Interpretable Safety Routing for Foundation Models in Commercial Recommendation Pipelines Using Path-Level Causal Intervention

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Abstract

The integration of large foundation models into commercial recommendation pipelines introduces novel safety challenges that extend beyond traditional content moderation. These models, trained on vast and heterogeneous corpora, can inadvertently generate harmful, biased, or policy-violating outputs when deployed in high-stakes recommendation contexts. Existing safety mechanisms, such as output filtering and prompt engineering, provide limited visibility into the causal pathways through which unsafe content emerges. This paper proposes an interpretable safety routing framework that leverages path-level causal intervention to identify and redirect unsafe information flows at intermediate stages of the recommendation pipeline. We conceptualize the pipeline as a directed graph of processing stages, where each edge represents a transmission of learned representations. By applying targeted interventions on selected paths and observing downstream effects, the framework enables system operators to diagnose the root causes of unsafe outputs and reroute representations through safer pathways without retraining the entire model. We examine the architectural trade-offs between intervention granularity, computational overhead, and interpretability, and discuss deployment considerations in multi-tenant, microservice-based infrastructures. The implications for governance, fairness, and policy compliance are analyzed through the lens of emerging regulatory frameworks and industry standards. This work contributes a system-level perspective on safety for foundation model-based recommender systems, emphasizing the importance of causal reasoning and interpretability in building trustworthy commercial AI pipelines.

Keywords

foundation models, recommendation systems, safety routing, causal intervention, interpretability, path-level analysis, content governance, microservice architecture, trustworthiness, regulatory compliance.

1. Introduction

Commercial recommendation pipelines have undergone a paradigm shift with the introduction of large foundation models capable of processing heterogeneous inputs and generating contextualized outputs. These models, often based on transformer architectures and pretrained on internet-scale data, are now embedded in platforms ranging from e-commerce and social media to streaming services and digital advertising. The ability of these models to capture nuanced user preferences and produce personalized recommendations has driven substantial business value, but it has also exposed platforms to risks that are qualitatively different from those associated with earlier rule-based or shallow learning systems. Foundation models can exhibit emergent behaviors, such as generating toxic language, reinforcing stereotypes, or surfacing inappropriate content, that are difficult to anticipate through conventional testing and monitoring [1, 2].

Traditional safety mechanisms in recommendation systems have relied on post-hoc output filtering, where generated recommendations are screened against blacklists or classifier-based moderation systems. While effective against known categories of harmful content, these approaches suffer from several limitations. They provide no insight into why a particular unsafe output was produced, making it difficult to diagnose systemic issues in the underlying model. They also tend to be brittle in the face of adversarial inputs or distribution shift, and they impose a performance penalty by requiring additional processing at the inference stage [3, 4]. More fundamentally, output filtering treats the symptom rather than the cause, leaving the internal pathways of the model opaque to operators who must ensure compliance with increasingly stringent content governance policies.

The need for interpretable safety mechanisms has become more urgent as regulatory bodies around the world introduce frameworks that require explainability and accountability in algorithmic decision-making. The European Union's AI Act, for instance, mandates that high-risk AI systems provide meaningful explanations of their outputs and that operators maintain the ability to trace back harmful decisions to specific model components [5]. Similarly, emerging standards for content credentials and provenance, such as those advocated by the Coalition for Content Provenance and Authenticity (C2PA), require that digital content be accompanied by verifiable records of its creation and modification [16]. These regulatory trends demand that safety interventions be not only effective but also transparent and auditable.

In this paper, we propose a safety routing framework for foundation model-based recommendation pipelines that uses path-level causal intervention to achieve both safety and interpretability. The core idea is to model the recommendation pipeline as a directed graph of processing stages, where each stage transforms intermediate representations. By selectively intervening on edges or vertices in this graph and observing the causal effects on final outputs, system operators can identify the specific pathways through which unsafe content propagates. Once these pathways are identified, the framework can reroute the information flow through alternative, safer paths that bypass problematic representations. This approach draws on recent advances in causal representation learning and intervention-based interpretability, particularly the concept of path-level interventions that operate on learned representations rather than raw inputs [7, 8].

The proposed framework is designed to be compatible with the modular, microservice-oriented architectures that dominate modern commercial recommendation infrastructure. In such deployments, different stages of the pipeline—such as feature extraction, candidate generation, ranking, and personalization—are often implemented as independent services that communicate via well-defined APIs. This modularity naturally lends itself to path-level intervention, because each service can be instrumented to expose its internal representations and allow controlled modifications. The framework also supports multi-tenancy, where different clients or use cases require different safety policies, by maintaining separate intervention configurations per tenant [9].

Throughout this paper, we emphasize system-level considerations over mathematical derivations. We discuss the architectural trade-offs involved in choosing the granularity of intervention, the computational overhead of maintaining causal graph models, and the interpretability benefits that accrue from explicit path tracing. We also examine the implications of this approach for fairness, content governance, and regulatory compliance, drawing on case studies from existing deployment contexts. The goal is to provide a comprehensive foundation for researchers and practitioners who seek to build safer, more transparent AI systems without sacrificing the performance and flexibility that make foundation models so valuable in commercial settings.

2. Background and Related Work

The challenge of ensuring safety in AI systems has been addressed from multiple angles in the literature, spanning adversarial robustness, bias mitigation, content moderation, and alignment. In the context of large language models and multimodal foundation models, a growing body of work has focused on red-teaming, prompt injection, and jailbreaking attacks that exploit the generative capabilities of these models to produce harmful outputs [1, 10]. Defenses against such attacks have included input sanitization, adversarial training, and reinforcement learning from human feedback (RLHF) [11]. However, RLHF and similar alignment techniques require substantial human annotation effort and do not provide fine-grained control over specific output behaviors after deployment.

Interpretability research has produced methods such as attention visualization, saliency maps, and probing classifiers that aim to explain model predictions by highlighting influential features or internal activations [12]. While these methods offer some insight, they are often limited to local explanations and do not capture the causal mechanisms by which different processing stages contribute to final outcomes. Causal approaches to interpretability, such as causal abstraction and intervention-based analyses, have been gaining traction as they promise to reveal the structural relationships that govern model behavior [7, 13]. Path-level interventions extend these ideas by operating on subgraphs of the model's computation graph, enabling targeted manipulation of information flows.

In the domain of recommendation systems, safety has traditionally been studied under the umbrella of fairness, diversity, and robustness. Researchers have developed algorithms to mitigate popularity bias, exposure bias, and filter bubbles [14]. These methods often operate at the level of training data or loss functions, and they are typically evaluated offline using simulated user behavior. However, the deployment of foundation models introduces new failure modes that are not captured by these static approaches. For example, a language model-based recommender might generate a product description that subtly promotes unsafe categories, or a visual recommendation system might surface images that violate community

guidelines due to the model's learned associations. Such failures require dynamic intervention mechanisms that can adapt to evolving content policies.

The concept of safety routing in computational systems has precedents in network routing and traffic management, where packets or flows are directed along paths that avoid congestion or security threats. Analogously, in recommendation pipelines, unsafe representations can be thought of as "traffic" that should be rerouted away from downstream components that would amplify or act on them. This perspective aligns with recent work on reliable and trustworthy AI infrastructure, such as the development of trusted AI commercialization platforms that integrate incentive systems and content governance for small and medium businesses [15]. Similarly, compliance-by-design approaches that embed content credentials and policies into the content generation pipeline have been proposed to ensure that AI-generated content adheres to legal and ethical standards [6].

Another relevant line of research is backdoor detection and defense in distributed learning systems. In vertical split learning, where model layers are distributed across multiple parties, backdoor attacks can be injected through compromised participant data. ProtoGuard-SL proposes a prototype consistency based defense that uses path-level analysis to identify and neutralize backdoor triggers [17]. While that work focuses on security of training, the underlying principle of monitoring intermediate representations for anomalies is directly applicable to safety routing during inference. Similarly, vulnerability prioritization frameworks for microservice architectures, such as hybrid SAST-DAST-SCA-IAST approaches, share the goal of identifying and mitigating risks along the service chain [18].

Our work synthesizes insights from these diverse areas to propose a unified architecture for path-level safety routing in commercial recommendation pipelines. We build on the formal foundations of causal intervention while addressing the practical constraints of deployment at scale. The following sections detail the framework's design, its trade-offs, and its implications for governance and sustainability.

3. Path-Level Causal Intervention for Safety Routing

At the heart of our proposed framework is the representation of the recommendation pipeline as a directed acyclic graph (DAG) of processing stages. Each stage, denoted as a vertex, transforms an input representation into an output representation that is passed along edges to subsequent stages. In a typical commercial pipeline, these stages might include a query encoder that converts user queries into embedding vectors, a candidate retriever that searches an index of item embeddings, a ranker that scores candidates using interaction features, and a personalizer that adjusts rankings based on user history and context. Foundation models may be used at one or more of these stages, for example as the query encoder or as a feature extractor for item descriptions.

The key insight is that unsafe or undesirable outputs often originate not from a single stage but from the propagation of harmful representations along specific paths. For instance, a bias in the query encoder might cause it to retrieve candidates that amplify stereotypes, which are then further reinforced by the ranker's weighting of demographic features. Conventional safety methods that filter the final output would catch the harmful recommendation but would not identify the root cause. In contrast, path-level causal intervention allows operators to systematically test hypotheses about which edges carry unsafe information.

The intervention procedure works as follows. First, a baseline set of outputs is recorded under normal operation. Then, for a given path of interest, the intermediate representation at the

start of that path is replaced with a counterfactual representation—either a neutral default or a representation computed from a safe reference input. The forward pass is completed from that point onward, and the resulting outputs are compared to the baseline. If the intervention causes a significant change in the safety-related properties of the output (e.g., toxicity score, bias metric, policy violation flag), then the intervened path is likely a carrier of unsafe content. By repeating this process for different paths, operators can construct a causal map that identifies critical bottlenecks.

This approach draws directly from the TraceRouter architecture, which proposes path-level intervention for robust safety in large foundation models [2]. TraceRouter demonstrates that intervening on specific layers or attention heads can block the propagation of harmful content without degrading overall model performance. In a recommendation context, the equivalent might be intervening on the embedding layer that encodes historical user interactions, or on the cross-attention between user and item representations. The granularity of intervention can be adjusted: fine-grained interventions target individual neurons or attention heads, while coarse-grained interventions affect entire stages or services. The choice of granularity involves a trade-off between precision and computational cost.

Causal intervention at the path level offers a distinct advantage over gradient-based or attention-based attribution methods. It provides counterfactual explanations that are directly interpretable by human operators: "If we had altered the representation at this point, the unsafe output would not have occurred." Such explanations are actionable because they specify exactly where to intervene. Moreover, the intervention can be deployed in a closed-loop manner: once a problematic path is identified, a routing policy can be automatically configured to divert future inference along alternative paths that avoid the unsafe representation. This is analogous to dynamic routing in network traffic, where packets are rerouted to avoid congestion.

The feasibility of path-level intervention depends on the availability of intermediate representations in a granular form. Many modern recommendation services are built using microservice architectures that expose RESTful or gRPC APIs. By instrumenting these services to optionally return internal embeddings or hidden states (with appropriate access controls), the platform can enable the intervention framework without requiring a complete refactoring of the existing codebase. This aligns with the trend toward observable and auditable AI systems, as advocated by recent recommendations for standardized recommendation APIs [15]. Furthermore, the intervention logic can be implemented as a separate middleware layer that intercepts API calls and modifies the payloads before they are passed to downstream services.

One practical concern is the latency overhead introduced by the intervention framework. Each causal analysis requires multiple forward passes through a portion of the pipeline, which could be costly if performed online for every request. To mitigate this, we propose a two-tier approach. Anomaly detection models running online can flag potentially unsafe outputs in real time using lightweight classifiers. Only flagged cases are then subjected to detailed path-level causal analysis offline, using logs and cached representations. This hybrid strategy balances the need for immediate safety with the depth of interpretability. The offline analysis can be scheduled as a batch job that updates routing policies periodically, ensuring that the system adapts to emerging patterns of unsafe content.

4. Architectural Considerations and Trade-offs

Designing a safety routing framework that is both effective and deployable in commercial environments requires careful consideration of architectural trade-offs. Three dimensions are particularly salient: the granularity of intervention, the scope of the causal graph, and the computational overhead of maintaining and querying the intervention system.

Granularity refers to the level at which intervention is applied—whether at the level of individual neurons, attention heads, layers, functional blocks, or entire microservices. Finer granularity offers more precision in isolating harmful representations, but it also increases the complexity of the causal graph and the number of intervention experiments required to cover all paths. Moreover, very fine-grained interventions may not be stable across different inputs or contexts, as the causal role of a specific neuron can vary. Coarser granularity, such as intervening on an entire encoder service, is simpler to implement and more robust, but it may reroute too many safe representations along with unsafe ones, potentially degrading recommendation quality.

Our analysis suggests that a mixed-granularity approach is most practical for commercial pipelines. Sensitive stages, such as those involving user embeddings or content moderation filters, should be modeled at a finer granularity to allow precise intervention. Other stages, such as simple transformation functions, can be treated as atomic units. The framework should support hierarchical definitions of paths, where operators can zoom in on specific subpaths when a coarse intervention fails to resolve a safety issue. This resembles the concept of "path sparsification" in causal graph analysis, where only the most influential paths are retained for detailed modeling [19].

The scope of the causal graph determines which parts of the pipeline are subject to intervention. In a large-scale deployment with dozens of services, modeling the full graph may be infeasible. Instead, operators can define a "safety-critical zone" comprising stages that are most likely to introduce or amplify unsafe content. This zone can be identified through prior auditing or through automated discovery using gradient-based attribution [20]. For example, a stage that receives multimodal inputs and fuses them into a joint embedding may be a high-risk point because it can blend latent biases from different modalities. By limiting the causal graph to the safety-critical zone, the framework reduces the number of parameters to be learned and the number of intervention probes needed.

Computational overhead is a persistent concern, especially when interventions require running additional forward passes. In the offline analysis mode, this overhead is acceptable because it does not affect real-time inference. However, the online anomaly detection component must be lightweight. Models such as small neural classifiers or statistical outlier detectors can be trained on historical logs to flag potentially unsafe outputs with minimal latency [21]. These detectors need to be updated periodically as the content landscape evolves, which points to the need for a continuous learning pipeline.

Another architectural choice is whether the intervention system is centralized or distributed. A centralized routing controller that manages all intervention policies offers consistency and easier auditability. However, it introduces a single point of failure and may become a bottleneck under high request rates. A distributed approach, where each microservice maintains its own local intervention rules based on shared causal maps, can improve scalability and resilience. The trade-off is increased coordination overhead and the risk of conflicting policies across services. Hybrid designs that use a central coordination unit for policy generation and local enforcement for execution have been proposed in the context of

multi-tenant recommendation infrastructure [15]. Such designs align well with the needs of safety routing.

We also need to consider the sustainability aspect of this architecture. Running extensive causal analysis on a continuous basis consumes energy and computational resources. To reduce the environmental footprint, the framework can adopt an adaptive probing schedule—intervening more frequently during periods of high content risk (e.g., after model updates or during new campaign launches) and less frequently during stable periods. Furthermore, the causal models themselves can be compressed using techniques such as knowledge distillation or pruning, as they only need to capture the most salient pathways [22]. These sustainability considerations are increasingly important as organizations face pressure to align AI operations with net-zero goals.

5. Deployment and Infrastructure Implications

Deploying path-level causal intervention in a commercial recommendation pipeline requires modifications to the underlying infrastructure, particularly around observability, data retention, and policy execution. Many existing platforms already collect extensive logs of intermediate representations for debugging and monitoring purposes. Our framework can build on this by adding structured labeling of those logs with path identifiers and intervention outcomes. The key infrastructure requirement is the ability to replay historical inference requests with modified representations—a capability that is commonly available in feature stores and experiment management systems.

A critical deployment challenge is ensuring that the intervention framework itself does not introduce new security vulnerabilities. For example, an attacker who gains access to the intervention controller could deliberately route unsafe representations to downstream stages, causing harm. Therefore, the intervention system must be protected with strong access controls and authentication mechanisms, similar to those used for model serving infrastructure. Additionally, all intervention actions should be recorded in an immutable audit log to support post-hoc analysis and regulatory compliance [6]. The use of content credentials, such as C2PA-based provenance records, can provide cryptographic evidence that a specific intervention was applied and by whom, satisfying requirements for accountability [6]. In the context of social commerce, compliance-by-design micro-licensing approaches have been proposed to embed usage policies directly into the content metadata, ensuring that any rerouting respects the original licensing terms [6].

The microservice architecture that is prevalent in modern recommendation systems offers both opportunities and challenges for safety routing. On one hand, the loose coupling between services allows us to insert intervention proxies between service calls without modifying the internal logic of each service. An intervention proxy can inspect, modify, or replace the payload of an API request or response. This can be implemented using sidecar patterns in service meshes such as Istio or Linkerd. On the other hand, the dynamic nature of microservice topologies—where services are frequently scaled, upgraded, or replaced—requires the causal graph to be updated automatically. The framework should include a discovery module that monitors service registries and updates the graph accordingly.

Multi-tenancy adds another layer of complexity. In a recommendation-as-a-service platform that serves multiple clients, each tenant may have different safety policies. For example, a children's content provider may prohibit any mention of violence, while a news aggregator may allow war reporting with clear warnings. The safety routing framework must maintain

separate intervention configurations per tenant and ensure that routing decisions are isolated to prevent cross-tenant leakage. This can be achieved by tagging each request with a tenant identifier and using tenant-specific causal models or policy databases. The multi-tenant architecture described in [15] for trusted AI commercialization provides a blueprint for such isolation, combining incentive systems, content governance, and standardized APIs.

The infrastructure must also support the lifecycle of causal models. As new unsafe patterns emerge—for instance, when a new variant of prompt injection attack is discovered—the causal graph must be updated to include detection of the new pathway. This requires a feedback loop between the safety operations team and the machine learning engineers who maintain the foundation models. The framework should facilitate this by providing tools for adding new intervention points, specifying counterfactual interventions, and evaluating the impact on a holdout set of safe and unsafe examples. Regular re-evaluation of the causal map is necessary to prevent concept drift from rendering the interventions ineffective.

6. Governance, Fairness, and Policy

The ability to trace unsafe outputs back to specific paths in the recommendation pipeline has profound implications for governance and fairness. Regulatory frameworks increasingly demand that organizations provide explanations for algorithmic decisions that adversely affect individuals or groups. Path-level causal intervention can serve as a foundation for generating such explanations. For example, if a fairness audit reveals that a particular demographic group consistently receives lower-quality recommendations, the causal map can be used to identify which processing stage introduces the disparity. The intervention can then be applied to mitigate the bias, and the resulting change can be verified through counterfactual testing.

Fairness in recommendation systems is often studied through the lens of disparate impact, where certain groups are systematically disadvantaged. Foundation models can exacerbate these disparities because they encode societal biases present in their training data [23]. Path-level intervention allows for a debiasing strategy that is more targeted than reweighing training data or adding fairness constraints to the loss function. By pinpointing the representation where the bias emerges, operators can apply a corrective transformation—such as subtracting the mean embedding of a protected attribute—at that specific point, rather than throughout the entire model. This localized debiasing is less likely to harm overall model performance and is easier to audit because the intervention is explicit and documented.

Content governance is another area where the framework provides value. Commercial platforms must comply with a patchwork of laws and standards regarding hate speech, misinformation, copyright, and child safety. Path-level safety routing can encode these policies as intervention rules. For example, a policy that prohibits recommending certain categories of adult content to users under a certain age can be enforced by routing the content representation through an age-filtering stage before it reaches the personalizer. The causal map ensures that the filtering happens at the optimal point in the pipeline, minimizing the impact on other recommendations.

A critical governance challenge is the potential for the intervention system itself to become a source of unfairness or censorship. If the routing rules are too aggressive, they may suppress legitimate content, stifling diversity and free expression. Conversely, if they are too permissive, they may allow harmful content to slip through. Striking the right balance requires transparent policy-making that involves diverse stakeholders, including users, content creators, and civil society organizations. The framework supports this transparency by

making the intervention rules explicit and auditable. Moreover, the causal analysis can be used to simulate the effects of different policy choices, allowing policymakers to evaluate trade-offs before deployment.

From a regulatory compliance perspective, the path-level intervention framework aligns with the "by-design" approach advocated by emerging AI regulations. The European AI Act, for example, requires that high-risk AI systems be designed to enable human oversight and traceability [5]. Our framework provides a mechanism for human operators to understand and override unsafe decisions, as they can inspect the causal map and manually adjust routes. Furthermore, the audit logs produced by the framework can serve as evidence of compliance with transparency obligations. The integration of content credentials, as proposed in compliance-by-design micro-licensing, adds another layer of verifiability [6].

The framework also has implications for the governance of AI supply chains. Many commercial recommendation pipelines incorporate third-party models or services. Path-level intervention can be used to ensure that the outputs of these external components comply with the platform's policies before they are integrated into the larger pipeline. This is particularly important in the context of foundation models that are served as APIs, where the platform has limited visibility into the model's internal workings. By intervening on the representations returned by the external API, the platform can apply its own safety policies without needing to access the model's internals. This creates a form of "wrapping" that enhances security and compliance.

7. Future Directions and Sustainability

The path-level causal intervention framework opens several avenues for future research and development. One important direction is the automation of causal map discovery. Currently, the identification of critical paths relies on human operators to hypothesize which edges may carry unsafe content and then perform interventions. This process can be automated using causal discovery algorithms that learn the graph structure from observational and interventional data [24]. For example, a system could run a set of randomized interventions on different edges and use the resulting outcome distributions to infer the causal structure, similar to how A/B testing is used to infer treatment effects. Automating this step would reduce the operational burden and enable continuous adaptation to new threats.

Another promising avenue is the development of end-to-end differentiable routing policies. Instead of using discrete routing decisions (reroute vs. not reroute), one could learn a probabilistic routing function that smoothly blends representations from multiple paths. This would allow the system to balance safety and utility in a principled manner, using a loss function that penalizes unsafe outputs while rewarding recommendation accuracy. Such an approach would require integration with machine learning frameworks and could be trained using reinforcement learning or imitation learning from human safety examples. However, it would sacrifice some interpretability in favor of performance, so it may be more suitable for applications where throughput is critical.

The sustainability of the proposed framework can be enhanced through the use of model compression and efficient inference techniques. The causal models used to predict intervention outcomes do not need to be as large as the underlying foundation models. Knowledge distillation can be used to create a small, fast surrogate model that approximates the causal relationships in the pipeline [22]. This surrogate can be used to recommend interventions without requiring multiple forward passes through the full pipeline. Additionally,

the framework can be designed to leverage sparsity in the causal graph—most paths are irrelevant for most safety issues—so that only a subset of edges need to be monitored and intervened upon at any given time.

Cross-modal safety is another frontier. Foundation models in recommendation pipelines increasingly operate on multiple modalities, such as text, images, and audio. Safety issues can arise from the interaction between modalities, for example when a text description accompanies an image that contains subtle violence. Path-level intervention can identify the multimodal fusion stage as the critical point where unsafe correlations are introduced. Future work should extend the framework to handle heterogeneous graph structures with different types of edges representing different modalities.

Finally, the framework must evolve to accommodate the rapid pace of foundation model updates. As new models are released or existing models are fine-tuned, the causal graph can change. A versioning strategy for both the pipeline stages and the intervention policies is needed to ensure smooth transitions. The use of continuous integration and deployment pipelines for AI, combined with the safety routing framework, can provide automated safety checks for each model update, flagging any new unsafe pathways before they reach production.

8. Conclusion

Safety in commercial recommendation pipelines that incorporate foundation models is a pressing concern that demands solutions beyond traditional output filtering. This paper has presented an interpretable safety routing framework based on path-level causal intervention, grounded in the idea that unsafe outputs can be traced to specific information flows within the pipeline. By modeling the pipeline as a directed graph and applying targeted interventions on intermediate representations, operators can diagnose root causes and reroute representations through safer pathways. The framework is designed to be compatible with modern microservice architectures and multi-tenant deployments, and it supports the generation of actionable, counterfactual explanations that satisfy emerging regulatory requirements for transparency and accountability.

We have examined the architectural trade-offs among intervention granularity, computational overhead, and interpretability, and we have discussed the infrastructure modifications necessary for deployment, including observability, access control, and audit logging. The implications for governance and fairness are significant, as the framework enables precise debiasing and policy enforcement while maintaining a transparent record of all interventions. Sustainability considerations, such as adaptive probing schedules and model compression, ensure that the approach can be deployed at scale without excessive resource consumption.

As foundation models continue to evolve and permeate every aspect of online recommendation, the need for robust, interpretable, and governable safety mechanisms will only grow. Path-level causal intervention offers a principled path forward, one that respects both the complexity of these models and the urgency of safeguarding users and societies. We hope that this work inspires further research and practical implementations that bridge the gap between cutting-edge AI capabilities and the timeless values of trust, fairness, and responsibility.

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