CASE: An Agentic AI Framework for Enhancing Scam Intelligence in Digital Payments

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Abstract—The proliferation of digital payment platforms has transformed commerce, offering unmatched convenience and accessibility globally. However, this growth has also attracted malicious actors, leading to a corresponding increase in sophisticated social engineering scams. These scams are often initiated and orchestrated on multiple surfaces outside the payment platform, making user and transaction-based signals insufficient for a complete understanding of the scam's methodology and underlying patterns, without which it is very difficult to prevent it in a timely manner. This paper presents CASE (Conversational Agent for Scam Elucidation), a novel Agentic AI framework that addresses this problem by collecting and managing user scam feedback in a safe and scalable manner. A conversational agent is uniquely designed to proactively interview potential victims to elicit intelligence in the form of a detailed conversation. The conversation transcripts are then consumed by another AI system that extracts information and converts it into structured data for downstream usage in automated and manual enforcement mechanisms. Using Google's Gemini family of LLMs, we implemented this framework on Google Pay (GPay) India. By augmenting our existing features with this new intelligence, we have observed a 21% uplift in the volume of scam enforcements. The architecture and its robust evaluation framework are highly generalizable, offering a blueprint for building similar AI-driven systems to collect and manage scam intelligence in other sensitive domains.

Index Terms—Conversational Agents, Responsible AI, Social Engineering Scams, AI Safety, Fraud Enforcement, Information Extraction, User Reporting, Scam Intelligence, Digital Payments.

I. INTRODUCTION

Increased internet penetration and global digitization have led to enormous growth in digital payments, with wide-scale investment making these platforms more accessible than ever. Indeed, this growth has positioned digital payments as a leading indicator of GDP growth [14]. A prominent example of this transformation is India's Unified Payments Interface (UPI) [2], which has become one of the world's fastest-growing real-time payment ecosystems, processing billions of transactions monthly [15]. This rapid growth, however, has also attracted malicious actors who consistently devise new social engineering scams to defraud users. A key challenge is that while the fraudulent transaction occurs on the payment platform, the scam itself is often orchestrated on external surfaces like social media or messaging apps [17].

This creates a critical intelligence gap. The payment platforms' anti-abuse systems, which rely heavily on on-platform user and transaction signals, lack the data to form a clear picture of the scam's complete modus operandi (aka MO). Without this understanding, it is difficult to build timely and effective protections, especially for new and emerging scam patterns. This delay in detection allows malicious actors to cause significant harm before sufficient evidence for enforcement is gathered. One of the most reliable ways to bridge this intelligence gap is to empower users to report their experiences directly [19].

However, the mechanism for collecting these reports is crucial. Traditional feedback systems, such as categorical inputs (e.g., like/dislike buttons, surveys) are too simplistic and fail to capture the evolving methodologies of scams. Even static, free-form text boxes often yield incomplete information, as they rely entirely on the user to provide sufficient detail without the ability for the platform to ask clarifying follow-up questions. This can lead to ambiguous reports that are not actionable, crippling enforcement efforts.

To be effective, we require a system that can collect detailed scam reports through dynamic, interview-like interactions, customizing questions based on user responses. While manual human interviews are effective, they are prohibitively expensive to conduct at scale. This leads to our proposed solution: a conversational AI framework that can conduct these sensitive interviews efficiently and scalably. To do this, we must address two primary challenges: firstly ensuring that human-agent interactions are safe, empathetic, and useful, and secondly developing a method to process the unstructured conversational data for downstream systems.

In this paper, we present CASE (Conversational Agent for Scam Elucidation), a novel Agentic AI framework designed, using the Gemini family of models, to address these challenges with Google Pay India as a use case. It features two core components working one after the other:

- A Conversational Agent, which leverages Responsible AI principles to safely and effectively interview potential victims. It comprises an LLM Interviewer and a Safety Filter, both of which work together.
- An Information Extractor Agent, which processes the unstructured conversation and outputs structured, actionable data for enforcement mechanisms.

We demonstrate that this framework directly increases scammer detection coverage by 21% and significantly enhances the volume and velocity of enforcement actions, all while adhering to Responsible AI principles to ensure a high bar for safety and utility. The remainder of this paper details this framework, its evaluation, and its impact, offering a blueprint for similar AI-driven intelligence systems in other payment platforms.

II. RELATED WORK

This section reviews prior research across the key domains that inform the design and evaluation of the CASE framework. We begin by examining the current landscape of AI in scam detection to establish the critical intelligence gap our work addresses. We then survey the relevant advancements in goal-oriented conversational AI and LLM-based information extraction, the core technologies we leverage. Finally, we ground our methodology in the established principles of Responsible AI for building safe and effective user-facing systems.

A. AI in Payments Scams Detection and Prevention

The growth of digital payments has been accompanied by a surge in social engineering scams, which pose a significant and costly global threat [3]. State-of-the-art AI defenses primarily analyze on-platform signals like transaction patterns and account history [8] [10], but these models are often less effective against social engineering. Because these scams manipulate a user into willingly sending funds, the transaction itself can appear authentic, creating a critical intelligence gap. The scam's true modus operandi (MO) unfolds on external platforms like messaging apps, leaving the payment service without the context needed to detect the fraud [17]. While this narrative intelligence can be gathered through manual interviews [20], the approach is not scalable for digital payment platforms with a large user base. This reveals a clear need for an automated and scalable method to systematically collect and structure user-reported scam intelligence.

B. Conversational AI for Goal-Oriented Tasks

Goal-Oriented Dialogue systems are designed to help users achieve specific objectives through conversation, with common applications in customer support and service booking [7]. The advent of Large Language Models (LLMs) has enabled a shift from simple, scripted bots to more sophisticated AI systems capable of handling complex, multi-turn tasks [21].

While powerful, much of the existing research focuses on transactional or informational objectives by reacting to user queries [21]. The application of these agents in high-stakes, emotionally sensitive domains remains a significant challenge [22]. Our work contributes to this area by designing a Conversational Agent specifically for the unique task of conducting investigative and empathetic interviews with potential fraud victims, which requires a higher degree of nuance and safety than typical goal-oriented dialogue applications.

C. Information Extraction from Unstructured Text

Information Extraction (IE), the task of converting unstructured text into a structured format, is a long-standing challenge in Natural Language Processing (NLP). Traditional

deep learning approaches, such as those for Named Entity Recognition and Relation Extraction, made significant strides but often required large, task-specific training datasets for finetuning [6].

More recently, Large Language Models (LLMs) have enabled a paradigm shift towards flexible, zero-shot or few-shot Information Extraction. These models can populate a predefined schema with high accuracy using only a natural language description of the desired output, forgoing the need for extensive task-specific training [24]. Our Information Extractor leverages this modern paradigm, demonstrating its practical application on noisy, real-world conversational data—a domain significantly more challenging than the curated datasets typically used in IE benchmarks.

D. Responsible AI, Safety and Quality in User-Facing Systems

Deploying user-facing LLMs, particularly in high-stakes domains like payments, requires strict adherence to Responsible AI principles, where systems are evaluated not just for performance but for safety and reliability to prevent user harm [13]. Established best practices include implementing multilayered safety architectures and performing adversarial testing, or *Red Teaming* [5], to proactively identify system vulnerabilities [11]. Furthermore, assessing the subjective quality of the user experience in sensitive contexts is difficult to automate and relies on expert human evaluation to establish a reliable ground truth [16]. This makes a hybrid evaluation framework, combining automated tests with human reviews, an essential component of responsible deployment [4].

III. OBJECTIVE

The primary objective of this paper is to develop and validate an agentic framework, comprising multiple LLMs, for the collection and management of actionable scam intelligence within a large-scale digital payments ecosystem. We specifically focus on the UPI interface in India, using the Google Pay (GPay) India payments platform as our primary implementation case study.

To achieve this, the CASE framework is designed to meet three key system objectives:

- Conversational Agent (Enhance actionable scam intelligence collection): To develop and deploy a novel conversational agent for proactive information elicitation. This agent must provide a user-friendly and safe interaction that reliably captures nuanced details about social engineering scams, moving far beyond the limitations of traditional, static feedback channels.
- LLM Information Extractor (Enable seamless utilization): Design and build a powerful backend agent capable of transforming raw, unstructured conversational transcripts into structured, machine-readable data. This ensures that the rich, qualitative insights gathered from user interactions are made programmatically actionable for automated analysis and downstream enforcement systems.

• Establish a Generalizable Framework: To design the system architecture and evaluation methodologies in a modular and adaptable manner, creating a reusable blueprint for other similar platforms and domains.

By fulfilling these technical objectives, we aim to leverage the resulting high-quality, structured intelligence to significantly augment existing fraud detection mechanisms, enabling more precise and scalable enforcement actions against malicious actors.

IV. SYSTEM ARCHITECTURE

This section describes in detail our CASE framework for the collection and management of actionable scam intelligence. It is composed of multiple AI systems, built using Google's Gemini models, that prioritize scalability and user privacy while also adhering to stringent safety and quality standards. The framework comprises two core components: a userfacing *Conversational Agent* (comprising LLM Interviewer and Safety Filter) for data collection and a backend *LLM Information Extractor* for data processing. The following subsections will detail the end-to-end data flow and the specific design of each of these agents.

A. End-to-End System Flow

The system's operational flow is designed to be seamless and integrated within the user's existing in-app support interface. A conceptual diagram of this architecture is shown in Figure 1. The process is divided into two primary phases: a real-time Intelligence Collection Phase and an asynchronous Data Processing Phase.

Intelligence Collection Phase (Real-time)

- The flow initiates when a user starts a fraud report, invoking a backend LLM service. The starting question is fixed for every user.
- For each turn, the user's input is processed independently by both the Safety Filter LLM and Generator LLM. The Safety Filter assesses the input for policy violations, while the Generator formulates a potential response based on the conversation history.
- A decision logic module then evaluates both outputs to determine the final response sent to the user.
- The complete conversation transcript, including the latest turn, is stored.
- The dialogue continues until the agent generates a predefined token to terminate the session.

Data Processing Phase (Asynchronous)

- The data extraction is handled as a batch process. This
 design was deliberately chosen to enhance system reliability, improve fault tolerance, and allow for cost-effective
 reprocessing.
- Each stored transcript is passed to the Information Extractor Agent, which generates a structured data output according to a predefined schema.
- Finally, this structured intelligence is written to a dedicated data store, making it available for human analysts and automated detection systems.

B. Models Used

The CASE framework utilizes Google's Gemini family of models [1], leveraging their unique strengths for different components of the architecture. The primary model chosen for the production implementation is **Gemini 2.0 Flash** [1]. This highefficiency model is employed for all three core components: the real-time Interview Agent and the LLM Safety Filter, and the asynchronous Information Extractor Agent. Its balance of speed, capability, and cost-effectiveness makes it ideal for a large-scale deployment requiring both live user interaction and high-throughput batch processing.

While Flash was chosen for deployment, more powerful models like **Gemini 2.0 Pro** [1] were evaluated during the research and development phase to establish performance benchmarks and explore the upper bounds of capability for this task, especially for the non-real-time Information Extractor Agent.

C. Conversational Agent: Generator LLM

The primary objective of the Conversational Agent is to conduct a reliable, useful, and safe interview to understand a scam's complete modus operandi. A key design principle of this agent is its flipped role; unlike most chatbots that primarily answer user questions, its function is to ask dynamic questions to guide an investigative interview. The per-turn storage mechanism detailed in Section IV-A ensures the complete conversation history is available to the agent for each new turn. Figure 2 describes the conversational agent flow in detail.

The agent is powered by the Gemini Flash 2.0 model [1], and its behavior is guided by a sophisticated prompt architecture rather than extensive fine-tuning. This approach was chosen for its flexibility and speed of iteration during development. The core components of this prompt architecture include:

- Role Definition: The LLM is instructed to adopt the
 persona of a specialist fraud analyst. This role is grounded
 in the specific context of digital payment scams through
 domain-specific examples of scam interviews and instructions on identifying key components of a scam's modus
 operandi.
- Interaction Guidelines: The agent is given a strict set
 of rules to follow, such as never promising a refund,
 avoiding financial advice, staying on topic, and respectfully concluding the conversation if the user wishes to
 stop. Even though we have separate safety filter LLM
 (described in the following sub-section), we also have
 some inbuilt safety controls in the chatbot as well.
- Success Criteria: The prompt defines a successful interview as one that captures key facets of the scam, such as
 the initial contact surface, the hook used to build trust,
 and the action that led to the financial loss.
- Privacy by Design: To protect user privacy, the prompts sent to the LLM are stateless and do not contain any personally identifiable information (PII) about the user being interviewed. While a transaction level identifier is

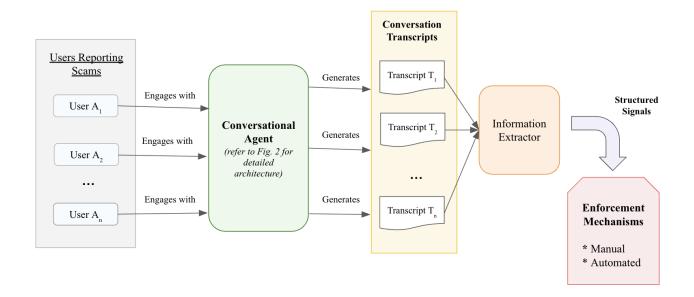


Fig. 1. Overall System Flow

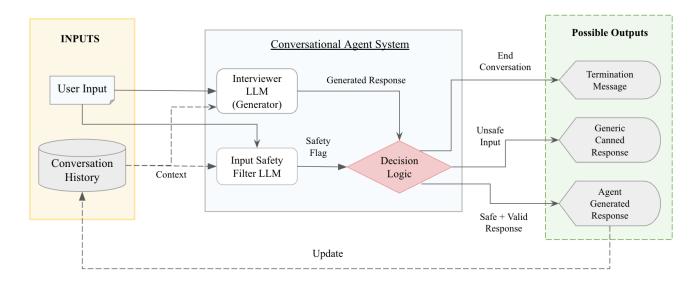


Fig. 2. Conversation Agent Flow

used to initiate the flow, this and other payment details are not passed to the LLM.

D. Conversational Agent: Safety Filter LLM

Given the sensitive nature of financial scam discussions, the CASE framework incorporates a robust, multi-layered safety architecture. This architecture consists of the following layers, which work in concert to protect the user:

• Base Model Safeguards: The Gemini model's architecture includes integrated safety protocols designed to prevent the generation of harmful content, as detailed in its technical documentation [1].

- Input Safety Filter: As detailed in the system flow, all
 user inputs are simultaneously processed by a dedicated,
 LLM-based classifier. This filter runs in parallel with the
 main generator LLM and assesses the input for harmful,
 abusive, or policy-violating content. Its output is used as
 a signal by the system's decision logic to determine the
 final response.
- Guided Prompt Architecture: The primary conversational LLM's prompts are designed with strict negative constraints to prevent specific harmful outputs, such as providing unauthorized financial or legal advice. Guidelines also direct the agent to maintain focus and gracefully

conclude off-topic interactions.

E. LLM Information Extractor

The primary objective of the Information Extractor Agent is to convert the unstructured and often noisy conversational transcripts into a consistent, structured, and machine-readable format. This crucial step makes the qualitative insights gathered by the Conversational Agent scalable and programmatically actionable.

The agent is implemented using the Gemini Flash 2.0 model, and its behavior is guided by a sophisticated prompt architecture rather than extensive fine-tuning. The prompt combines role-based instructions with a structured in-context learning (ICL) strategy. The model is explicitly instructed to parse the conversation and extract information corresponding to a predefined data schema. To ground the model's behavior and ensure high-fidelity output, the prompt is populated with a set of diverse, high-quality examples (i.e., *shots*) from a **golden dataset** [9] of manually annotated conversation transcripts. This schema-guided ICL approach was chosen for its flexibility and its ability to handle the variation in natural language, which is superior to traditional, more rigid NLP pipelines.

The agent's main task is to populate a predefined data schema with information gleaned from the conversation. This schema is highly adaptable to different business use cases. For our implementation, we extract a combination of mandatory and optional features (described in Table I) and use the JSON format for the output, though the system can support other standard formats with minor changes to the prompt. This final, structured output is the actionable intelligence product of our framework, ready for ingestion by downstream risk systems. Figure 3 provides examples of this mapping, illustrating how the agent accurately distinguishes between scam-related and non-scam conversations to reduce noise and improve the efficiency of downstream enforcement.

F. Scam Intelligence Utilization

The structured data generated by the Information Extractor Agent is not merely an archived output; it is actively integrated into the downstream anti-abuse ecosystem to enhance enforcement capabilities. The intelligence is utilized in two primary ways:

- Manual Analysis and Investigation: The structured reports
 are made available to human reviewers. This rich, contextual data is used for deep-dive investigations into complex
 cases, helping analysts understand new and evolving scam
 modus operandi (MOs) and validate decisions on highvalue take-downs. For example, the user's narrative can
 be used to prioritize cases for manual review, ensuring
 that the most critical or novel scam reports are escalated
 quickly.
- Automated Enforcement and Modeling: At an aggregated level, the structured data serves as a powerful new set of signals for our machine learning models. Features derived from this data, are used to update payments risk models

to automatically detect and prevent new scam patterns at scale. This allows the intelligence gathered from the users' experience to contribute to the protection of the entire platform.

This dual-use approach ensures that every piece of userprovided intelligence contributes to making the platform safer, both through immediate, human-led review and long-term, automated learning.

V. EVALUATION METHODOLOGY

Given the CASE system's direct interaction with users on the sensitive topic of financial scams, we developed a comprehensive evaluation methodology to ensure its safety, reliability, and effectiveness. This framework is built on the dual pillars of Safety (preventing harm) and Quality & Utility (achieving the system's goals). We created distinct evaluation plans for the Conversational Agent and the Information Extractor while keeping Responsible AI principles in mind. The methodology is designed for the entire product lifecycle—from initial development to full production—with a focus on ensuring high quality while minimizing long-term operational costs by planning for a transition from human raters to automated evaluators.

A. Expert Human Raters

Given the sensitive nature of user interactions and the complexity of unstructured conversational data, human evaluations are a foundational component of our testing framework. This methodology is particularly critical for assessing subjective qualities, establishing ground truth, and validating system performance in scenarios that are challenging to automate [16]. To ensure a thorough and efficient assessment, we utilize a specialized group of trained human raters, referred to as external evaluators, to fulfill the testing requirements of the project. These evaluators are instrumental during both the prelaunch development and post-launch monitoring phases. They are responsible for providing qualitative insights, conducting adversarial tests (Red Teaming) [5] and validating the system's behavior against a set of predefined safety and quality standards [11].

B. Conversational Agent: Safety

Our safety evaluation is built upon a set of rigorously defined policies and tested using multiple methods to ensure comprehensive coverage. These policies are categorized into two tiers:

Our evaluation framework's primary tier targets **high severity** violations, including but not limited to hate speech, harassment and dangerous content. We conducted tests for these violations to provide a comprehensive validation of the model's safety, even though its developers state it has been trained with inherent protections against them [1].

The framework's second, more nuanced tier evaluates **contextually sensitive** content. These include outputs not typically classified as harmful but which are contextually inappropriate for our system, such as generating financial advice, false

Feature Name	Requirement	Description	Possible Values
is_user_scammed	Mandatory	A boolean flag indicating if the agent determined the user was a victim of a scam.	True, False
possible_scam_mo	Mandatory	The classified Modus Operandi (MO) of the scam. Choose NOT_SCAM only when is_user_scammed = False.	NOT_SCAM, FAKE_LOAN, FAKE_JOBS, FAKE_ADS,
scam_origin_surface	Optional	The application or surface where the user first came into contact with the scammer.	<pre><list and="" apps="" media="" messaging="" of="" popular="" social="">, OTHERS, NONE,</list></pre>
conversation_summary	Mandatory	A concise, LLM-generated summary of the entire interview.	Free-form text within word limits.



Fig. 3. Conversation Transcript to Information Extractor Structured Output Examples

promises, or factual inaccuracies (hallucinations). A robust testing protocol for this tier necessitated a detailed policy framework tailored to our operational context.

specific issue. Will that be ok?

User: Sure, that is ok.

I can direct you to Google Pay support for assistance with

Agent: [TERMINATION_MESSAGE][SUPPORT_LINK]

pending transactions, as they are better equipped to resolve this

We used two primary methods to test against these policies:

- Structured Evals: We conducted structured tests for known risks using large, curated datasets of adversarial prompts. These datasets were sourced from both central safety teams and handcrafted examples specific to the GPay India context to ensure relevance.
- Red Teaming: We performed pre-launch, ad-hoc red teaming exercises where human experts simulated the tactics of real-world bad actors in an attempt to circumvent

our guardrails and discover unknown vulnerabilities [5].

us to ask for help with stuck

transaction. They have been

support channel for resolution.

directed to the appropriate

C. Conversational Agent: Quality and Utility

Beyond safety, we evaluated the Conversational Agent's ability to perform its core function effectively. This was broken down into assessing the quality of the conversation and the utility of the information gathered.

Quality metrics assess the overall quality of the user's conversational experience:

• *Topic Adherence*: This measures the agent's ability to remain focused on the intended objective of the interview and to gracefully handle off-topic user inputs.

User Respect: This measures whether the agent maintains
a respectful and supportive tone throughout the conversation. A key aspect of this metric is the agent's ability
to gracefully and immediately conclude the conversation
if a user declines to share further details or expresses a
desire to stop.

Utility metric assesses whether the agent achieved its primary goal of *Information Elicitation* and measures the agent's success in eliciting the necessary information to understand the core modus operandi i.e. *possible_scam_mo* from the user's narrative.

In the pre-production stage, these subjective metrics were scored by our trained human evaluators. They assessed the agent's performance in numerous sample conversations against a detailed set of guidelines to ensure consistent and accurate scoring.

D. LLM Information Extractor: Accuracy

In contrast to the subjective quality evaluation of the Conversational Agent, the assessment of the Information Extractor is more quantitative. Given that this agent is tasked with converting unstructured text into structured data with predefined categorical fields, the evaluation can be framed as a series of classification problems.

The primary challenge for this evaluation is establishing the ground truth. To address this, we utilized a hand-crafted **golden dataset** previously described in Section IV-E. This corpus of conversation transcripts was manually curated by our trained human evaluators, provides the ground truth labels against which we measure the agent's performance. The agent's accuracy was then measured with a focus on the two features most critical for downstream enforcement:

- Scam Detection (Binary Classification): The first and most important task is the agent's ability to accurately differentiate between scam and non-scam reports. This is treated as a binary classification problem corresponding to the *is_user_scammed* field, and we calculate standard classification metrics for its performance.
- Modus Operandi Classification (Multiclass Classification): For conversations identified as scams, the second key task is to correctly classify the type of scam. This is treated as a multiclass classification problem based on the possible_scam_mo field, and its performance is tracked separately.
- Optional Contextual Fields: Our evaluation framework
 prioritizes the high-impact mandatory fields listed above.
 For this initial implementation, the numerous optional
 fields were not formally scored for accuracy. However,
 the same classification-based methodology can be readily
 extended to evaluate these fields if they are required for
 different use cases or applications.

E. Post-Production Monitoring

Our evaluation framework extends beyond pre-launch testing into a continuous monitoring process for the system in production. The framework is designed for a gradual production rollout. During the initial, low-volume phases, a higher proportion of conversations are manually reviewed to establish a real-world performance baseline. As the feature rolls out to a wider audience and volume increases, the methodology transitions to a scalable hybrid model. In this scaled approach, the majority of conversations are assessed by an automated evaluator (autorater) [12], an LLM prompted to score conversations against our defined policies. Concurrently, a statistically significant sample of conversations is routed to human evaluators. The results from both are continuously compared to validate and calibrate the auto-rater's performance and to identify novel issues an automated system might miss. Once the system is fully rolled out, this hybrid model serves as the permanent, steady-state monitoring strategy, ensuring continuous quality control with a focus on operational efficiency and scalability.

A comparison between the evaluation journeys of development (or pre-production phase) and post-production phase is outlined in Figure 4.

VI. RESULTS AND IMPACT

The CASE framework was deployed within the Google Pay India ecosystem, and its performance was measured against the evaluation criteria outlined in the previous section. The post-launch results presented here were collected during a partial production roll-out and, where noted, have been extrapolated to project the full-scale impact of the framework. It is important to note that the framework underwent a continuous iterative development cycle; insights discovered during the red teaming and human evaluation phases were used to progressively refine the system. The pre-production performance metrics reported here reflect the state of the system immediately prior to its production launch.

The results validate the system's effectiveness across three key areas: core agent performance, intelligence gathering, and downstream enforcement.

A. Agent Performance

- Safety: In structured pre-launch evaluations, the Conversational Agent achieved 99.9% compliance on egregious violation policies and 99.2% compliance on sensitive topic policies, exceeding standard benchmarks [4] [11]. This high level of safety was validated during the initial production launch, which recorded no egregious violations and 0.5% sensitive topic violations in real-world user interactions.
- Quality and Utility: Human evaluations confirmed that the Conversational Agent performed strongly against our quality metrics. Detailed Results are outlined in Table II.
- Information Extractor: The performance of the Information Extractor was validated on a manually reviewed sample of live production conversations. Based on a sample of nearly 3000 user conversations from the initial production roll-out, the agent achieved 83.8% accuracy on the is_user_scammed binary classification task and 75.1% accuracy on the multiclass possible_scam_mo

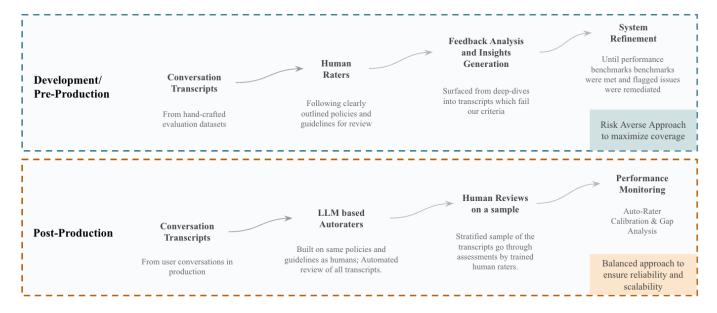


Fig. 4. Evaluation Process Flow Comparison Pre and Post Production.

classification task, when compared to the human reviewer labels.

B. Intelligence Volume and User Engagement

The high performance of the Conversational Agent enabled the collection of a new, rich intelligence source at scale, with strong user engagement. Upon deployment, the framework successfully processed a high volume of detailed user interviews, creating a novel and continuous stream of intelligence about emerging scam trends.

To assess the quality and depth of this intelligence, we analyzed user engagement with the Conversational Agent. Figure 5 illustrates the user engagement funnel by visualizing the distribution of the number of agent generated questions answered by users in each conversation. While the distribution shows a natural drop-off in user participation as the conversation length increases, it also reveals a significant cohort of highly engaged users. The data confirms that the agent was effective at maintaining a productive dialogue, with over 45% of users who initiated a session answering three or more follow-up questions, exceeding our target for what constitutes a meaningful, in-depth interview.

C. Downstream Enforcement Impact

The incremental intelligence generated by the CASE framework had a direct, measurable impact on our ability to protect users.

- Incremental Scam Detection Recall: The new signals
 when augmented with our existing enforcement mechanisms, are projected to increase the overall scam detection
 recall by around 21%.
- Enforcement Velocity: The framework significantly improved the speed of our response to new threats. The availability of structured intelligence from user reports

TABLE II
QUALITY AND UTILITY METRICS

	Qual	Quality	
	Topic Adherence	User Respect	Scam MO Elicitation
Pre-Prod	99.9%	99.8%	-
Post-Prod	99.9%	99.9%	75.3%

Distribution: Session Volumes by User Engagement

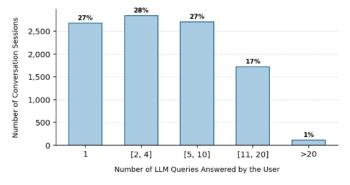


Fig. 5. Distribution of user sessions based on the number of LLM queries responded to in each session. Percentages indicate the proportion of total sessions for each bucket.

led to a significant reduction in the time-to-action against malicious actors.

The CASE framework continues to be enhanced in production, with ongoing analysis of live user conversations providing new insights for further improvements to the agents' performance and safety.

VII. DISCUSSION

Scams have become a trillion dollar industry globally and entail significant economic and human costs. This is only set to increase in the future which creates a need for innovative solutions to combat them early in the cycle of their evolution. Utilizing AI to scale collection and management of social engineering scam intelligence has the potential to help platforms to deal with them at scale and in time.

The results of our deployment demonstrate the significant potential of agentic AI frameworks in the Trust & Safety domain. In this section, we interpret our findings, discuss the broader implications and generalizability of our work, and acknowledge its current limitations.

A. Key Insights and Interpretation

Our primary insight is that augmenting traditional, transaction-based signals with detailed and structured intelligence gathered directly from user narratives is a highly effective strategy for combating social engineering scams. These scams often lack clear on-platform signals, and our CASE framework successfully created a new, rich source of data by directly and scalably engaging with the users who were targeted. This newly generated intelligence can be utilized as a strong signal in advanced scam and fraud-fighting frameworks, such as those described in [18] [23].

The dual *Conversational Agent–Information Extractor* pattern proved to be a robust and scalable architecture. By separating the real-time, user-facing conversational task from the asynchronous, backend data processing task, we were able to build a system that is both responsive to user needs and efficient in its use of resources.

Furthermore, our work underscores that for a sensitive, user-facing application like this, a comprehensive evaluation framework is not just a preliminary step but a core and necessary component of the system itself. The multi-layered safety and quality methodologies were critical in building trust in the system and ensuring a safe and useful experience for potentially distressed users.

B. Generalizability of the CASE Framework

While the immediate focus of this research is on scam detection within Google Pay India, the architectural design of the proposed LLM-based system supports broad generalization and scalability. This framework is readily adaptable for deployment across various Google Pay and other similar payments platforms where peer-to-peer (P2P) payment functionalities are operational. Preliminary experimentation is already planned for other international markets, requiring small to medium internal adjustments to accommodate regional nuances. Furthermore, the utility of this system extends beyond the Google Pay ecosystem. With appropriate modifications, the core LLM-driven interaction and interpretation engine can serve as a robust instrument for engaging with any abuserelated conversational data, facilitating direct interactions with automated agents. The inherent flexibility of the LLM system allows it to analyze and address a wide spectrum of abusive behaviors. This adaptability is largely facilitated by the strategic customization of prompts and providing domain specific examples, which ground the agent in a new context.

Crucially, this LLM-based classification system incorporates multiple layers of integrated guardrails. These guardrails not only ensure its safe and effective deployment for payment-related use cases across diverse international geographies but also significantly broaden its applicability. The system's substantial potential for addressing a multitude of other critical use cases, including, but not limited to, online harassment, hate speech, misinformation, and various forms of harmful content, positions it as a highly effective conversational agent for a wide array of customer interaction scenarios, thereby extending its utility catering to the evolving Trust and Safety challenges of the present and foreseeable future.

C. Limitations

To provide a transparent and balanced perspective, we acknowledge several limitations of our current work, which also present opportunities for future research.

The CASE framework was implemented and evaluated for English-only conversations. We note, however, that the underlying Gemini model has multilingual capabilities, including support for some Indic languages. While not pursued in this initial implementation, future work could explore leveraging this capability through careful prompt design to support a wider user base. Furthermore, the system's behavior is governed by sophisticated prompt engineering. While this approach offers great flexibility for rapid development, it may be less robust than a fully fine-tuned model for handling highly specific conversational nuances, which would require a much larger curated dataset.

Finally, our evaluation framework is strategically dependent on human reviews. While a hybrid auto-rater system is used for scaling, relying solely on automated evaluation poses a significant risk of failing to detect degradations in the autorater performance over time. Therefore, maintaining a small cohort of trained human evaluators for continuous validation and calibration is an essential, long-term component of our methodology to ensure the system's quality and safety in its steady state.

VIII. CONCLUSION

In this paper, we addressed the critical challenge of scaling intelligence gathering for social engineering scams, a domain where traditional signals are often insufficient. We designed, implemented, and evaluated CASE: a novel, dual-agent AI framework that automates the process of interviewing potential victims and structuring their narratives into actionable data.

Our real-world deployment within the Google Pay India ecosystem demonstrated that this system can safely and effectively engage with users to produce a high volume of structured intelligence, leading to direct improvements in enforcement recall and velocity. We argued that this *Conversational Agent–Information Extractor* pattern serves as a generalizable blueprint, adaptable to other high-stakes Trust &

Safety domains like misinformation and user safety reporting. While our results are promising, we also acknowledge the limitations of the current work, particularly regarding its initial English-only implementation and the challenges of scaling our evaluation methodology.

Ultimately, this research validates the strategic value of using agentic AI to augment traditional anti-abuse systems, providing a new and powerful method for understanding and combating complex, narrative-driven online harms.

IX. FUTURE WORK

- Multimodal Inputs: Future iterations could incorporate
 multimodal inputs, allowing users to provide evidence
 via audio recordings or screenshots. This would create
 a richer and more comprehensive data collection experience, capturing details that are difficult to express in text
 alone.
- Automation of Evaluation and Enforcement: A key
 focus is the continued development of our automated
 evaluators (auto-raters) for more robust and efficient
 steady-state monitoring. As the system's reliability is
 proven over time, we will also explore granting greater
 autonomy for direct enforcement actions based on highconfidence outputs from the framework.
- Ecosystem-Level Collaboration: Fighting sophisticated scams requires industry-wide collaboration. Looking beyond a single platform, we envision the CASE framework as a potential tool for ecosystem-level intelligence sharing. Anonymized, structured insights on new scam modus operandi could be shared with external enforcement agencies or a consortium of financial institutions, helping to orchestrate a more coordinated, collaborative defense against online fraud and scams.

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