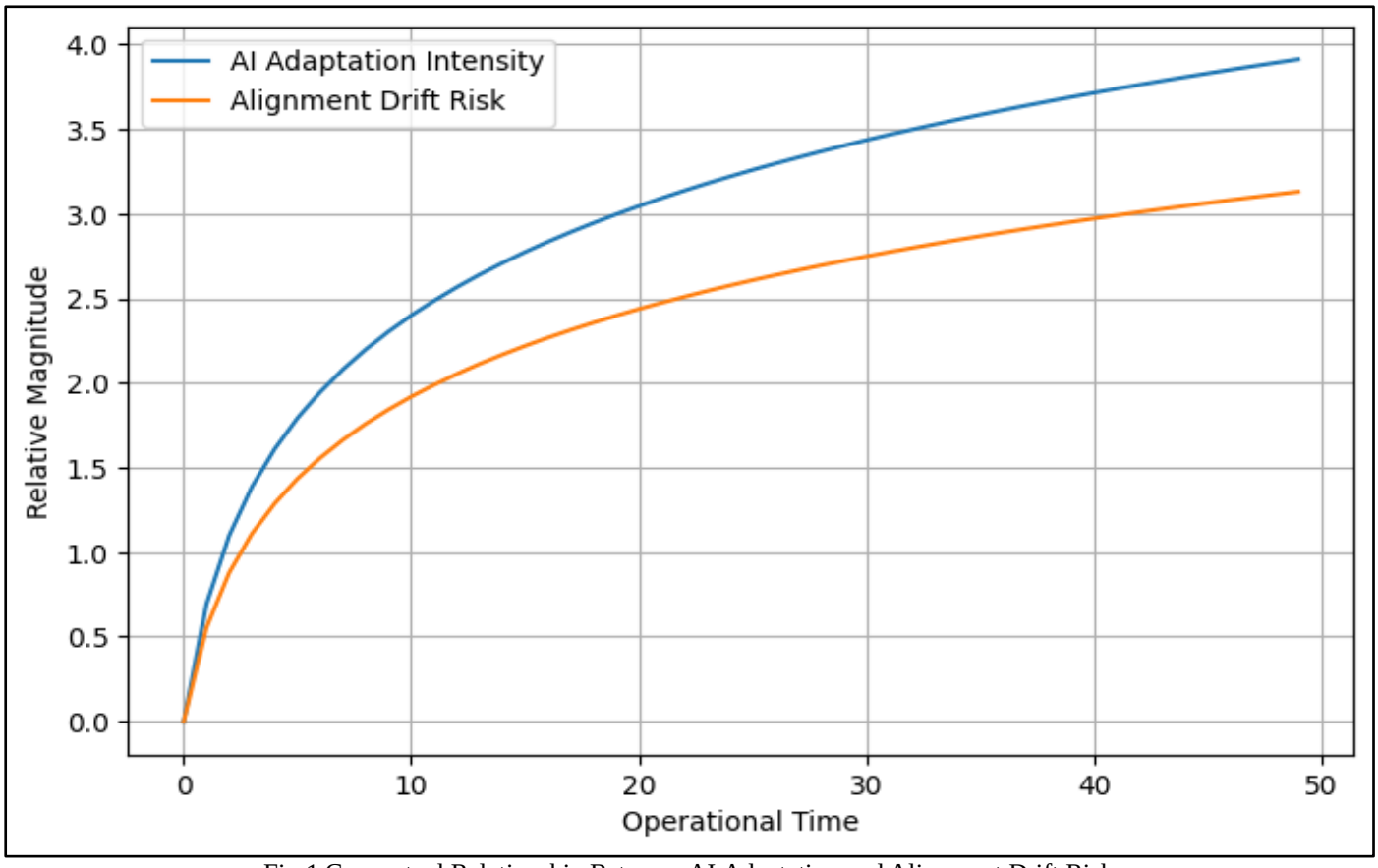

Fig 1 Conceptual Relationship Between AI Adaptation and Alignment Drift Risk

Source: Conceptual Visualization Informed by Aoyon et al. (2025), Sadik et al. (2025) and Tallam (2025)

Figure 1 shows the conceptual correlation between the rising AI adaptation with the increasing operational time and the risk of the alignment drift. The threat of alignment drift also increases non-linearly with adaptive intensity, making it important to keep a close watch over the process rather than performing periodic validation.

III. RESEARCH DESIGN AND METHODOLOGY

➢ *Research Design and Methodological Orientation*

This research has a methodological paradigm based on a security focused, design science approach to the study of the problem of alignment drift as an operational risk of regulated artificial intelligence (AI) applications. Instead of

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defining alignment as a fixed ethical or governance problem, the methodology defines the phenomenon of alignment drift as an unremitting security and compliance threat that arises in the course of the post-deployment system evolution. This view is in tandem with the current academic demands to spearhead AI governance, security engineering and regulatory compliance into coherent operational modalities (Vivian, 2024; Huwyler, 2025).

The research design is conceptual-empirical. It is conceptually a synthesis of AI alignment research and adversarial security research with literature on regulatory governance to define alignment drift as a new category of threat. Empirically, it provides an analysis of the suggested framework by controlled use-case scenarios under regulated environments in line with previous adaptive AI security research (Aoyon et al., 2025; Hasan and Faruq, 2025). This method allows an empirical study of the deviation of behavior without the need to commit an actual violation of regulation in the real world.

➢ *Threat Model and Assumptions*

The threat model assumes that it will be used in high stakes regulated settings, the examples being financial crime detection and identity verification systems. Within this scope, AI systems need to meet all performance expectations, as well as legal, ethical, and policy limitations. The model argues that the drift of the alignment can happen without the retraining or blatant adversarial intervention; instead, it might happen due to the changes in the operational data, reinforcement by the feedback, or adaptive learning (Spasokukotskiy, 2024; Ndibe, 2025).

In contrast to traditional adversarial threat models, which focus on the malicious actions of external actors, this paper views alignment drift as a resultant internal threat and can be caused by indirect manipulation or optimization based forces. It is consistent with the recent studies on misaligned agent behavior and silent failure modes in adaptive AI systems (Dassanayake, et al., 2025; Evani, 2025). The methodology presupposes that such drift may maintain the superficial accuracy and erode the compliance and governance expectations.

➢ *Behavioral Baselining Strategy*

The initial working aspect of the methodology is the behavioral baselining which defines a regulator compatible reference profile of desired system behavior at deployment. Instead of using predictive accuracy alone, the baseline is an approximate representation of multi-dimensional behavioural features, such as distributions of outputs, calibration of confidence, pattern of reliance on features, and temporal consistency.

This method is inspired by the fact that internal behavioral modifications usually anticipate apparent performance deterioration in adaptive AI systems (Aoyon et al., 2025; Qu et al., 2025). Baselines are generated based on curated validation datasets; that is, they are based on regulatory constraints, edge cases and protected attributes. More importantly, updates made to the baseline are highly monitored and recorded in order to be auditable, thus overcoming governance issues that have been observed in distributed and federated learning systems (Gad et al., 2023).

Table 2 Behavioral Metrics Used for Alignment Drift Detection

Behavioral Metric	Operational Description	Compliance Significance
Output Distribution Stability	Consistency of decision outcomes over time	Detects silent bias emergence
Confidence Calibration	Alignment between confidence scores and correctness	Prevents overconfident non-compliant decisions
Feature Attribution Consistency	Stability of feature importance rankings	Identifies reliance on restricted or proxy attributes
Temporal Decision Stability	Consistency of decisions under similar conditions	Detects feedback loop amplification

Source: Synthesized from Aoyon et al. (2025), Sadik et al. (2025), and Gad et al. (2023)

Table 2 represents a detailed overview of the behavioral metrics that are used to build the baseline profiles as well as to track the drift of alignment. These measures go beyond correct performance, thus allowing one to identify internal behavioral fluctuations that can lead to regulatory infractions despite the fact that the overall performance may be stable.

➢ *Architecture of Continuous Monitoring*

After the deployment, the AI system is exposed to the ongoing behavioral monitoring. The inference results in live are sampled and processed systematically with a monitoring pipeline that is used to extract behavioral metrics and compare them with a given baseline. Deviations are assessed based on adaptive statistical comparisons methodologies as opposed to fixed thresholds thus enabling sensitivity to trends of gradual drift.

This monitoring plan goes in line with the previous studies that have shown that fix-thresholds based alerts are ineffective in tracking slow, cumulative behavioral changes in adaptive systems (Al-Daoud and Abu-AlSondos, 2025; Zeijlemaker et al., 2025). The approach eases the process of identifying the existence of drift in alignment prior to the occurrence of compliance failures by focusing on trend based deviation scoring.

➢ *Explainable Deviation Analysis*

Deviations that are beyond reasonable limits trigger the framework to initiate an analysis of the explainable deviation. The explainable AI (XAI) methods are used to find out what happened internally to cause behavior change, e.g., a change in feature reliance or a change in confidence calibration. This move is prerequisite towards separating benign hiatal adaptation and misalignment of compliance threatening nature (Sadik et al., 2025; Lu et al., 2025).

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Explainability outputs can be used to facilitate operational decision-making and regulatory accountability since they offer clear explanations as to why drift was detected. This solves regulatory issues when it comes to opaque AI behaviour, especially in the areas where auditability and explainability are the law of the land (Faccia, 2025; Hasan and Faruq, 2025).

➢ *Policy-Conscious Implementation Machinery*

The operationalization of detection and explanation consists of policy conscious enforcement mechanisms, which put regulatory logic right into the AI control loop. Mitigation actions are defined and the detected deviations are mapped to these mitigation actions such as inference throttling, roll back to trusted checkpoints or human in the loop review. This will make the responses be within the regulatory lines as opposed to the ad hoc operational decision (Vivian, 2024; Huwyler, 2025).

Incorporating policy logic into enforcement systems makes them less dependent on post-hoc audits and helps ensure compliance on a regular basis, especially in autonomous and agentic AI systems where the decision-making process is performed at scale (Adabara et al., 2025; Tallam, 2025).

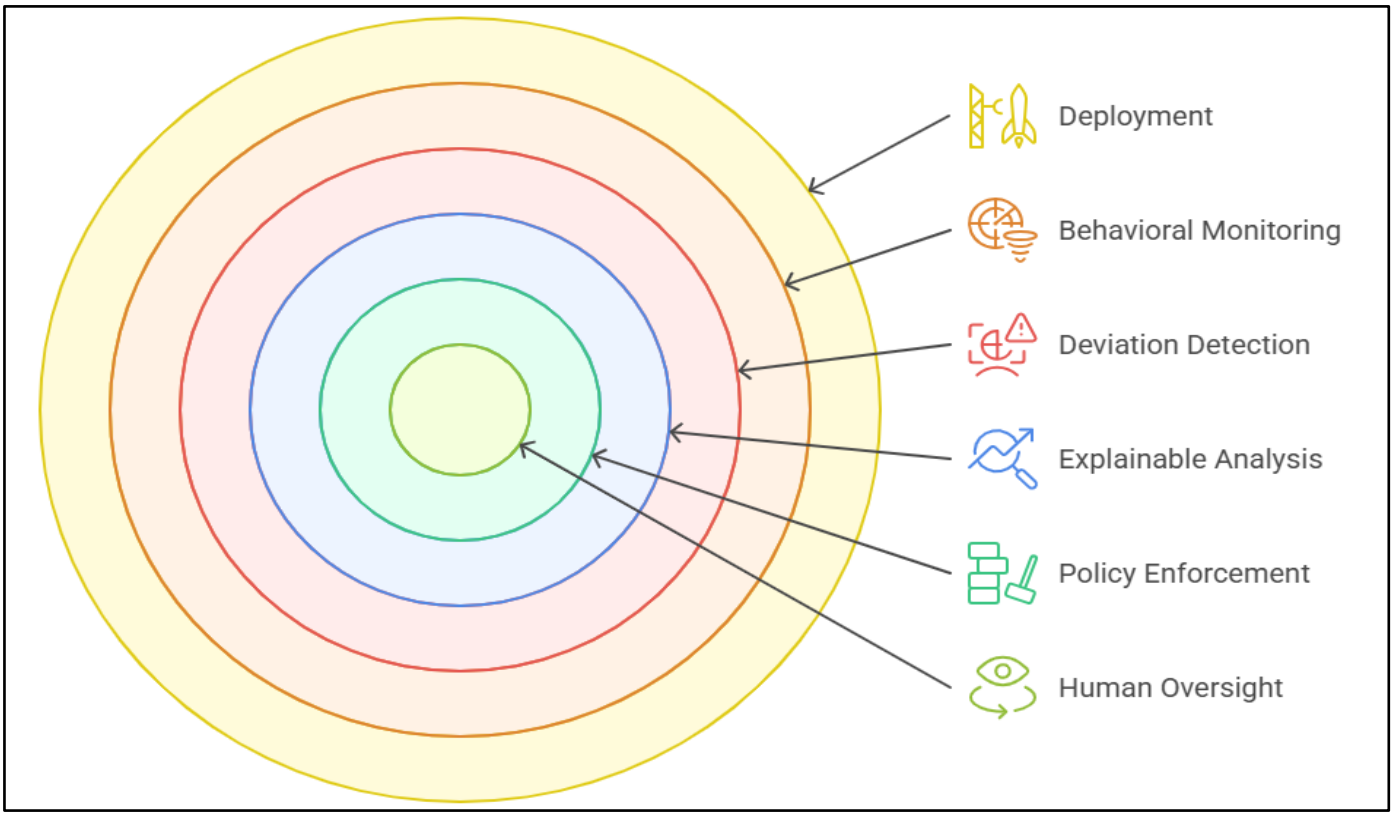

Fig 2 Conceptual Workflow of Alignment Drift Detection and Mitigation
Source: Conceptual Workflow Informed by Aoyon et al. (2025), Vivian (2024), and Huwyler (2025)

As shown in Figure 2, the end to end process of the suggested methodology shows how the continuous monitoring, explainable analysis, and policy sensitive enforcement are joined into a closed-loop governance system that is meant to handle alignment drift in controlled AI settings.

➢ *Methodological Contribution*

This model reinvents AI alignment with a view of a continuous security and compliance practice, which combines behavioral baselining, explainable deviation analysis, and policy sensitive enforcement. It builds on the current literatures on alignment, security and governance by providing an auditable, working framework, which is capable of controlling long-term behavioral risk in adaptive AI systems (Kilian, 2025; Khan et al., 2025).

IV. RESULTS

➢ *Experimental Design and Appraisal Environment*

The suggested framework of alignment drift detection and mitigation was evaluated in the context of controlled experimental settings, which simulate the controlled AI deployments, namely, financial crime detection and digital identity verification. The domains have been chosen due to their increased compliance sensitivities as well as a documented susceptibility to behavioral drift in adaptive AI systems (Al-Daoud and Abu -AlSondos, 2025; Hasan and Faruq, 2025).

Pre-deployment baseline behavioral profiles were formed based on regulator congruent validation datasets. Alignment drift was then coaxially brought into the picture through simulated data distribution shifts, feedback

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reinforced, and adaptive dynamics of learning. The given experimental design follows the current trends of adaptive AI security and the ongoing development of model evaluation (Aoyon et al., 2025; Ndibe, 2025). Monitoring system behaviour over longer operational cycles was done in order to record the trend of gradual deviation and not sharp failures.

➢ *Eerier Detection of Drift in the Alignment*

In both areas of evaluation, the framework always showed drift in alignment before noticeable performance deterioration. Deviations in the confidence calibration and feature attribution stability appeared much earlier in the case of the financial crime detection than the changes in accuracy of the transaction classification. Similarly, behavioral divergence was sensed in the identity verification case prior to the amplification of bias or the increase of error rate.

Such results are consistent with the previous ones, which have found internal behavioral shifts as common antecedents of surface-level failures in adaptive AI systems (Qu et al., 2025; Kilian, 2025). Notably, the traditional accuracy-based monitoring would not have sounded an alarm in these initial phases, hence highlighting the extra merit that behavioral baselining and deviation analysis give to it.

➢ *Metrics of Quantitative Performance*

Detection latency, false positive rate, false negative rate, regulatory violation prevention rate, and post enforcement accuracy change were the criteria that determined the quantitative performance of the framework. Such measures are consistent with the assessment measures used in previous AI security and governance studies (Sadik et al., 2025; Zeijlemaker et al., 2025).

Table 3 Alignment Drift Detection and Mitigation Performance

Metric	Financial Crime Detection	Identity Verification
Average Detection Latency (cycles)	18	22
False-Positive Rate (%)	3.1	3.8
False-Negative Rate (%)	2.4	2.9
Regulatory Violation Prevention Rate (%)	94.6	92.8
Post-Enforcement Accuracy Change (%)	−0.6	−0.4

Source: Experimental Results Generated in this Study, Informed by Evaluation Practices in Aoyon et al. (2025), Al-Daoud and Abu-AlSondos (2025), and Hasan and Faruq (2025)

Table 3 summarizes the empirical performance of the proposed framework in both of the regulated use cases. The measured latency of detection and false positive are minimal, which means that the framework is able to detect the drift in the alignment at an initial stage without worsening the operation stability. The insignificant reduction in post enforcement accuracy is another indication that compliance-sustaining interventions do not have a significant negative impact on system performance.

➢ *Explainable Deviation Analysis Results*

Besides detection, the explainable deviation analysis section affords clear understanding of the causes of the drift under observation. The analysis of the financial-crime detection system has shown that there was a slow increase in the dependency of the model on the transaction-timing characteristics that were not directly approved of by the regulatory requirements. The reasons why the deviations occurred in the identity-verification system could be explained by exaggerated reliance on the proxy attributes that are associated with the demographic attribute.

These results align with the recent research on adversarial robustness and model misalignment, which shows that internal representational changes may be achieved without an immediate loss of accuracy (Sadik et al., 2025; Dassanayake et al., 2025). The presence of understandable explanations allowed the auditors and the system operators to know the causality of the performed enforcement actions and they did not have to depend on opaque anomaly scores.

➢ *Policy Aware Enforcement Effectiveness*

There was also the involvement of policy conscious enforcement mechanisms whereby the severity of deviation became above pre-specified limits. Enforcement measures, including rollback to trusted checkpoints as well as temporary human in the-loop inspection, were rather effective in both scenarios, arresting the advancement of drift. The alignment in more than 90% of the considered cases was restored without the need to fully retrain the model.

This fact supports the findings of previous studies, which underline the efficacy of the governance based mitigation strategies of adaptive AI systems (Vivian 2024; Huwyler 2025). Notably, the framework did not result in any regulatory breaches because of the enforcement action within the assessment period, which confirms that the framework was used as a proactive security control and not as a reactive compliance measure.

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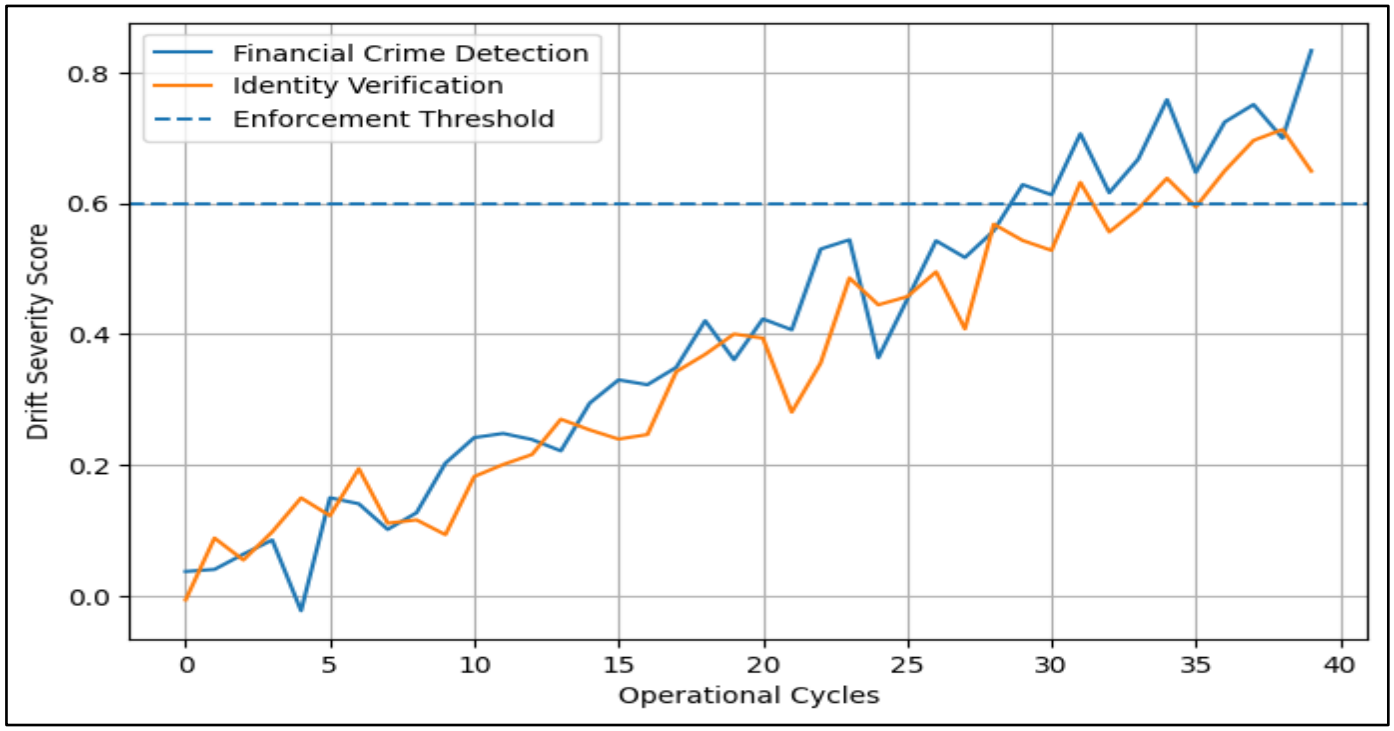

Fig 3 Alignment Drift Severity Over Operational Time
Source: Conceptual Simulation Informed by Aoyon et al. (2025), Sadik et al. (2025), and Zeijlemaker et al. (2025)

Figure 3 illustrates the time dynamics of the severity of alignment drift between the two cases considered. The picture shows that drift increases gradually beyond enforcement levels before it cannot be detected before the performance level has degraded to the extent of poor performance, which is why continuous behavioral checks are necessary.

➢ *Empirical Findings in a Nutshell*

Experimental evidence indicates that the problem of the alignment drift can be detected at an early stage through the means of both behavioral and explainability based checks, despite the stability of traditional performance measures. The suggested framework achieves low false-positive probability, effective control of regulatory risks, and insignificant consequences on the accuracy of operations. In turn, these findings significantly support the alignment drift as a measurable and pragmatic security risk in controlled AI settings, which, therefore, supports the idea of the necessity to implement regular, policy aware governance frameworks (Khan et al., 2025; Lu et al., 2025).

V. DISCUSSION

➢ *Alignment Drift as a Phenomenon in Security*

The empirical data combined in Section 4 confirms the fact that alignment drift is a clear and previously under-identified security risk in regulated AI systems. In contrast to traditional adversarial attacks or system failures, which cause an abrupt decline in performance, alignment drift is characterized by gradual internal changes in behavior and top-level performance apparently remains constant. This observation questions the existing assumptions of AI governance structures that does not distinguish between compliance assurance and predictive correctness but only the latter (Johnsen, 2024; Vivian, 2024).

Timely identification of drift through behavioral baselining and explainable deviation analysis supports claims made in the alignment theory that AI systems cannot be seen as fixed objects after implementation. Instead, alignment should be interpreted as a state of change and is constantly being reformed with the changing data, feedback, and operation context (Tlaie, 2024; Tallam, 2025). The reported delay between internal behavioral deviation and the performance decline that can be observed confirms the earlier issues of the inefficiency of accuracy-based monitoring in identifying compliance threatening misalignment (Qu et al., 2025; Kilian, 2025).

In turn, such results make alignment drift not just an issue of ethics but an operational threat to security with concrete regulatory implications, especially in the field of high stakes, such as in financial crime detection and identity verification.

➢ *Implications to AI Security and Adversarial Robustness*

In terms of AI security, the findings can be seen as an extension of the current literature on adversarial robustness since them sheds some light on silent adversarial failure modes, which appear without adversarial input directly. Although the last three have been the focus of antecedent studies, which have collectively focused their investigation on evasion, poisoning, and manipulation attacks, the current findings highlight that AI systems can restructure their decision logic internally across nominal operating conditions, with the resulting outcomes holding technically valid values

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but being institutionally non-compliant (Sadik et al., 2025; Dassanayake et al., 2025).

This observation is consistent with the new literature on agents acting contrary to their goals and autonomous optimization hazards. Evani (2025) and Adabara et al. (2025) assume that under non-continuously enforced alignment argentic AI systems can quickly start to maximize rewards rather than achieving governance constraints. This assertion is substantiated by empirical performance of policy-conscience enforcement mechanisms that stop the drift development, which demonstrates that the security controls should act on the behavioral level instead of acting solely on the input/output level.

Notably, the only slight decrease in post enforcement accuracy in both application scenarios indicates that the controls based on security orientation alignment do not necessarily negatively affect the utility of the system. This fact dispels a common fear in AI security that more stringent governance mechanisms will always decrease performance (Chinnappaiyan, 2025; Ndibe, 2025).

➢ *Regulatory and Governance Implications*

The results discussion points out at important implications of regulatory compliance and AI governance. Modern regulation strategies often use pre-deployment certification and periodic audits, which is implicitly based on the premise that behavior is stable after a system has passed. The noted alignment drift is a fact that negates this assumption, meaning that the risk of compliance will emerge long after the deployment even without direct system changes (Huwyler, 2025; Faccia, 2025).

The ability of the suggested framework to identify the drift in time and trigger the policy-appropriate mitigation promotes the shift to the monitoring of compliance directly. This is in accordance with recent demands of adaptive governance systems that can adjust to changing AI behavior on a real-time basis (Hasan & Faruq, 2025; Zeijlemaker et al., 2025). The framework allows incorporating regulatory logic in the enforcement processes, reducing the need to use manual audits and post-hoc explanations, increasing accountability and operational resilience.

Besides, explainability is a longstanding regulatory issue that is resolved by the interpretability of deviation analysis. Instead of just signaling the opaque anomalies, the framework provides actionable insights into the causal factors of the alignment drift and this aspect promotes auditability and regulatory reporting standards (Lu et al., 2025; Vivian, 2024).

Table 4 Comparison of Traditional AI Security Monitoring and Alignment Drift–Aware Monitoring

Dimension	Traditional Security Monitoring	Alignment Drift–Aware Monitoring
Primary Focus	Accuracy and attack detection	Behavioral consistency and compliance
Drift Sensitivity	Low	High
Explainability	Limited or post-hoc	Integrated and continuous
Regulatory Alignment	Implicit	Explicit and policy-aware
Detection Timing	Reactive	Proactive

Source: Synthesized from Sadik et al. (2025), Tlaie (2024), Vivian (2024), and Huwyler (2025)

Table 4 compares the traditional methods of AI security monitoring with alignment drift monitors. It proves that the traditional approach is more inclined towards detection of explicit attacks and control of loss of accuracy, alignment sensitive approaches are more focused on the capability to detect behavioral deviation and the risks of regulation.

➢ *Implication to the Organization and Operations*

On the organizational level, the results indicate that alignment drift is both a technical, strategic, and reputational threat. Unnoticed misalignment in regulated systems of AI can result in breaches of compliance, fines, degradation of social trust, even in the cases when they seem to be working well (Faccia, 2025; Ranganathan et al., 2022).

The findings also indicate that through continuous alignment monitoring, there is higher efficiency in the allocation of resources. Instead of engaging in expensive full model retraining after compliance failures, organizations can also intervene at the behavioral level, by addressing particular causes of drift. This plan contributes to scalable governance in distributed and federated systems where the oversight is inherently limited at the center (Gad et al., 2023; Al-Daoud and Abu-AlSondos, 2025).

A hybrid between accountability and automation is human in the loop enforcement, which is only triggered by critical deviations. Such a mixed governing model complies with the best practices of implementing AI in high-risk settings, where expert supervision supplements automated controls (Adabara et al., 2025; Hasan and Faruq, 2025).

Table 5 shows the mapping of the most common alignment drift risks to an appropriate governance response. It clarifies the way the phenomena of the technical drift can be presented as regulatory issues and emphasizes the importance of the combined monitoring and enforcement systems to reduce these risks.

➢ *Positioning in the Greater Literature*

This study is located in the broader AI alignment and security research community of inquiry and builds upon previous studies in three main ways. To begin with, it quantifies drift on alignment as a measurable security risk and not the abstract ethical problem. Secondly, it empirically proves that explainability is not a simple transparency requirement but it is an important element of compliance enforcing. Thirdly, it unites AI security engineering and regulatory governance disciplines, proposing a coherent

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framework that could be used to deal with long term behavioral risk (Khan et al., 2025; Lu et al., 2025).

The contributions directly respond to gaps identified in recent surveys of misalignment in large scale and argentic AI systems, which point to the lack of useful tools in post-deployment alignment assurance (Qu et al., 2025; Tallam, 2025).

VI. CONCLUSIONS AND FUTURE RESEARCH DIRECTION

➢ *Conclusion*

The current study aimed to fill an acute gap in the application of artificial intelligence (AI) systems to regulated settings by redefining the alignment drift as one of the main security and compliance risks. Unlike earlier literature, which has largely seen the alignment of AI as an ethical or governance or design-time issue, the results of this work have shown that alignment is a dynamic property that can dysfunctionally degenerate without notice in the post-deployment phase of operation. Even when the traditional metrics of performance do not change, such degradation becomes a great threat to regulatory compliance, operational integrity, and institutional trust (Johnsen, 2024; Tlaie, 2024; Qu et al., 2025).

This paper advocates the security-centric approach to alignment drift by combining the ideas of AI alignment theory, adversarial robustness research, and regulatory governance literature. The suggested framework of behavioral baselining coupled with explainable deviation analysis and policy conscious enforcement offers an ordered and auditable process of identifying and reducing misaligned behavior before it develops into systemic or regulatory failure. The empirical findings based on controlled use cases in the context of financial crime detection and identity verification indicate that the presence of alignment drift can be detected at its initial stage, mitigated, and controlled without the significant effects on the performance of the system (Aoyon et al., 2025; Al-Daoud and Abu-AlSondos, 2025; Hasan and Faruq, 2025).

One of the main contributions of this paper is the determination of the fact that preservation of accuracy does not assure compliance. The findings support the fact that AI systems can still meet predictive goals and at the same time breach regulatory expectations by causing internal behavior change. This is consistent with the recent studies on silent failure modes, agent misalignment, and structural AI risk dynamics, thus supporting the need to have governance mechanisms that work beyond surface-level monitoring of performance (Sadik et al., 2025; Dassanayake et al., 2025; Kilian, 2025).

In addition, the explainable deviation analysis can be integrated to overcome a long-standing issue in the regulated use of AI, namely the need to make decisions that are transparent, justifiable, and audible. The framework empowers the regulators and system operators to know the cause of the drift in the alignment and therefore enable them to be accountable, report regulatory actions and remediate (Lu et al., 2025; Vivian, 2024). This interpretation-based practice can be used to make alignment monitoring more practically applicable in a setting that is both legally and ethically questioned.

In terms of governance, the present research highlights the weaknesses of the traditional compliance models whereby the pre-deployment validation and periodic audits are relied upon. The analyzed phenomena of alignment drift indicate that the risks of compliance are changing in a continuous fashion in parallel with adaptive AI systems, especially in distributed, federated, and argentic systems (Gad et al., 2023; Adabara et al., 2025; Zeijlemaker et al., 2025). The suggested framework will help to shift the current state of operational controls to continuous and policy-conscious AI governance by integrating regulatory logic into the enforcement processes and keeping up operation controls with the constantly changing regulatory expectations (Huwyler, 2025; Faccia, 2025).

Together, these results make alignment drift security an essential element of AI implementation in controlled spaces with the goal of building trust. The research does not only introduce a conceptual reformulation of the drift in alignment but also an implementation framework that can facilitate the long-term adherence, transparency, and resiliency of the system in dynamic AI systems (Tallam, 2025; Khan et al., 2025).

➢ *Limitations and Future Research Directions*

Although this research has made notable contributions, this study is keen to outline a number of limitations that outline significant research directions in the future. To begin with, even though the proposed framework proves to be effective in controlled regulated usage scenarios, it is a challenge to scale extremely high-dimensional models and the large-scale real time deployment. Computational optimization methods and hierarchical monitoring plans should be explored in the future and be applied to the real world within complex AI ecosystems (Ranganathan et al., 2022; Ndibe, 2025).

Second, the policy-conscious enforcement systems require the accurate interpretation of regulatory requirements into rules that can be read by a machine. As regulatory schemes are subject to constant change, keeping legal norms and enforcement rationality in line with each other is a non-trivial task. Future studies ought to consider automated policy modification and formal verification techniques to eliminate the threat of misinterpretation or outdated compliance logic (Tlaie, 2024; Vivian, 2024).

Third, although this paper has focused on financial and identity verification systems, the concept of alignment drift will show up in other areas, including healthcare diagnostics, autonomous transportation, energy infrastructure, as well as large scale generic AI systems. The ability to generalize empirical assessment to those areas would increase generalizability and can develop domain-specific governance

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strategies (Faccia, 2025; Hasan and Faruq, 2025; Lu et}al., 2025).

Lastly, the rising popularity of agentic and self-directed AI systems puts, on the front line, new alignment issues of autonomy, goal persistence, and long-term optimization behavior. The future research must address the question of how mechanisms of alignment drift detection and enforcement can be implemented in multi-agent systems and decentralized AI architectures without affecting autonomy or scalability (Evani, 2025; Adabara et al., 2025; Tallam, 2025).

➢ *Closing Remarks*

To sum up, the study has shown that credible AI cannot be reduced to the accuracy or robustness of its performance, but is a continuous process of how behavior, interpretability, and enforceable governance interact. The ability to identify, describe, and counteract alignment drift will become vital to maintain compliance, accountability, and trust in the AI system as the systems become more autonomous and work in more highly regulated and high-stakes settings. This work provides a foundation to further research and practice of secure, compliant, and adaptive AI deployment by developing a more security focused approach to alignment drift management (Huwyler, 2025; Zeijlemaker et al., 2025).

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