# Can Large Language Models Automate the Refinement of Cellular Network Specifications?

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#### Abstract

Cellular networks serve billions of users globally, yet concerns about reliability and security persist due to weaknesses in 3GPP standards. However, traditional analysis methods, including manual inspection and automated tools, struggle with increasingly expanding cellular network specifications. This paper investigates the feasibility of Large Language Models (LLMs) for automated cellular network specification refinement. To advance it, we leverage 200,000+ approved 3GPP Change Requests (CRs) that document specification revisions, constructing a valuable dataset for domain tasks. We introduce **CR-EVAL**, a principled evaluation framework, and benchmark 16 state-of-the-art LLMs, demonstrating that top models can discover security-related weaknesses in over 127 out of 200 test cases within five trials. To bridge potential gaps, we explore LLM specialization techniques, including fine-tuning an 8B model to match or surpass advanced LLMs like GPT-40 and DeepSeek-R1. Evaluations on 30 cellular attacks identify open challenges for achieving full automation. These findings confirm that LLMs can automate the refinement of cellular network specifications and provide valuable insights to guide future research in this direction.

## **1** INTRODUCTION

Cellular networks connect over five billion users worldwide, relying on extensive 3GPP specifications to ensure functionality and reliability [1, 2]. However, these specifications have long been known to suffer from design flaws and underspecification, making them susceptible to security threats such as DoS attacks and user tracking [3-5]. Strengthening the reliability of cellular networks requires proactive specification refinement, a continuous process of identifying and treating potential weaknesses to enhance standards [6, 7]. While manual weakness analysis [4, 8, 9] has traditionally been effective, it is increasingly infeasible due to the escalating complexity of cellular systems and the rapid expansion of specification documents<sup>1</sup>. Automated approaches, such as formal verification[10-12] and NLP [13-15], offer valuable insights but still require significant expert involvement, lack scalability, and struggle to adapt to evolving specifications. More critically, they focus primarily on detecting weaknesses, which is only the first step in refinement. Effective specification refinement extends beyond mere detection—it requires scalable, automated approaches to systematically address and resolve weaknesses within evolving standards.

Recent advancement of Large Language Models (LLMs) [16– 18] has led to their remarkable applications, from solving complex computer tasks [19] to accelerating scientific discoveries [20]. In this context, we investigate *automated cellular specification refinement*, a previously unthinkable yet now plausible concept with LLMs. Beyond their emergent abilities [21], several key observations suggest they can: 1) Advanced natural language processing abilities [22–24], strong knowledge retention [25–27], and reasoning capabilities [28– 30] enable interaction with intricate cellular specifications; 2) Scalability via in-context learning and fine-tuning [23, 31, 32] allows adaptation to evolving standards. 3) Early research has demonstrated LLMs' potential in related tasks, such as identifying inconsistencies in specifications [15] and extracting security-relevant clauses [33].

Despite their potential, refining cellular specifications presents unique challenges, including understanding obscure technical jargon, systematically analyzing lengthy and complex specification fragments to identify or modify weaknesses, and inferring implicit background knowledge not explicitly stated in the context. These complexities, often beyond those listed, may not be fully captured by LLMs during their general-purpose training. To understand this gap, we focus on the **security aspects of cellular specifications** and critically investigate three research questions:

- **RQ1**: How well can modern LLMs perform the task of refining cellular specifications?
- **RQ2**: How can general-purpose LLMs be better adapted to the domain-specific tasks?
- **RQ3**: What challenges remain before LLMs can be reliably deployed for refining active specifications?

We first address the challenge of domain data scarcity, which poses a significant constraint on the application of data-driven LLMs. Unlike the well-established CVE database for software security, there is currently no widely recognized dataset dedicated to cellular specification refinement. The GSMA's CVD program [34] hosts only limited known

<sup>&</sup>lt;sup>1</sup>3GPP standards expanded from 59,258 pages in Release 8 (LTE) to 117,951 pages in Release 15 (5G) and 195,752 pages in Release 18 as of March 2025.

vulnerabilities with minimal details, while disclosed vulnerabilities are typically reported in academic literature case by case. To address this, we leverage 200,000+ approved Change Requests (CRs) from 3GPP standards, which document specification revisions along with expert comments. Our key insight is that **revisions correcting prior clauses inherently reveal weaknesses in earlier specification versions**, tightly aligning with our goal of refining cellular specifications. We apply LLM-based semantic filters to identify the CRs pertinent to specification weaknesses, especially those security-related ones. This strategic use of CRs forms the foundation for our answering the research questions.

To systematically evaluate LLMs' domain-specific capabilities (RQ1), we propose CR-EVAL, a principled evaluation framework for cellular specification refinement. Leveraging CRs, we formalize the abstract specification refinement goal into three LLM-tractable sub-tasks: fill-cr (uncovering potential weaknesses in specifications), outline-revision (proposing necessary revisions given weaknesses), and diffanalysis (ensuring revisions address identified weaknesses). Our benchmark comprises 200 high-quality security-related test cases. Using LLM-as-a-Judge [35], validated via human studies, we comprehensively evaluate ten open-source LLMs, four proprietary models, and additionally three SOTA reasoning models. CR-EVAL effectively differentiates the domainspecific abilities of these models. Even in the hardest yet imperative sub-task, fill-cr, the state-of-the-art reasoning model GPT-o3-mini can discover weaknesses in over 127 out of 200 test cases within five trials. Meanwhile, a metaanalysis of model release timelines further indicates that newer LLMs exhibit progressively stronger domain-specific capabilities. These findings suggest that LLMs hold promise for automating cellular specification refinement.

To address how general-purpose LLMs can be effectively adapted for refining cellular specifications (RQ2), we explore two approaches: domain-adaptive fine-tuning and prompting. We highlight our successful fine-tuning of open-source LLMs using a three-stage training recipe-continual pretraining, fine-tuning, and preference enhancement-coupled with our novel rationale augmentation technique. The resulting domain-specialized 8B LLM achieves remarkable improvements, nearly tripling the performance of its base counterpart (LLaMA-3.1-8B) in the diff-analysis task and even surpassing advanced models like GPT-40 and DeepSeek-V3 in the fill-cr task. Various experiments are conducted to explore the recipe, including its scalability and extensibility to more advanced base models. However, we also pinpoint that general-purpose LLMs are not off-the-shelf solutions for refining active cellular specifications. For RO3, we study our domain-specialized LLM's detection performance on 30 existing cellular attacks. Although it successfully identifies all

SpecNumber	CRNum	Re	VNum Current version			x.y.z
Title	A desc	cripti	ve title	ve title Date Written d		
Categorgy	e.g., ``F"	-> C	orrection Release e.g., Rel-1			
Reason for change			Filled in free text			
Summary of ch	ange		Filled in free text			text
Consequences	if not appro	ved	Filled in free text			
Original st	Original statements Track changes Revised statement			statements		

Figure 1: Structure of 3GPP Change Request coversheet (see Tables 12 and 13 in Appendix G for an example).

cases, the study reveals key challenges with LLMs in inspecting active specifications, including the need for additional calibration mechanisms to ensure reliability and implicit reliance on the completeness of analyzed clauses.

As the emerging 6G technology integrates additional features [36, 37], it inevitably drives the evolution of 3GPP standards and raises security concerns about new specifications. Our study demonstrates that LLMs present a timely and effective opportunity for automated cellular specification refinement. Our main contributions are three-fold:

- New insight. We pioneer LLM adoption for cellular specification refinement and strategically leverage CRs as domain data to form the foundation of a systematic study.
- **Principled domain-specific evaluation.** We establish an evaluation framework, **CR-EVAL**, which enables the community to understand the domain-specific abilities of modern LLMs. Using **CR-EVAL**, we conduct an extensive measurement across 16 representative frontier LLMs.
- Towards domain-specialized LLMs. We explore avenues for domain specialization, including an effective fine-tuning recipe. We test on known cellular attacks to identify areas for further improvements in steering LLMs.

## 2 BACKGROUND

#### 2.1 Change Request

Cellular specifications, standardized by the 3rd Generation Partnership Project (3GPP), define the operation of cellular network systems, ensuring interoperability across vendors. As cellular networks evolve from 2G through 5G and beyond, specifications undergo updates through a structured process involving *technical specification groups* (*TSGs*) and industry stakeholders. To manage these updates, 3GPP employs a Change Request (CR) procedure to revise specifications for various purposes, including keeping consistent with a change in an earlier release (*A*), addition of feature (*B*), functional modification of feature (*C*), editorial modification (*D*), and correction (*F*) [38]. 3GPP individual members (e.g., Qualcomm, Apple) raise CRs using a template coversheet [39]. As illustrated in Figure 1, each CR has key blocks, including meta-information, expert rationales that explain the necessity of revisions, and the proposed clause modifications. The modifications are tracked by the word processor software's "revision mode" and surrounded by proposer-decided context statements. The **approved** CRs are implemented in newer versions, which are used in this work.

#### 2.2 Specification Weakness

Cellular specifications suffer from weaknesses, ranging from minor ambiguities and undefined behaviors to fundamental design flaws. While these weaknesses may go unnoticed under typical conditions, they can become threatening in specific scenarios. A large number of CRs aim to address weaknesses in the specifications, motivating our research in this work. Broadly speaking, these weaknesses can lead to various negative consequences, including performance degradation, interoperability failures, and security vulnerabilities. In this work, we focus primarily on those weaknesses that pose security risks, among which the severest ones may be exploited by malicious entities to disrupt normal service operations. While we focus on specification-level weaknesses, their implications are far-reaching. Design flaws within specifications lead to vulnerabilities in compliant implementations and thus propagate through the whole cellular network system. Issues like under-specification lead to implementations and configurations that fail to meet essential requirements. We provide a survey of common specification weaknesses and, if exploitable, their associated attack vectors in Appendix H. However, it would be unfair to place blame solely on specification drafters, particularly when observing the immense volume and complexity of cellular specifications. Current refinement practices depend on human experts to identify weaknesses and propose CRs, a labor-intensive approach that lacks a systematic evaluation framework. These challenges highlight the critical need for automated tools capable of refining cellular specifications.

#### 2.3 Large Language Model

We identify LLMs as an opportunity for automated cellular specification refinement. Modern LLMs (e.g., GPT [24] and LLaMA [40]) utilize the decoder-only Transformer architecture [41] and are trained on the next-token-prediction task [24] formulated as:

$$P(x_1, \cdots, x_N) = \prod_{i=1}^N P(x_i | x_1, \cdots, x_{i-1}),$$
(1)

where  $P(x_i|x_1, \dots, x_{i-1})$  represents the probability of predicting token  $x_i$  given the preceding sequence  $x_1, \dots, x_{i-1}$ , with tokens typically operating at the subword level. During inference, LLMs can be used for left-to-right text completion or, more frequently, responding to user queries provided as prompts. A standard prompt structure [42], compatible with most mainstream LLMs, consists of system instruction and user message. The LLM generates an appropriate response to the given input. Typically, users can resort to prompting in a zero/few-shot manner, articulating demands precisely [27] and providing demonstrations [43]. However, relying on these prompting techniques suffers inherent limitations, for example, performance bottleneck and poor scalability [44, 45]. To obtain better performance, fine-tuning updating model parameters for specific tasks—provides a promising avenue [46, 47].

## 3 SPECIFICATION REFINEMENT GUIDED BY CHANGE REQUESTS

#### 3.1 Key Insight

Effective application of LLMs in domain tasks requires highquality domain data, whether for evaluation or training purposes. However, large-scale human labeling for our task of specification refining is largely impractical due to the high demand for expertise. To address this, we propose to utilize CRs as valuable data sources. Specifically, CRs that correct existing statements are especially suited for our purpose as they inherently reflect specification weaknesses in earlier versions. Categories such as *F* (correction), *D* (editorial modification), and potentially others, encompass various specification weaknesses discussed in this work<sup>2</sup>. Key elements of our focus include *expert rationales R* (*reason for change R<sub>r</sub>* and *consequences if not revised R<sub>c</sub>*<sup>3</sup>), summary of change S'<sub>rev</sub>, original statements S<sub>oria</sub>, and revised statements S<sub>rev</sub>.

#### 3.2 Dataset Curation

Before diving into **RQ**s, we detail our curation of four domain datasets used for different purposes, illustrating the CR processing pipeline in Figure 2. These datasets include:

- **CR-EVAL**: A benchmark of 200 security-related CRs for evaluating domain-specific capabilities.
- **CR-INSTRUCT**: All CR-converted data for fine-tuning open-source LLMs on domain tasks.
- **CR-SEC**: Security-related CR data for enhancing LLMs' focus on security weaknesses.
- CR-MIX: A dataset for domain-specific continual training.

#### 3.2.1 CR-EVAL

**Collection.** We first query the official database<sup>4</sup> to obtain a complete list of CRs, filtering only those approved by *TSGs* to

<sup>&</sup>lt;sup>2</sup>To maximize the usage of constrained data, we operationally sustain all valid CRs and employ semantic filtering to identify those security-related ones and those benefiting our domain training, as detailed in Section 3.2. <sup>3</sup>In the following, it is equivalently used as "Consequences if not revised". <sup>4</sup>https://www.3gpp.org/ftp/Information/Databases/



Figure 2: Overview of the data-processing pipeline with change requests.

ensure content reliability. A parallel crawler queries the CR search service<sup>5</sup>, retrieves FTP paths, and downloads raw CR files from the 3GPP FTP server<sup>6</sup>, yielding 205,374 valid CRs. Revisions within *doc/docx* files are tracked via Office Word's *Track Changes* mode. Despite format evolution, 3GPP has maintained standardized CR coversheets. We implemented a parsing script to extract key elements, discarding CRs that failed to process. This resulted in 189,904 structured CRs.

Annotating security relevance. We implement an LLMbased process to annotate the security relevance of CRs based on expert rationales *R*. Using LLaMA-3.1-70B with the instruction in Prompt 3, this approach identifies 4,869 securityrelated CRs. To ensure precision, we cross-reference these annotations with security-related CRs documented by [48], yielding 529 intersecting cases. This is followed by a manual verification as a small portion of CRs prove unsuitable as task instances. For example, CRs proposing entirely new statements have empty original statements *S*<sub>orig</sub>, rendering them invalid for the fill-cr task. Ultimately, we curate a set of 200<sup>7</sup> high-quality security-related CRs for **CR-EVAL**.

#### 3.2.2 CR-INSTRUCT and CR-SEC

After obtaining security-related CRs for evaluation, we have 185,035 security-unrelated CRs and 4,669 security-related CRs for the training set. We convert all the CRs into task instances based on task formatting templates, which we introduce in Section 4.2.

**Decontamination.** To precisely reflect the benefits of domainadaptive fine-tuning, we try our best to minimize leakage of test cases in **CR-EVAL**. Following established practices [16, 27, 43], we employ a rigorous and proactive decontamination strategy at the level of task instances. We exclude training samples that exhibit 20-gram overlaps with any test case answers, where a gram is defined as a lowercase, whitespace delimited word. This approach prevents both direct test case leakage and the occurrence of suspicious task instances. Furthermore, we remove training samples associated with existing attacks discussed in Section 6 using the same 20-gram matching criterion. From this point on, the task instances of **CR-EVAL** are frozen and isolated.

**Cleaning.** Invalid task instances, as discussed in processing **CR-EVAL**, are also present in the training set. To address this, we down-sample task instances through a two-step filtering process. First, we exclude invalid instances based on heuristic rules (e.g., extremely short queries and missing task placeholders). Second, inspired by [18, 50, 51], we implement another semantic filtering to remove low-quality samples and those irrelevant to specification weaknesses. We use LLaMA-3.1-70B to evaluate their educational value for specification analysis, following Prompt 4. Instances deemed to lack educational value are removed, and the remaining samples constitute our **CR-INSTRUCT** dataset. We clone security-related samples to create **CR-SEC**, comprising three subsets, each aligned with a specific domain task.

#### 3.2.3 CR-міх

We incorporate **3GPP standards** to enhance the LLM's comprehension of cellular networks. Concretely, we utilize the *python-docx* library to extract the main body of 2,445 specifications from the TSpec-LLM dataset [52]. These specifications, spanning the 21 to 55 series and ranging from Release 8 to Release 19, cover essential aspects of cellular networks. We retain tables and figure captions while omitting figures due to intractability. We also borrow a generaldomain reasoning enhancement dataset, the **CoT collection dataset** [53]. To mitigate catastrophic forgetting [54], we include the **Wikipedia dataset** [55] and the **ArXiv split** from the RedPajama dataset [56]. We filter these general-domain datasets using keyword-based heuristics to identify documents specifically relevant to cellular networks and security, ensuring focused domain adaptation.

## 4 BENCHMARKING LLMS FOR CELLULAR SPECIFICATION REFINEMENT

In this section, we introduce our evaluation framework, **CR**-**EVAL**. We present high-level design principles of our domainspecific evaluation (Section 4.1), formulate specification refinement as LLM-tractable tasks (Section 4.2), establish a benchmark (Section 4.3), and explain our LLM-as-a-Judge metric (Section 4.4). After conceptual explanations, we delve into the setup and results of our measurements.

<sup>&</sup>lt;sup>5</sup>http://netovate.com/cr-search/

<sup>&</sup>lt;sup>6</sup>https://www.3gpp.org/ftp

<sup>&</sup>lt;sup>7</sup>The success of compact benchmarks like HumanEval [49] (164 examples) and GPQA [25] (448 examples) demonstrates that small benchmarks can be effective, with faster and cheaper evaluation as an additional advantage.

#### 4.1 Design Principles of CR-EVAL

Ideally, we request that **CR-EVAL** satisfies the following criteria before providing a reliable evaluation:

- **Practical utility:** The evaluation should emphasize realworld utility by directly assessing LLMs' performance in scenarios that mirror actual specification refinement workflows in production environments.
- Certifiable correctness: Each involved test case should incorporate a reference answer with the confirmation of human experts to ensure reliability.
- Security focus: While weaknesses may incur various negative consequences like operational inefficiency, this evaluation focuses on security-related ones.
- Automatic evaluation: The evaluation should be highly accessible and ensure a high standard of evaluation quality. Thus, an effective automatic metric is in high demand.

## 4.2 Formalizing Specification Refinement into LLM-Tractable Tasks

In response to **practical utility**, we devise three domain subtasks that mirror the real-world process of refining cellular specifications, as illustrated in Figure 3.

- Fill CR (S<sub>orig</sub> → R): This task positions LLMs as expert reviewers, requiring them to discover potential weaknesses in given statements. This task is relatively challenging as models receive minimal contextual information.
- Outline Revision  $(S_{orig} + R \rightarrow S'_{rev})$ : Once specification weaknesses are identified, the next step is to revise the corresponding clauses. To simplify the task, we require the model to outline a revision plan.
- Diff Analysis ( $|S_{rev} S_{orig}| \rightarrow R$ ): This task serves as a posterior verification step, supporting real-world scenarios where editors assess whether revisions exactly imply the identified weaknesses.

Our study emphasizes scenarios where LLMs operate in a zero-shot setting, meaning that no examples appear in prompts. LLMs receive a general task instruction without any case-dependent inductive information (see Prompt 1 of the fill-cr task), honestly reflecting their intrinsic ability to handle the given task instance with minimal human intervention. This aligns with our pursuit of a fully automated pipeline. We use pre-defined task templates to transform CRs into task instances, each comprising a well-documented instruction, a structured test case, and a reference answer. An illustrative example is provided in Figure 3.

#### 4.3 Benchmark Establishment

The use of CRs, which expose real-world specification weaknesses in 3GPP standards, aligns with our requirement for



Figure 3: Illustration of task formulation on CR-EVAL.

certifiable correctness. The semantic categorization operation in Section 3.2.1 ensures adherence to the security focus principle. Examples of the fill-cr task are provided in Examples 1 to 3. Qualitatively, the test cases in CR-EVAL feature well-structured, focused specification clauses rich in cellular network terminology (e.g., AUTS, VLR/SGS, and synchroniza*tion failure message*). To assess the representativeness of the 200 selected test cases, we conduct a comprehensive structural analysis. The benchmark exhibits extensive release and specification coverage, progressive difficulty levels, and longcontext complexity. Further details and statistical results are in Appendix E. CR-EVAL serves as a holistic assessment of LLM capabilities, encompassing extensive domain knowledge, systematic reasoning, precise instruction following, effective long-context processing, a deep understanding of cellular specification weaknesses, and acute awareness of security-related vulnerabilities.

#### 4.4 Automatic Metric: LLM-as-a-Judge

We require an effective metric to evaluate the correctness of LLM responses. Although we have reference answers derived from CRs, conventional string-matching-based metrics like ROUGE or BLEU have been widely reported to correlate poorly with human evaluation in text generation tasks [57–59]. Recent research has shown promising results in utilizing GPT models to assess LLM outputs [35, 51, 60], a paradigm

termed LLM-as-a-Judge. This paradigm has been successfully applied to security tasks [61, 62], including evaluating LLMs' reasoning about code vulnerabilities. We adopt LLM-as-a-Judge to enable an effective **automatic evaluation**.

Following prior work [35, 61, 62], we use a referenceaware, point-wise LLM-as-a-Judge setting, where each LLMgenerated answer is scored by comparing it to the reference answer provided at the start of the context. As the reference answers are typically self-contained, we omit the original questions from the context. LLM-as-a-Judge evaluates responses using a 5-point Likert scale [63], where the positive two points indicate acceptance, allowing differentiation between varying degrees of acceptance. The detailed prompt template is shown in Prompt 5, with minor task-specific variations. We instantiate the LLM-as-a-Judge with GPT-40 [17], the most advanced LLM at the time of writing. For consistent scoring, we prompt LLM-as-a-Judge to directly give back the scoring and greedily decode with temperature as 0.

We validate the reliability of our final LLM-as-a-Judge setup through a human study, involving eight participants, all PhD students majoring in network security. The study includes two rounds: an alignment test and a judgment approval test. Detailed settings and results are provided in Appendix F. Key findings include:

- Availability: Manual checking is extremely labor-intensive, underscoring the need for efficient automatic methods. LLM-as-a-Judge is rather fast and accessible.
- **Conformity:** Human participants frequently disagree on accepting LLM responses while LLM-as-a-Judge typically yields agreements with the majority of participants.
- **Reliability:** Although human participants may have distinct judgment criteria, most LLM-as-a-Judge's evaluations are acceptable for them after calibration.

#### 4.5 Evaluation Setup

**Models.** Our evaluation captures the currently highest achievable performance of LLMs within three categories: 1) mediumsized LLMs with 7–14 billion parameters, 2) advanced LLMs, including giant-sized and closed-source models, and 3) SOTA reasoning models. Table 6 details the models.

**Metrics.** We evaluate LLM performance on **CR-EVAL** using pass@k [49]. The pass@k metric measures the success rate by allowing k independent attempts and considering the best result among the k completions. Given  $n \ge k$  completions, where  $c \le n$  completions are correct (i.e., accepted by the LLM-as-a-Judge), the unbiased pass@k score is computed as: pass@k :=  $1 - \frac{\binom{n_k c}{k}}{\binom{n}{k}}$  Specifically, we report the cumulative pass@k score over all test cases, with a maximum of 200. Following established practices [49, 64, 65], we set the sampling temperature to 0.8 and top-p to 0.95. Balancing reliability and cost, we sample n = 10 completions.

#### 4.6 Evaluation Results

General performance. As shown in Table 1, the three tasks vary in difficulty, from the easiest outline-revision to the hardest fill-cr. The outline-revision task, primarily a summarization task, is well-handled by most models, with some smaller models (Qwen-2.5-7B, GLM-4-9B) even outperforming closed-source counterparts (e.g., GPT-40). In contrast, the diff-analysis task reveals a significant gap between mediumsized and advanced LLMs, highlighting the challenge of identifying implicit specification weaknesses even when given structured version comparison. The fill-cr task emerges as an extremely challenging task, with even advanced models like GPT-40 achieving limited success. Recent reasoning models (GPT-o3-mini, Gemini-2.0-flash-thinking) demonstrate superior performance, particularly in the diff-analysis and fill-cr tasks. This suggests that reasoning-optimized LLMs hold a significant advantage in tasks requiring deep contextual understanding and structured reasoning.

**Propagation of LLM improvements to domain tasks.** A meta-analysis of LLM release timelines and their performance in **CR-EVAL** (e.g., pass@5 scores in diff-analysis across progressively released GPT models) reveals a clear trend: Improvements in general-purpose LLMs indeed transfer to domain-specific tasks. This highlights their growing potential in tackling tasks of mobile systems, at least for refining cellular specifications as explored in this study.

**Failures of certain well-recognized LLMs.** Meanwhile, we also notice that certain widely recognized LLMs, e.g., DeepSeek-R1 and Claude-3.5-Sonnet, perform relatively poorly in the fill-cr task. Another intriguing phenomenon is an inverse scaling [66] observed in the Qwen-2.5 family, where the largest 72B model performs the worst in the fill-cr task compared to its smaller-sized cousins. These underscores *the potential gap between general-purpose LLMs and domain-specific task requirements* while emphasizing the importance of **CR-EVAL** in helping practitioners identify models with the strongest domain-specific capabilities.

**Domain-specialized LLM.** While we defer a detailed discussion of our efforts for LLM domain specialization to the next section, we report in Table 1 the performance of our domain-specialized LLM, **CRITIC**-LLaMA-3.1-8B<sup>8</sup>, which is obtained by fine-tuning LLaMA-3.1-8B on domain datasets. **CRITIC**-LLaMA-3.1-8B nearly triples pass@5 scores of its base model in the diff-analysis and fill-cr tasks. Notably, it outperforms its **contemporary** proprietary models like GPT-40, solving almost twice as many fill-cr test cases. Despite these advancements, we have to acknowledge that state-of-the-art LLMS, particularly the most recent reasoning models, continue to improve at an unprecedented pace. At the time of writing, the

<sup>&</sup>lt;sup>8</sup>We name it **CRITIC**, for the model can act as a **critic** for cellular specifications, and its power can be attributed to Change **R**equests.

Model			<b>Fill CR</b> $S_{orig} \rightarrow R$			<b>line Revision</b> $_{ig} + R \rightarrow S'_{rev}$		<b>Diff Analysis</b> $ S_{rev} - S_{orig}  \rightarrow R$		
		pass@1	pass@3	pass@5	pass@1	pass@3	pass@5	pass@1	pass@3	pass@5
			Med	ium-sized	l LLMs					
GLM-4-9B	2024/06	14.5	23.3	27.8	172.7	188.3	191.0	28.7	50.1	61.3
Mistral-7B-v0.3	2024/06	9.1	16.1	19.8	163.4	182.5	186.5	26.0	44.9	54.9
InternLM-2.5-7B	2024/07	12.9	25.9	33.5	158.9	185.3	190.8	21.9	42.4	54.7
Qwen-2.5-7B	2024/09	13.9	24.9	29.9	175.5	189.3	191.6	32.0	55.7	68.2
Qwen-2.5-14B	2024/09	17.6	27.4	30.8	183.6	193.9	196.0	85.8	119.1	130.1
LLaMA-3.1-8B	2024/07	6.1	13.2	18.1	126.4	164.2	174.0	27.4	48.3	59.8
CRITIC-LLaMA-3.1-8B	Ours	27.2	42.3	57.8	160.5	182.4	186.7	106.4	137.9	148.4
		Adva	nced LLMs	s (giant-si	zed/closed	l-source)				
LLaMA-3.1-70B	2024/07	7.4	13.4	16.4	144.4	168.9	174.8	40.5	64.3	76.1
Qwen-2.5-32B	2024/09	18.0	28.8	33.7	183.2	190.6	192.6	77.2	106.7	116.6
Qwen-2.5-72B	2024/09	15.2	22.4	25.7	186.2	195.5	197.7	79.4	105.5	114.1
DeepSeek-V3	2024/12	8.4	13.8	16.7	188.4	195.1	197.0	95.6	121.5	128.8
GPT-3.5-turbo	2024/01	11.2	20.1	24.2	146.2	166.3	170.7	42.2	63.6	71.7
GPT-40-mini	2024/07	18.2	27.5	31.2	173.0	182.3	183.5	52.4	74.0	81.8
GPT-40	2024/08	16.0	25.3	29.2	176.8	186.3	188.0	88.0	113.5	122.6
Claude-3.5-Sonnet	2024/06	9.5	16.2	19.3	172.6	182.5	184.9	77.7	106.3	118.1
			Rea	asoning m	nodels					
DeepSeek-R1	2025/01	9.2	15.8	19.4	192.0	197.2	198.3	119.2	143.7	151.3
GPT-o3-mini	2025/01	89.0	116.6	127.9	186.8	192.5	194.0	132.5	154.4	162.0
Gemini-2.0-flash-thinking	2025/01	79.0	114.8	127.3	166.8	177.6	179.2	139.8	164.0	169.5

Table 1: LLMs' performance in CR-EVAL, highlighting the best results for reasoning and non-reasoning models.

most advanced reasoning models like GPT-o3-mini have surpassed our domain-specialized model, which was trained on earlier, medium-sized foundation models. We further demonstrate in Section 5.1.4 that fine-tuning on domain-specific data can be effectively extended to more powerful foundation models, demonstrating its future utility. Overall, these results highlight the impact of domain-specific fine-tuning in bridging the gap between general LLM capabilities and domain-specific requirements.

**Takeaway.** LLMs demonstrate varying degrees of abilities in the specification refinement tasks. Specifically, newer models with stronger general-domain abilities usually lead to stronger domain-specific abilities as well. **CR-EVAL** enables the practitioners to understand which LLM is better.

## 5 DOMAIN-SPECIALIZED LLMS FOR SPECIFICATION REFINEMENT

We explore strategies to adapt general-purpose LLMs for domain specialization, focusing on two key methods: domainadaptive fine-tuning and lightweight prompting.

#### 5.1 Method 1: Fine-Tuning

Building on previous successful practices in developing specialized LLMs in other domains [26, 67, 68], we resort to fine-tuning to achieve domain specialization, with its advantages explained in Appendix A. We propose a three-stage expertise training framework that mirrors human expert development. We also propose a necessary data augmentation operation (rationale augmentation in Section 5.1.2) for converting CRs into high-quality training data.

#### 5.1.1 Three-stage training framework

This framework, as illustrated in Figure 4, cultivates domain knowledge, problem-solving abilities for refining cellular specifications, and sensitivity to security-related weaknesses. **Stage 1: Domain-Adaptive Continual Training (DACT).** LLMs typically undergo pre-training on massive text corpora, through which they develop general-purpose capabilities rather than become adept in specific domains. Domain-Adaptive Continual Training (DACT) refines an LLM's learned distribution through incremental training on domain data [46, 69, 70]. As we cannot assume that foundation models have adequately acquired domain knowledge during their initial pre-training, we incorporate a DACT stage, which shares the same paradigm with pre-training as follows:

$$\mathcal{L}_{\text{DACT}}(\theta) = -\mathbb{E}_{x \sim \mathcal{D}_{\text{DACT}}}\left[\sum_{i=1}^{n} \log p_{\theta}(x_i | x_{< i})\right], \quad (2)$$



Figure 4: High-level overview of the training framework for domain specialization.

where x is a sequence from the domain dataset  $\mathcal{D}_{\text{DACT}}$ ,  $x_i$  is its *i*-th token,  $x_{<i}$  represents preceding tokens, and  $p_{\theta}$  is the probability distribution modeled by parameters  $\theta$ . This objective minimizes the expected negative log-likelihood of predicting the next token given the context. We instantiate  $\mathcal{D}_{\text{DACT}}$  with **CR-MIX** introduced in Section 3.2.

**Stage 2: Task-Specialized Tuning (TST).** After the continual pre-training stage, we fine-tune LLMs in domain tasks during the Task-Specialized Tuning (TST) stage. This stage is designed to help LLM master the basic ability to analyze cellular specifications. Fine-tuning during this stage utilizes our **CR-INSTRUCT** dataset, which encompasses all CR data, and relies on labeled samples:

$$\mathcal{L}_{\text{TST}}(\theta) = -\mathbb{E}_{(x,y)\sim\mathcal{D}_{\text{TST}}}\left[\sum_{t=1}^{T_y}\log p_{\theta}(y_t \mid x, y_{< t})\right], \quad (3)$$

where  $\mathcal{D}_{\text{TST}}$  represents the **CR-INSTRUCT** dataset. The model is trained to minimize the conditional negative log-likelihood of the target output y given the input x, as determined by its parameterized distribution  $p_{\theta}$ . The **CR-INSTRUCT** dataset incorporates diverse task formulations, enabling the model to learn each CR through multiple contexts. This multi-task learning paradigm encourages the model to generalize reasoning skills across the three target tasks.

**Stage 3: Security-Centric Tuning (SCT).** We expect the model to analyze specifications from the security perspective. Inspired by [71], we frame security-centric analysis as a style-controlled text generation problem. This approach leverages security-related CRs, which reveal real-world security issues, to shape security-centric analysis, enhancing operational

feasibility. The objective for the SCT stage is defined as:

$$\mathcal{L}_{\text{SCT}}(\delta\theta) = -\mathbb{E}_{(x,y)\sim\mathcal{D}_{\text{SCT}}} \left| \sum_{t=1}^{I_y} \log p_{\theta+\delta\theta}(y_t \mid x, y_{< t}) \right|, \quad (4)$$

where  $\mathcal{D}_{SCT}$  denotes security-related task instances of the target task from **CR-sec**. The parameter  $\delta\theta$  corresponds to the additional adapter implemented using Low-Rank Adapter (LoRA) [72], which allows for parameter-efficient adaptation and preserves most of the model's original capabilities[73].

#### 5.1.2 Rationale augmentation

Manual inspection reveals a limitation of training samples derived from CRs: expert rationales R in CRs are mainly concise declarative statements, rather than detailed reasoning (see Figure 5 for an example). This gap hinders effective LLM training, as insufficient rationales lead models to memorize answers instead of developing problem-solving skills [47, 53, 74]. This impact is pronounced in **CR-EVAL** tasks (cf. Section 5.1.4), where fine-tuning directly on CR-converted data alone degrades performance.

To address this issue, we introduce rationale augmentation, generating refined, rationale-rich responses for LLM training. Following prior work on training with rationales [30, 53, 75], we adopt a backward-rationalization strategy: A rationale generator  $P_0$  processes a complete task instance—comprising task instruction T, test case Q, and original answer A—and applies backward reasoning to produce a rationale-augmented answer  $A^*$ , following augmentation principles C, as formulated by  $A^* \leftarrow P_0(T \mid Q \mid A; C)$ . We enforce pedagogically oriented principles C to enhance instructional effectiveness while preserving answer consistency (cf. Prompt 2). This

#### >>> REASON FOR CHANGE

The <selected-user-profile-index> element requires correction

#### >>> SUMMARY OF CHANGE

>>> REASON FOR CHANGE

The element is defined in the <anyExt> element of the <mcvideo-Params> element.

>>> CONSEQUENCES IF NOT REVISED

The spec is inconsistent because based on the current definition the element cannot be security protected.



The <selected-user-profile-index> element requires correction due to its current placement within the <anyExt> element of the <mcvideo-Params> structure. This positioning can lead to ambiguity in the security handling of this element, particularly concerning its confidentiality and integrity protection. Elements intended to carry sensitive information should be clearly defined and not buried within less specific structures like <anyExt>, which may not be adequately safeguarded under the current specifications.

#### >>> SUMMARY OF CHANGE

The <selected-user-profile-index> element should be explicitly defined as a direct child of the <mcvideo-Params> element, rather than being nested within <anyExt>.

#### >>> CONSEQUENCES IF NOT REVISED

If the proposed changes are not made, the specification will remain inconsistent and potentially insecure...

#### Figure 5: Example of rationale augmentation.

improves domain data quality, aligning CR-based training with the high reasoning demands of specification refinement. Moreover, rationale augmentation introduces a new scalability dimension: Multiple distinct rationales can support the same correct answer. By sampling rationale generators with high temperatures, we generate diverse rationale-augmented answers per task instance, maximizing the value of each CR.

#### 5.1.3 Implementation

**Rationale augmentation.** We employ LLaMA-3.1-70B and GPT-40 for rationale augmentation of **CR-INSTRUCT** and **CR-SEC**, respectively. We prompt the rationale generators with a 0.8 temperature to encourage rationale diversity and a top-p of 0.95 to minimize sampling noise. Our default rationale number per instance is three for TST and five for SCT. Note that the reference answers on **CR-EVAL** are not augmented as we wish to align with human experts completely. **Training configurations.** Constrained by resource limit, our experiments are primarily on LLaMA-3.1-8B [18], the most powerful 8B model at the inception of this project. We fine-tune all parameters for DACT and TST while integrating LoRA adapters[72] (r = 256,  $\alpha = 512$ ) for SCT. We provide our exhaustive training choices in Appendix C, including learning rates and batch sizes.

**Compute infrastructure.** All experiments were conducted on a server running Ubuntu 20.04.5 LTS operating system. The machine is equipped with an Intel Xeon Platinum 8468V processor (96 cores, 192 threads), 2 TB of system memory, and 8 NVIDIA H800 GPUs with 80 GB of VRAM each.

**Software.** Our project is implemented based on Python 3.12, CUDA 11.8, PyTorch 2.4.0, and HuggingFace's transformer library. To accelerate training, we achieve data parallel through DeepSpeed [76]: we adopt ZeRO stage-2 with a world size of 4 for 8B models and stage-3 with a world size



Figure 6: Extensibility to advanced base models.



of 8 for 70B models. We use Flash-Attention 2 [77] to improve throughput and use gradient checkpointing to reduce memory requirements. For evaluation, we deploy inference endpoints using vLLM [78]. The entire project consumes around 12,800 lines of code, decomposed in Table 7.

#### 5.1.4 Performance analysis of fine-tuning

While the excellent performance of the resulting model has been reported in Section 4.6, We explore the recipe's extensibility to advanced base models and evaluate the effectiveness of rationale augmentation in this section.

**Extensibility to advanced base models.** We extend the domain-adaptive fine-tuning to closed-sourced GPT-4o-mini<sup>9</sup> and the LLaMA-3.1-70B with a larger parameter count, using the **CR-sec**. As shown in Figure 6, domain-adaptive fine-tuning yields performance improvements across all models. Interestingly, LLaMA-3.1-8B and LLaMA-3.1-70B converge to similar levels, indicating that domain data quality, rather than model size, is the primary bottleneck in certain cases. Meanwhile, GPT-4o-mini consistently maintains superior performance, particularly on the fill-cr task. This suggests that applying our training methodology to advanced foundation models could further specialize LLMs.

**Scaling along rationale**<sup>10</sup> **dimension.** Beyond increasing model size and training data, rationale augmentation offers

<sup>&</sup>lt;sup>9</sup>Fine-tuning GPT models is officially accessible via https://platform.openai. com/finetune. Considering cost affordability, we select GPT-4o-mini as a representative example of closed-source models.

<sup>&</sup>lt;sup>10</sup>For clarity, we use the term "rationales" as a shorthand to refer to those distinct rationale-augmented answers in the following contents.

another scaling dimension to enhance performance, enabling better utilization of constrained domain data. We evaluate this approach using **CR-sec** in the diff-analysis task with various rationale generators. The landscape of scaling up rationales is depicted in Figure 7. **Training without rationales degrades performance, confirming that raw task instances offer limited learning value,** underscoring the necessity of rationale augmentation. Typically, more capable rationale generators bring about more performance improvement, potentially due to better knowledge distillation [79]. In most cases, the benefits of incorporating more rationales show evident gains and then reach a plateau. An exception is observed with LLaMA-3.1-8B, where training with highly diverse rationales (e.g., 20) generated by itself leads to model collapse (see Appendix D.3 for a preliminary explanation).

We also explore the ability transfer between **CR-EVAL** tasks (Appendix D.1), track the behaviors of the domainspecialized model (Appendix D.2), ablate the three training stages (Appendix D.4), and scale up model training along the data dimension (Appendix D.5).

#### 5.2 Method 2: Prompting Methods

Another potential method to achieve domain specialization is prompting, which involves crafting well-suited instructions to steer general-purpose LLMs. Prompting is lightweight, as it requires no additional model training. However, it also suffers from limitations, including model capacity bottleneck, lack of systematic methodology, reliance on human expertise, limited performance scalability, restricted transferability across models, and sometimes practical policy constraints.

We conduct experiments to assess the effectiveness of various prompting methods on CR-EVAL. Due to space limit, we present details in Appendix B and summarize the main results here: (1) We ask one author to manually rephrase instructions or query GPT-40 to refine instructions. These types of prompt engineering yield limited performance improvements, as shown in Table 2. (2) We further explore advanced prompting techniques, including zero-shot CoT [29] and few-shot CoT [28]. While zero-shot CoT enhances reasoning density and offers slight improvements (up to 4% in the best cases), these gains remain modest. Few-shot CoT can even degrade performance, particularly for GPT-40-mini, likely due to increased context length and the lost-in-the*middle* effect [80]. (3) We also investigate prompting in a human-in-the-loop scenario to assess whether LLMs can effectively leverage expert guidance in the fill-cr task:

- **Distilled references:** Emulating expert guidance, we use GPT-40 to condense reference answers into single-sentence root cause analyses without weakness disclosure.
- Enumerable directions: From 1,922 common root causes of specification weaknesses (e.g., "poor failure managem ent"), GPT-40 selects the five most relevant as guidance.

Table 2: Impact of prompt refinement on diff-analysis.
"Inst." represents Instruction.

LLaMA-3.1-8B		CRITIC-L	LaMA-3.1-8B
pass@1	pass@5	pass@1	pass@5
27.4	59.8	106.4	148.4
22.0	49.8	106.3	146.3
18.5	45.2	106.4	150.2
22.0	48.3	105.3	143.7
	pass@1 27.4 22.0 18.5	pass@1         pass@5           27.4         59.8           22.0         49.8           18.5         45.2	pass@1         pass@5         pass@1           27.4         59.8         106.4           22.0         49.8         106.3           18.5         45.2         106.4

Distilled references (pass@5: 103.2) The potential root cause that incurs problems lies in mismatched authentication methods or unsupported features across devices and network components.

 Enumerable hints (pass@5: 81.4)

 The potential specification issues are: inadequate authentication, authentication mechanisms, protocol misalignment, authentication flaws, specification updates.

Figure 8: Results and examples of incorporating expertise. We test on the fill-cr task and the pass@5 of the tested checkpoint with no hint is 57.8.

We present examples and corresponding results in Figure 8. The findings show that LLM like **CRITIC**-LLaMA-3.1-8B can benefit significantly from additional guidance, achieving up to a 78.5% improvement in the challenging fill-cr task and making the augmented LLM comparable to reasoning models. We hypothesize that expert knowledge serves as external hints, whereas reasoning models generate such hints by themselves, enabling more directed reasoning about specification weaknesses. It is worth noting that while the distilled reference approach assumes access to preliminary high-quality expert analysis, enumerable directions remain easily accessible in production environments. These results highlight another promising pathway for enhancing domain specialization in LLMs by incorporating expert knowledge.

**Takeaway.** Appropriately implementing domain-adaptive fine-tuning can effectively bolster LLM specialization in domain tasks. While prompting methods can provide a lightweight means of adaptation, their impact is sometimes limited.

## 6 CAN LLMS REPLACE HUMANS IN SPECIFICATION REFINEMENT?

To stress-test LLMs, we conduct case studies on known cellular attacks to assess how far LLMs are from fully automating specification refinement. As observed earlier, the bottleneck of LLM-driven specification refinement lies in weakness detection (fill-cr), which is the focus of this section.

We evaluate **CRITIC**-LLaMA-3.1-8B on existing attacks. Since fill-cr focuses on identifying weaknesses rather than synthesizing attacks, we decide to separate it: 1) **CRITIC**-LLaMA-3.1-8B analyzes potential weaknesses across 10 trials.

Table 3: Evaluation of known attacks using CRITIC-LLaMA-3.1-8B (C). Hermes results (H) are selfreported in Al Ishtiaq et al. [14]. We indicate the version where the flawed specification was identified. We use symbols (I) (implementation flaw), (C) (configuration flaw), and (N) (non-deterministic).

1       AUTH REJECT Attack [81]       4G NAS (15.0.0)       ✓         2       Blind DoS Attack [82]       4G RRC (14.2.2)       ✗         3       Cutting off the Device [10]       5G NAS (16.2.0)       ✗         4       Deletion of allowed CAG list [14]       5G NAS (17.8.0)       ✓         5       DoS with RRCSetupRequest attack [10]       5G RRC (15.5.1)       ✗         6       Denying all network services [4]       4G NAS (12.8.0)       ✓         7       Denying selected service [4]       4G NAS (12.8.0)       ✓         8       DETACH REQUEST attack [3]       4G NAS (12.8.0)       ✓         9       Downgrade to non-LTE services [4]       4G NAS (12.8.0)       ✓         10       Downgrade via ATTACH REJECT [4]       4G NAS (12.8.0)       ✓         11       Energy Depletion with RRCSETUP [14]       5G RRC (17.0.0)       ✓         12       Exposing NAS Sequence Number [10]       5G NAS (16.0.2)       ✓         13       Exposure of SQN [83]       3G AKA (15.0.0)       ✓         14       IMSI Catching [84]       4G NAS (12.7.0)       ✓	~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
3       Cutting off the Device [10]       5G NAS (16.2.0)       ✗         4       Deletion of allowed CAG list [14]       5G NAS (17.8.0)       ✓         5       DoS with RRCSetupRequest attack [10]       5G RRC (15.5.1)       ✗         6       Denying all network services [4]       4G NAS (12.8.0)       ✓         7       Denying selected service [4]       4G NAS (12.8.0)       ✓         8       DETACH REQUEST attack [3]       4G NAS (12.8.0)       ✓         9       Downgrade to non-LTE services [4]       4G NAS (12.8.0)       ✓         10       Downgrade via ATTACH REJECT [4]       4G NAS (12.8.0)       ✓         11       Energy Depletion with RRCSETUP [14]       5G RRC (17.0.0)       ✓         12       Exposing NAS Sequence Number [10]       5G NAS (16.0.2)       ✓         13       Exposure of SQN [83]       3G AKA (15.0.0)       ✓         14       IMSI Catching [84]       4G NAS (12.7.0)       ✓	シシシンシン
4       Deletion of allowed CAG list [14]       5G NAS (17.8.0)       ✓         5       DoS with RRCSetupRequest attack [10]       5G RRC (15.5.1)       ✗         6       Denying all network services [4]       4G NAS (12.8.0)       ✓         7       Denying selected service [4]       4G NAS (12.8.0)       ✓         8       DETACH REQUEST attack [3]       4G NAS (12.8.0)       ✓         9       Downgrade to non-LTE services [4]       4G NAS (12.8.0)       ✓         10       Downgrade via ATTACH REJECT [4]       4G NAS (12.8.0)       ✓         11       Energy Depletion with RRCSETUP [14]       5G RRC (17.0.0)       ✓         12       Exposing NAS Sequence Number [10]       5G NAS (16.0.2)       ✓         13       Exposure of SQN [83]       3G AKA (15.0.0)       ✓         14       IMSI Catching [84]       4G NAS (12.7.0)       ✓	シシシンシン
4       Deletion of allowed CAG list [14]       5G NAS (17.8.0)       ✓         5       DoS with RRCSetupRequest attack [10]       5G RRC (15.5.1)       ✗         6       Denying all network services [4]       4G NAS (12.8.0)       ✓         7       Denying selected service [4]       4G NAS (12.8.0)       ✓         8       DETACH REQUEST attack [3]       4G NAS (12.8.0)       ✓         9       Downgrade to non-LTE services [4]       4G NAS (12.8.0)       ✓         10       Downgrade via ATTACH REJECT [4]       4G NAS (12.8.0)       ✓         11       Energy Depletion with RRCSETUP [14]       5G RRC (17.0.0)       ✓         12       Exposing NAS Sequence Number [10]       5G NAS (16.0.2)       ✓         13       Exposure of SQN [83]       3G AKA (15.0.0)       ✓         14       IMSI Catching [84]       4G NAS (12.7.0)       ✓	\ \ \ \ \
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13         Exposure of SQN [83]         3G AKA (15.0.0)         ✓           14         IMSI Catching [84]         4G NAS (12.7.0)         ✓	\ \ \
14         IMSI Catching [84]         4G NAS (12.7.0)         ✓	\ \
01 1	1
15 IMSI Cracking [9] 4G RRC (15.0.0)	1
16 IMSI Cracking [9] 5G NAS (15.0.0)	1
17 Incarceration with RRCRELEASE [10] 5G RRC (15.5.1) ✓	1
18 Installing Null Cipher/Integrity [10] 5G RRC (15.5.1) ✓	1
19 Lullaby Attack [10] 5G RRC (15.5.1) ✓	1
20 Measurement report [4] 4G RRC (12.3.0) ✗	1
21 NAS COUNT update attack [14] 5G NAS (16.4.0) ✓	1
22 NAS Counter Reset [10] 5G NAS (16.0.2) ✓	1
23 Neutralizing TMSI Refreshment [10] 5G NAS (16.2.0)	1
24 Paging channel hijacking [3] 4G RRC (12.5.0) ✗	1
25 SERVICE REJECT attack [4] 4G NAS (12.8.0) ✓	1
26 Signaling DoS Attack [85] 4G NAS (16.8.0) ✓	1
27 SUCI Catching Vulnerability [86] 5G NAS (15.0.0)	1
28 Synchronization Failure Attack [81] 4G NAS (15.0.0) ✗	1
29 Uplink NAS Counter Desync [10] 5G NAS (16.0.2) ✓	1
30         5G AKA DoS Attack [87]         5G NAS (15.2.0)         ✓	1
31 AKA Bypass [82] 5G RRC (①) ✗	-
32 EMM Information Vulnerability [88] 4G NAS (①) ✓	-
33 Impersonation attack [89] 4G NAS (ℂ) ×	-
34 Malformed Identity Request [90] 4G NAS (①) ✗	-
35 RLF report [4] 5G RRC $(①)$ 🗸	-
36 S-TMSI Catching [82] 4G NAS (ℕ) ✓	-

2) GPT-40 evaluates each analysis according to Prompt 6, determining whether combining the discovered weakness with the corresponding threat model sufficiently derives the final attack. 3) We manually validate accepted analyses for reliability. Following Al Ishtiaq et al. [14], we examine totally 36 types of existing attacks, collecting relevant specification statements, threat models, and attack descriptions for each. Specification statements were successfully located for 30 attacks, forming the basis of our case studies, while the remaining 6 were excluded due to reliance on implementation or configuration flaws.

The attack list and results are presented in Table 3. **CRITIC**-LLaMA-3.1-8B successfully detects all 30 types of attacks. In comparison, the formal analysis method Hermes [14]

## Table 4: Examples of CRITIC-LLaMA-3.1-8B analyses for the *Incarceration with RRCRELEASE attack* [10].

#### Accepted CRITIC-LLaMA-3.1-8B response

The current specification allows the RRCRelease message to be sent unprotected under certain conditions. This poses a significant security risk, particularly if these messages contain sensitive information or instructions that could be intercepted or modified by malicious entities. The inclusion of optional fields such as de-prioritisation information and cell reselection priorities in the RRCRelease message further exacerbates this risk, as these fields can convey critical operational data that, if leaked, could disrupt network performance or lead to unauthorized access.

#### Rejected CRITIC-LLaMA-3.1-8B response

The current specification allows the RRCRelease message to be sent unprotected, which can lead to significant security vulnerabilities. Since the RRCRelease message may contain sensitive information, such as redirected carrier information or suspend configuration details, sending it unprotected could allow unauthorized entities to intercept this data.

identifies 19 of these attacks. Representative examples of **CRITIC**-LLaMA-3.1-8B's responses are shown in Table 4. It demonstrates the ability to reason about potential weaknesses diversely, which we attribute to the incorporation of multiple rationales during training. Remarkably, even the rejected responses provide valuable insights, unveiling other negative consequences with unprotected *RRCRelease* message. While these results are promising, we also identify key challenges that hinder the direct deployment of LLMs for automated cellular specification refinement.

- Requirements for effective calibration: While LLMs' ability to produce diverse interpretations can be useful, it inevitably increases false positives. Their inherent hallucination issues [91] further exacerbate this, making blind reliance infeasible. For weakness verification, current practices primarily delegate this responsibility to human analysts [3, 10, 13]. Extending this practice to LLM-based analysis would be impractical due to the sheer volume of generated weaknesses. Crucially, we argue that even with full autonomy, decision-making should not be ceded to LLMs. Rather than blaming LLMs, the focus should be on developing effective calibration mechanisms to reduce human effort. Without them, unverified proposals risk overwhelming analysts instead of aiding them.
- Completeness of analyzed clauses: Our manually curated set of attack-related specification clauses provides an idealized benchmark, containing sufficient context for analysis. This partially explains why CRITIC-LLaMA-3.1-8B achieves perfect detection of known attacks despite its limitations in addressing all test cases in CR-EVAL. However, practical challenges emerge when refining active

specifications, particularly in identifying vulnerabilities arising from complex interactions across multiple sources.

**Takeaway.** Despite their potential, LLM-driven cellular specification refinement should not be over-relied on. At the current stage, human-in-the-loop oversight is still necessary to validate LLM-provisioned proposals of specification refinements.

## 7 LIMITATIONS AND FUTURE WORKS

Due to cost constraints, our measurement study does not cover all existing LLMs; instead, we focus on recent state-ofthe-art models as representative examples. Future work may include newly released LLMs. Our systematic exploration consumed over 32,120 H800 GPU hours, but computational constraints prevented us from exploring other promising directions, e.g., scaling to giant LLMs like LLaMA-3.1-405B. Nevertheless, our experiments in Section 5.1.4 demonstrate the feasibility of extending domain specialization to stronger base models. This work mainly explores fine-tuning and prompting to enhance LLMs' domain-specific capabilities. Alternative approaches such as reinforcement learning and agentic AI may further boost domain specialization, which we leave for future work. Additionally, while our focus is on the security aspects of cellular specifications, our future work could extend LLM-driven specification refinement to address other types of weaknesses following similar methodologies.

## 8 RELATED WORKS

## 8.1 Weakness Discovery of Cellular Specs

Although cellular specification refinement is rarely studied, well-established practices exist for weakness discovery.

**Manual inspection** by domain experts has led to numerous vulnerability findings, including data plane attacks [8, 92, 93], attacks against emergency systems [94, 95], key reinstallation [96], user tracking [4, 86, 97], side channel attacks [9, 98], and fingerprinting [99, 100]. While it allows for the discovery of sophisticated attacks, relying on manual inspection cannot ensure covering all aspects of cellular networks, especially as cellular networks grow increasingly complicated and specifications become more voluminous. That's why automated tools are in demand.

**Formal verification** is widely used in evaluating cellular protocols [3, 10–12, 14, 101, 102]. However, their applications require significant manual effort to build formal models and craft verification properties, inherently limiting automation and scalability. Moreover, a huge semantic gap exists between abstract formal models and natural language specifications, leading to incomplete exploration of complicated cellular systems. This challenge is further exacerbated by the inherent state explosion problem of formal methods.

NLP techniques have been adopted to uncover specification flaws [13–15, 48, 103]. Atomic [13] applies textual entailment to detect risky descriptions in 3GPP standards. Several approaches fine-tune encoder-based transformer models (e.g., RoBERTa [104]) for different purposes: CREEK [48] identifies security-related CRs, CellularLint [15] detects inconsistencies, and Hermes [14] constructs state machines for formal analysis. These methods focus on information extraction rather than direct vulnerability detection, still relying on human expertise and facing scalability challenges.

#### 8.2 LLMs for Cellular Network

The human-like intelligence of modern LLMs, specifically generative ones such as GPT [17], has catalyzed numerous studies on their potential applications in cellular networks, raising the question of whether they can serve as key enablers of network automation. Existing research predominantly investigates whether LLMs can comprehend domain knowledge through question-answering tasks. For example, GSMA has officially launched the Open-Telco LLM Benchmark project [105] to evaluate LLMs on interacting with complex standards. Similar efforts include SPEC5G [33], TSpec-LLM [52], and TeleQnA [106]. Beyond knowledge comprehension, preliminary studies explore whether LLMs can facilitate real-world scenarios. For instance, Wen et al. [107] employ LLMs to detect and explain runtime anomalies in the O-RAN data plane, while Kotaru [108] investigate their potential for enabling natural language interfaces to retrieve and analyze 5G operator network data. In this work, we stress-test LLMs in a productive setting, evaluating their effectiveness in refining cellular specifications-a task that directly impacts the efficiency of practitioners, particularly those working with voluminous cellular specifications.

#### 9 CONCLUSION

Currently, cellular network specification refinement remains labor-intensive and unsystematic. In this work, we pioneer the adoption of LLMs for automated cellular specification refinement. To advance it, we tackle the domain data scarcity challenge by transforming change requests of 3GPP standards into utilizable task instances. We establish a principled evaluation, CR-EVAL, enabling the community to assess the domain-specific capabilities of the rapidly advancing LLMs. In this context, we enhance LLM domain specialization by contributing an effective domain-adaptive training recipe and understanding the efficacy of various prompting methods. Our case studies on 30 known cellular attacks reveal the remaining challenges in achieving fully automated LLMbased cellular specification refinement. This study sheds light on the potential of LLMs in refining cellular specifications and provides a foundation for future advancements.

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#### A Why Fine-Tuning?

In this work, we explore fine-tuning methods to improve LLMs in cellular specification refinement. Several compelling reasons motivate our resorting to fine-tuning: **1** Refining cellular specifications is reasoning-heavy, knowledge-intensive, and expertise-driven. There exists a gap between LLMs' general-purpose training objectives and the task's specialized requirements. **2** As we cannot assume that general-purpose LLMs inherently possess all the fundamental components necessary for expert-level analysis, we demand an approach that enables building these capabilities from the ground up. **③** The cellular security community continuously evolves with ongoing research and new discoveries. This necessitates a scalable approach capable of knowledge ingestion. Fine-tuning effectively fulfills all the expectations outlined above [47, 109, 110]. <sup>(4)</sup> Furthermore, for domain-specific tasks, fine-tuned models may achieve either higher performance at fixed cost or lower cost at fixed performance. These benefits align with the success of specialized LLMs in various fields, including medicine [26], finance [67], and math [68].

#### **B** Limits of Prompting Methods

#### **B.1** Why Prompting Methods Fall Short

As for the usage of LLMs, the naive method is to prompt advanced LLMs to solve target tasks in either zero-shot or fewshot manners. However, this approach suffers several critical limitations. **1** Prompting remains an art instead of a systematic science, making it challenging to easily craft effective prompts. 2 Crafting prompts is not effort-free while the effectiveness heavily relies on human expertise. This contradicts our objective of automated analysis. <sup>3</sup> Prompts are typically model- and case-dependent, limiting their scalability and transferability across different scenarios and different models. Moreover, the effectiveness of even well-crafted prompts fundamentally depends on the underlying model's capabilities. As such, model limitations will bottleneck outcomes. Our fine-tuning methods directly enhance model abilities. G For more practical considerations, weakness analysis is a sensitive topic, and utilizing third-party LLM services introduces the risk of information leakage. Besides, LLM service providers often enforce strict regulations and may restrict or block security-related queries. This calls for the development and local deployment of specialized LLMs.

## **B.2** What If Using Prompting Methods

Prompt baselines. As we cannot enumerate all possibilities of prompts, we empirically show the performance of several representative prompt settings. First, we ask one project member to rephrase the default instruction to test the impact of phrasing variance on LLM performance. Second, we utilize GPT-40 to refine the default instruction provided in CR-EVAL tasks by requesting more LLM-friendly variants, generating two stronger prompt baselines. We follow default testing configurations with only the task instruction altered. The results are shown in Table 2. Comparing different prompt settings, we observe the sufficiency of the default instruction, which simply describes the task plainly. We also notice that the performance of CRITIC-LLaMA-3.1-8B is not strongly dependent on the default instruction, which CRITIC-LLaMA-3.1-8B encounters in the training stage. Besides the powerful ability obtained through domain-adaptive fine-tuning, another implicit benefit is that it eliminates the need for users to engage in extensive prompt engineering to achieve optimal performance. This is evidenced by the smaller variance of CRITIC-LLaMA-3.1-8B's performance across multiple prompt settings.

**CoT prompting.** We explore the impact of recognized reasoningenhancing techniques. Specifically, we evaluate two representative approaches, few-shot CoT [28] and zero-shot CoT [29], applying them to LLaMA-3.1-8B, GPT-40-mini, and **CRITIC**-LLaMA-3.1-8B. We instantiate few-shot CoT with three randomly sampled training samples, each with

	υυ		
	Stage 1 (DACT)	Stage 2 (TST)	Stage 3 (SCT)
Corpus	СК-міх	CR-instruct	CR-sec
Training method	Pre-training	Supervised	Supervised
Learnable parameters	Full parameters	Full parameters	LoRA ( $r = 128, \alpha = 256$ )
Learning rate	2e-6	2e-5	1e-4
Global batch size	256	128	64
Weight decay	0%	10%	0%
Gradient clipping	1.0	1.0	1.0
Training epoch	1	1	1
Parameter precision	BF16 + TF32	BF16 + TF32	BF16 + TF32
Warmup ratio	10%	3%	3%
Scheduler type	Cosine	Cosine	Cosine
Max sample length	512	12,000	12,000

LLaMA-3.1-8B GPT-4o-mini CRiticLM 97 / 200 128 / 200 184 / 200 Zero-shot CoT Incorrect Correct Zero-shot CoT Incorrect Correct 16 56 14 91 18 155 Zero-shot CoT Incorrect Correct 83 12 17 10 117 11 T T Incorrect Correct Incorrect Correct Incorrect Correct Instruction Only Instruction Only Instruction Only Few-shot CoT ncorrect Correct 19 48 21 80 Few-shot CoT ncorrect Correct 3 104 Few-shot CoT Incorrect Correct V ▼ ncorrect 19 76 23 32 61 114 Incorrect Correct Incorrect Correct Incorrect Correct Instruction Only Instruction Only Instruction Only ▼0⊏ 200

Figure 9: Impact of CoT prompting, conducted on diffanalysis. We use pass@10 to ease the sample-wise comparison and report the overall performance under diverse CoT settings for model-level comparison.

augmented rationales. As shown in Figure 9, the incorporation of zero-shot CoT enhances reasoning density, leading to higher pass rates across all three models. We observe that introducing few-shot CoT may adversely impact the performance of models. The task instances typically span long context, e.g., the 3-shot setting additionally costs 8,287 tokens of GPT-4o-mini. We hypothesize that the performance degradation stems from the *lost-in-the-middle* phenomenon inherent in LLMs [80], where long or irrelevant context will lead LLMs to behave worse. Besides, the inference cost also increases when employing additional shots.

#### C Complementary Experimental Setup

We list all main training configurations in Table 5. We choose a high rank r = 256 for the LoRA adapter and set  $\alpha = 2r$  as recommended by Biderman et al. [73]. We apply LoRA adapters to all linear layers in the model. All three training stages employ AdamW optimizer [111] with  $\beta_1$  as 0.9 and  $\beta_2$  as 0.999. The settings of learning rates are  $2 \times 10^{-6}$  for DAPT,  $2 \times 10^{-5}$  for TST, and  $1 \times 10^{-4}$  for SCT. For batch size, we employ 256 for DAPT, 128 for TST, and 64 for SCT. All the training stages consume one epoch with the analogous learning scheduler: the learning rate is linearly warmed up for several training steps and then cosine decreases to 1/20 of the peak learning rate. Gradient accumulation is adopted to achieve large batch sizes with constrained GPU memory.

#### Table 6: Models evaluated in this work.

Model	Model size	Open-source	Context window
LLaMA-3.1-8B	8B	Y	128K
Qwen-2.5-7B	7B	Y	128K
GLM-4-9B	9B	Y	128K
InternLM-2.5-7B	7B	Y	1M
Mistral-7B-v0.3	7B	Y	128K
LLaMA-3.1-70B	70B	Y	128K
GPT-3.5-turbo	Unknown	Ν	16,385
GPT-40-mini	Unknown	Ν	128K
GPT-40	Unknown	Ν	128K
Claude-3.5-Sonnet	Unknown	Ν	200K
DeepSeek-R1	671B	Y	128K
GPT-03-mini	Unknown	Ν	200K
Gemini-2.0-flash-thinking	Unknown	Ν	1M

Table 7: Module-level lines of code counted using *cloc*.

Component	LoC
Data collection and processing	4,946
Training	3,419
CR-eval	2,203
User study	2,241
Total	12,809



Figure 10: Patterns of diversity gain when augmenting rationales using different models: LLaMA-3.1-8B, GPT-4o-mini, GPT-40, and LLaMA-3.1-70B. The rationales correspond to the diff-analysis task. We use Euclidean distance to measure the similarity between rationales while the sample-level diversity gain is measured as the minimal distance of the *i*-th rationale against the set of the previous (i - 1) rationales plus the original answer. We plot the variance across different task instances.

#### D **Additional Experiment Results**

#### **D.1 Correlation between CR-EVAL Tasks**

We explore the correlation between the **CR-EVAL** tasks by evaluating whether the knowledge acquired by training on the source task can transfer to the target task. We train base models with CR-sec of the source task and evaluate the trained model in the target task. The results are shown in Table 8. We notice that the knowledge is clearly transferable between tasks, which substantiates the efficacy of our multitask learning design in the TST stage.

Table 8: Cross-task performance: models are trained on source tasks with CR-sEc and evaluated on target tasks using pass@5.

			Source	
		<b>Outline Revision</b>	Diff Analysis	Fill CR
et	Outline Revision	177.9	183.6	169.8
arget	Diff Analysis	77.8	124.2	74.4
Ta	Fill CR	31.9	27.2	33.5

#### **Tracking Model Behaviors D.2**

We study why CRITIC-LLaMA-3.1-8B can excel in cellular specification refinement and, consequently, on CR-EVAL. We analyze the model's behavior by collecting next-token predictions during processing the diff-analysis task of CR-EVAL. Formally, we obtain a set of softmax-normalized next-token prediction probabilities denoted as  $p_i^j \in \mathbb{R}^{|V|}, i \in [1, S_i], j \in [1, N]$ , the embedding space. We employ a feature extractor (i.e., where N denotes the number of test cases in **CR-EVAL**,  $S_i$ represents the sequence length of predicted tokens for the *j*-th test case under greedy search, and |V| is the vocabulary size. To mitigate varying completion lengths, we perform hierarchical aggregation: computing the mean prediction

distribution within each sample  $(\frac{1}{S_j}\sum_{i=1}^{S_j} p_i^j)$ , and then averaging across all N samples. This processing condenses the LLM's behavior on CR-EVAL into a single probability distribution  $P_{\text{LLM}} \in \mathbb{R}^{|V|}$ , where each dimension represents the model's averaged behavior for a vocabulary token. Due to the huge vocabulary size, e.g., |V| = 131,072for LLaMA-3.1 models, we focus on tokens with probabilities higher than  $\frac{1}{|V|}$ , which represent frequently used vocabulary in LLM outputs. We conduct a comparative analysis between P<sub>CRITIC</sub>-LLaMA-3.1-8B and P<sub>LLaMA-3.1-8B</sub>, with key observations presented in Table 10. Significantly, CRITIC-LLaMA-3.1-8B yields higher probabilities for security-related tokens, and notably transitions from employing generic descriptions (e.g., "\_errors" and "\_risks") to more specific terminologies (e.g., "\_interception" and "\_confidentiality"). As the P<sub>LLM</sub> is normalized, an increase in certain token probabilities inevitably results in the reduction of others. This transition aligns with our objective of developing a more domain-specialized model.

#### **D.3 Exploring Diversity Gain of Rationales**

Building upon our scalability analysis rationales in Section 5.1.4, we study why training with more rationale-augmented answers can benefit CRITIC-LLaMA-3.1-8B and why this improvement finally plateaus. We analyze the semantic differences between rationales by measuring their distances in OpenAI's text-embedding-3-large) to project each rationale into the embedding space. We then observe the diversity gain brought by progressively adding new rationales. The diversity gain corresponding to the *i*-th rationale of the *j*-th task instance is defined as the minimum distance between the new

Table 9: Impact of training stages, with rigorous decon-tamination to minimize memorization.

	Diff Analysis		Fill	CR
	pass@1	pass@5	pass@1	pass@5
LLaMA-3.1-8B	27.4	59.8	6.1	18.1
+ SCT	73.3	124.2	12.7	33.5
+ TST + SCT	95.8	145.3	25.3	49.9
+ DACT + TST + SCT	106.4	148.4	27.2	57.8

rationale and the union of existing rationales and the original answer, formalized as:  $\min_{k < i} |r_{i,j} - r_{k,j}|_2 \cup |r_{i,j} - a_j|_2$ where  $r_{i,j}$  denotes the *i*-th rationale for the *j*-th task instance,  $a_i$  is the original answer, and  $|\cdot|_2$  represents the Euclidean distance in the embedding space. Our analysis in Figure 10 reveals that the marginal diversity gain per new rationale diminishes as the number of rationales increases. This trend correlates with the observed improvement of CRITIC-LLaMA-3.1-8B as we increase the rationale number. We stipulate that this convergence occurs because additional rationales fail to introduce new insights, and the remaining diversity gains stem from the altered wordings. Notably, when using LLaMA-3.1-8B as the rationale generator, we observe diversity gains with both a higher mean and significantly greater variance compared to other models. This observation partially explains the inferior performance of LLaMA-3.1-8B as the rationale generator and provides insights for choosing appropriate rationale generators.

#### D.4 Ablating Training Stages

To assess the contributions of each training stage, we conduct an ablation study. As shown in Table 9, each stage positively contributes to **CRITIC**-LLaMA-3.1-8B's performance on **CR-EVAL** tasks. The SCT stage, closely aligned with security-centric analysis, yields the most significant improvement. Training with security-irrelevant samples in TST also boosts performance by enhancing generalization in tackling specification weaknesses. The DACT stage, designed to complement LLMs with domain knowledge, provides modest gains, likely because base LLMs (e.g., LLaMA-3.1-8B) already possess relevant domain knowledge [69].

#### D.5 Scaling Along the Data Dimension

We examine how model performance evolves with increasing training data volume. We focus on the diff-analysis task, as it is the most distinguishing task in **RQ1**. Training data scales approximately logarithmically, with each data point representing a full training run using default hyperparameters. As illustrated in Figure 11, results reveal two key trends: 1) performance consistently improves with more data, and



2) performance gains exhibit diminishing returns, aligning with observations of established scaling laws [18, 23, 31].

## D.6 Examining Existing Attacks

**Considered threat models.** The settings of the threat model strictly follow their corresponding original papers. In gross, we consider both passive and active attacker models.

- **Passive Adversary:** This attacker can eavesdrop on overthe-air radio broadcast channels, such that they can analyze and deduce information from intercepted messages.
- Active Adversary: This attacker can establish and operate a rogue base station to inject malicious traffic directed at UEs. While they are assumed to have full knowledge of the protocol specifications, they lack access to cryptographic keys, except for public keys.

For certain scenarios, we suppose the attacker also knows some identity information of the victim UE, like the C-RNTI. Alternatively, the attacker might have a hypothesis about the victim's identity information and seek to verify it.

#### E Structural Analysis of Datasets

We demonstrate the representativeness of **CR-EVAL** for evaluating cellular specification refinement. We also provide statistics about the training dataset size.

Sample length of CR-EVAL. We analyze the sample length distribution of test cases in CR-EVAL at the token level, as demonstrated in Figure 12. The test cases of CR-EVAL typically contain thousands of or even tens of thousands of tokens, presenting rigorous challenges that specifically test models' long-context capabilities. Moreover, LLMs suffer the problem of *lost-in-the-middle*, meaning that the models claiming long context cannot effectively leverage the information given in their context [80]. Models without sufficiently effective long context (less than the claimed maximum token number) cannot tackle the test cases in a single inference.

**Release coverage of CR-EVAL.** We provide the statistics of the target releases of CRs in **CR-EVAL**, which is illustrated in Figure 13. **CR-EVAL** demonstrates extensive release coverage and excellent diversity, with its involved CRs spanning



Figure 12: Distribution of token counts of test cases in CR-EVAL, with three tasks combined.



Figure 13: Release distribution of CRs in CR-EVAL.

				# Samples	# Tokens	# Response tokens
Series 33 (50)			<b>CR-EVAL</b> (outline-revision)	200	898,521	15,642
Series 2-			CR-EVAL (diff-analysis)	200	1,194,454	73,239
CR-eval (200)			CR-EVAL (fill-cr)	200	883,054	73,239
			CR-міх (shared)	3,729,713	1,433,683,482	1,433,683,482
Series 29 (19)			CR-INSTRUCT (shared)	1,123,692	4,892,550,046	661,498,363
		Others (6)	<b>CR-sec</b> (outline-revision)	13,860	44,085,131	3,087,016
Series 23	(33)	Series 36 (12)	<b>CR-sec</b> (diff-analysis)	14,325	56,114,617	5,427,157
Jelles 23	Se Se	ries 38 (13)	<b>CR-sec</b> (fill-cr)	15,370	53,544,878	6,305,663

Figure 14: (Left) Distribution of CRs in CR-EVAL across different specification series. (Right) Token statistics of the datasets at both the sample and token level, based on the tokenizer of the LLaMA-3.1 herds [18].

from Release 5 to Release 17. Covering CRs of old releases in CR-EVAL is necessary as historical security vulnerabilities can provide insights for refining contemporary cellular specifications. Intriguingly, we observed more security-related CRs during Release 8 and Release 15, which correspond to the introductions of LTE and 5G, respectively [48]. This underscores the importance of automated cellular specification refinement methods, particularly during major technological transitions. To ensure rigorous identification of securityrelevant CRs, we cross-referenced our annotations with those from Chen et al. [48]. While this early decision enhanced the reliability of our security relevance annotations, it also brought about an unexpected consequence, specifically, CR-EVAL currently excludes test cases from Release 18 onward. Future work will address this by developing an extended version of **CR-EVAL** incorporating more recent CRs.

**Specification coverage of CR-EVAL. CR-EVAL** encompasses 200 CRs distributed across 74 distinct specifications, demonstrating its extensive scope. We provide a coarsegrained summary of the specification distribution according to the belonging to standard series in Figure 14 (left). Unlike previous works that primarily focus on a limited set of specifications such as NAS and RRC, CR-EVAL provides comprehensive coverage across the 3GPP ecosystem. Yet the broad coverage makes it impractical for us to establish a human-level baseline on **CR-EVAL**.

Token number of all datasets. We present the dataset decomposition in Figure 14 (right). Note that we count the token number of data after rationale augmentation. As the auto-regressive LLMs are trained through the next token prediction task [24], the dataset size at the token level can more precisely show how much the LLMs can learn from the training. For the continual pre-training paradigm, e.g., DACT in our framework, all tokens are learnable while only the response tokens can be learned for the supervised fine-tuning paradigm. Scaling law [23, 31, 32] demonstrates that LLMs can consistently gain benefits through continual training investment. An implicit side of the scaling law is what the training dataset teaches the model. That's the rationale behind our finding that a limited number of security-related domain data CR-sec contributes significantly to the performance improvement on CR-EVAL. This underscores the crucial importance of developing high-quality domain datasets closely relevant to our target task, cellular specification refinement. Difficulty of CR-EVAL. The difficulty of test cases can be naturally measured through their global solving rate, defined as the proportion of model trials capable of solving them. We reuse the model predictions in Section 4.6 and aggregate the



Figure 15: Solving rates of all models on the three tasks.

solving rates across all model trials (10 trials per model). We provide the statistics in Figure 15. The final CR-EVAL aligns with our design principle of progressive challenge levels. At a macro level, the three tasks exhibit distinct difficulty tiers, as evidenced by their mean solving rates. For example, the fill-cr task presents the highest challenge by providing the model with minimal information while demanding an in-depth understanding of potential weaknesses within the specification clauses. At a micro level, each task comprises test cases of varying difficulty, as substantiated by our demonstrations in Section 4.6. While all test cases passed our manual verification process, ensuring that they provide sufficient information for task completion, they incorporate different implicit confounding factors, e.g., the provided context specification statements and the expected response quality. Among the three tasks, both the diff-analysis and fill-cr are challenging enough to differentiate LLMs' domain-specific abilities, despite rapid advances in LLM development.

Table 10: Full list of CRITIC-LLaMA-3.1-8B's token prediction behavior on CR-EVAL. The ratios are relative to base model (LLaMA-3.1-8B). Note: '\_' denotes the blank character in tokens.

Token	Ratio	Token	Ratio
_safeguard	138.70×	_degrade	79.21×
_improper	58.78×	Failure	$61.47 \times$
	39.49×	_challenges	47.90×
_interception	32.64×	_interruptions	$24.07 \times$
inadvertently	21.85×	reuse	16.60×
misuse	13.98×	_operational	16.38×
_susceptible	12.34×	_cryptographic	10.98×
_legal	10.49×	degraded	10.07×
_disrupt	6.90×	_misunderstanding	6.5×
unintended	6.77×	privacy	5.43×
_ fail	4.66×	_protecting	4.66×
_unprotected	4.31×	risk	3.82×
_ambiguity	3.70×	invalid	3.73×
spoof	3.41×	trust	3.62×
_reliability	3.29×	_disruptions	3.10×
_incorrectly	2.88×	_confidentiality	2.96×
_legitimate	2.84×	_protected	2.86×
unauthorized	$2.62 \times$	_compromise	2.83×
_integrity	$2.62\times$	_dereg	2.56×
leaks	2.51×	_ambigu	2.36×
breaches	2.35×	compliance	2.34×
_intercepted	2.27×	_manipulation	$2.32 \times$
_authenticity	2.14×	_inconsistency	2.23×
disruption	1.97×	threats	2.11×
_rejection	1.85×	_degradation	1.95×
_securely	1.77×	_vulnerability	1.77×
_lack	1.67×	_ambiguous	$1.70 \times$
_safety	1.63×	authenticated	1.66×
failures	1.62×	robust	1.61×
attacks	1.56×	_interoper	1.54×
_compromising	1.48×	_inability	$1.52\times$
authorized	1.46×	malicious	1.47×
_uutilofizeu failed	$1.40 \times$	intended	1.46×
unable	$1.32\times$	_Privacy	1.34×
incorrect	1.27×	_consistency	$1.23\times$
_availability	1.27×	_compromised	1.22×
_authenticate	1.15×	_confusion	1.14×
_authentieate	1.11X	authentication	1.14×
_security	1.07×	consistent	$1.05 \times$
_predictable	0.96×	_unexpected	0.97×
_attacker	0.91×	certificate	0.91×
inconsistencies	$0.91\times$	_disabled	0.91× 0.88×
authorization	0.80×	_error	0.80×
vulnerabilities	0.81×	inconsistent	0.80×
_vulnerable	$0.31\times$ $0.72\times$	errors	0.30× 0.71×
_vunicrable risks	0.72× 0.64×	_comply	$0.71 \times 0.54 \times$
unclear	0.53×	_comply reliable	$0.54\times$
_barred	0.33× 0.45×	_compatibility	$0.32\times$ $0.43\times$
_flexibility	$0.43\times$ $0.42\times$	negative	0.43× 0.41×
damage	$0.42\times$ $0.40\times$	difficulties	$0.41 \times$ 0.20×
uainage	0.40X	_unitcutties	0.20X

#### F Human Study for LLM-as-a-Judge

We conducted the human study with eight PhD students specializing in network security. Their research experience in the field ensures the quality of our evaluation. The human study concerning the reliability of LLM-as-a-Judge consists of two rounds, whose system snapshots are presented in Figure 19 and Figure 20: 1) Alignment test: Participants were presented with 25 samples, each consisting of an LLM response and the corresponding reference answer. Participants are tasked to accept or reject the LLM responses based on their alignment with the reference answers. This round evaluates Human-as-a-Judge under the fair setting with LLMas-a-Judge, aiming to test their alignment. 2) Judgment approval test: Participants are additionally presented with the LLM-as-a-Judge's judgment and its posterior explanation. Participants are asked to approve or disapprove the LLM-asa-Judge's judgment. This round aimed to calibrate the rigor degree of humans and show the acceptableness of LLM-as-a-Judge's decisions from the perspective of human annotators.

The 25 LLM responses used in the human study belong to GPT-40 and a preview version of **CRITIC**-LLaMA-3.1-8B for diff-analysis and fill-cr. We randomly sample 12 acceptable and 13 unacceptable samples based on the LLM-as-a-Judge to ensure representativeness. We collected a total of 8 \* 25 \* 2 = 400 responses, which are presented in Table 11. The time consumed by the LLM and each participant during the study is shown in Figure 16. The LLM completed the task in 36 seconds, significantly faster than the participants, who averaged 77 minutes and 12 seconds. This suggests the unavailability of a large-scale study with human judgments and highlights the LLM-as-a-Judge's potential for time-efficient automation in evaluating LLM responses [35, 51, 60]. The percentage of agreement between each participant and the LLM-as-a-Judge with the remaining participants is shown in Figure 17. For example, we compare Participant 1 and LLM-as-a-Judge with the consensus of Participants 2-8. The LLM generally achieved a higher agreement rate, comparable to the participants' average of approximately 82.5%. This indicates that the LLM's judgments align closely with participant consensus, supporting its reliability as an automated judge. Figure 18 presents participants' agreement with the LLM before and after receiving its explanations. Of 200 decisions, 163 consistently align with the LLM. Notably, 19 cases shifted from approval to rejection after the explanation, 10 shifted the opposite way, and 8 remained disapproved. These patterns suggest that human participants and the LLMas-a-Judge may hold different judgment criteria, which are effectively calibrated through the explanations provided in the judgment approval test. These findings demonstrate our finally instantiated LLM-as-a-Judge's reliability in automating the evaluation of model answers at a notable expert level.



Figure 16: Time consumed (in minutes) by the LLM and each participant during the study.



Figure 17: Results of the leave-one-annotator-out experiments comparing agreement between individual annotators and majority decisions. For each test case, we evaluate the agreement between a single annotator (either a human participant or LLM-as-a-Judge) and the majority vote of the remaining N - 1 participants. The majority vote serves as the consolidated judgment from the excluded annotators.



Figure 18: Participants' agreement with the LLM before and after receiving the LLM's explanations.

#### Instruction >

#### Reference Report

#### · Reason for Change

The revision addresses the need for clarity and organization in the management information exchange process. The original specification combined port-specific and bridge-specific information into a single table, which could lead to confusion and inefficiencies. By separating these into distinct tables, the revision ensures that information is categorized based on its applicability, whether to specific ports or to the bridge as a whole. This separation aligns with the transport mechanisms, where Port Management Information is carried in a Port Management Information Container and Bridge Management Information in a Bridge Management Information Container. Furthermore, the revision addresses the ambiguity in handling DS-TT neighbor discovery when DS-TT is incapable of performing this function. The original specification implied the use of a specific NW-TT port container for such cases, which was not logical since neighbor discovery is a function of the NW-TT as a whole. By moving this information to the Bridge-specific table, the revision clarifies that the NW-TT, rather than a specific port, is responsible for this function.

#### Consequences if not Revised

Failure to implement these revisions could lead to significant inefficiencies and confusion in the management of SGS networks. Without the separation of Port and Bridge Management Information, there is a risk of miscommunication and errors in the exchange of information, as the current specification implies the use of specific NW-TT



Reject

#### Drafted Report

#### · Reason for Change

The previous specification was limited to port management, which did not fully address the needs of modern telecommunications networks that utilize sophisticated Time-Sensitive Networking (TSN) bridging capabilities. By expanding the scope to include bridge management information, the network can handle more complex configurations and operations, essential for meeting the stringent demands of industrial applications and other high-performance use cases. This holistic management approach is crucial for ensuring consistent and efficient traffic management, neighbor discovery, and per-stream filtering and policing, which are integral for maintaining the quality and reliability of service in 5GS.

#### Consequences if not Revised

Without these updates, 5GS networks may face several challenges, such as:

Inefficiency in Network Management: Limiting management operations to ports alone would overlook the crucial aspect of bridge management, thereby failing to optimize the complete network topology.

Potential for Network Bottlenecks and Errors: Inadequate handling of bridge

management could lead to suboptimal traffic forwarding and scheduling, causing delays and packet loss.

Reduced Flexibility and Scalability: The lack of integrated bridge management might hinder network adaptations necessary for evolving requirements in diverse use scenario

Accept

## Submit

#### **Current Sample**

1 1 Round Sample

Round	Progress

Туре	Chosen	Lim
Reject	0	15
Accept	0	15

#### Figure 19: System snapshot of the first round of human study, Alignment Test.

ogged in as Participant					<b>∑</b> 02
Instruction >	Your previous judgment: Accept	LLM-as-a-judge: Reject	Click to see LLM-as-a-judge's explanations.		
Reference Report		Drafted Report		Subm	nit
- Reason for Change		· Reason for Change		Sav	e
the call (not related to the	ambiguity regarding the handling of SIP messages related to access transfer) received from a remote UE during an ongoing , there was a lack of clarity on when these messages should b	regarding session managen	ss critical flaws and ambiguities in the existing specifications ent and media forwarding during access transfers. The		
server. The only exception PS to CS access transfer for the exact moments for disc prevent inconsistent call st revisions clarify the handli	ading to potential undefined actions in the SCC AS and MSC was in subclause 12.3.4.3, which provided some guidance fo or calls in an early phase on the originating side. By specifyin carding and acting on SIP messages, the revisions aim to ates and ensure proper call handling. Furthermore, the ing of SIP messages related to the call received from the SC ing consistent and predictable behavior across different	should be forwarded or dis or inappropriate session ha Session Continuity: The u ongoing sessions, especiall (e.g., PS to CS). Reliability of Communica	By specifying the conditions under which SIP messages carded, the revision mitigates issues related to message drops ndling during access transfers. pdates emphasize the necessity of maintaining continuity for y during transitions between different access technologies <b>tion</b> : The inclusion of specific procedures for managing SIP ares that communication remains robust, particularly when ltaneous sessions.	Current S 2 Round	Sample 1 Sample
Consequences if no	t Revised	<ul> <li>Consequences if not</li> </ul>	Powierd	Round Pr	ogress
remote UE inconsistently.	For instance, if messages are forwarded towards the SC UE	•	changes could lead to several negative outcomes, including:		
prematurely, it could lead to inconsistent call states between the SCC AS and SC UE, especially if the SC UE has already transitioned to the CS domain. Additionally, if SIP messages are delayed in being sent to the MSC server, it could result in unnecessary call		Disrupted Call Continuit	Disrupted Call Continuity: Without the revised SIP message handling procedures,		
			there is a risk of lost messages and interruptions in ongoing calls, especially during access transfers. This can lead to dropped calls or poor user experience.		D
	ng user experience and network reliability. By not addressing of operational inefficiencies and degraded service quality.		ures: Ambiguities in the existing process might lead to	Approve	0
$\langle \rangle$	Disapprove		Approve		

#### Figure 20: System snapshot of the second round of human study, Judgment Approval Test.

00:50

Idx	LLM-as-a-Judge	1	2	3	4	5	6	7	8
1	Accept	Accept	$R \rightarrow A$	Reject	$R \rightarrow A$	Accept	Accept	$R \rightarrow A$	$R \rightarrow A$
4	Accept	Accept	Accept	Accept	Accept	$R \rightarrow A$	Accept	Accept	$R \rightarrow A$
5	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept
7	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept
9	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept
11	Accept	Accept	$R \rightarrow A$	Reject	Accept	Accept	Accept	Accept	Accept
15	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept	$R \rightarrow A$
16	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept
18	Accept	Accept	Accept	Accept	Accept	Accept	$R \rightarrow A$	Accept	Accept
22	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept
24	Accept	Accept	Accept	Accept	Accept	$R \rightarrow A$	Accept	Accept	Reject
25	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept
2	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject
3	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject	$A \rightarrow R$
6	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject
8	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject
10	Reject	$A \rightarrow R$	Reject	Reject	Reject	$A \rightarrow R$	$A \rightarrow R$	$A \rightarrow R$	Reject
12	Reject	$A \rightarrow R$	Reject	Reject	Reject	Reject	Reject	Reject	$A \rightarrow R$
13	Reject	$A \rightarrow R$	Reject						
14	Reject	Reject	Accept	Accept	Reject	Reject	Reject	Reject	Reject
17	Reject	Reject	Accept	Reject	Reject	Reject	$A \rightarrow R$	Reject	$A \rightarrow R$
19	Reject	Reject	Reject	Accept	Reject	$A \rightarrow R$	$A \rightarrow R$	$A \rightarrow R$	$A \rightarrow R$
20	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject
21	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject	$A \rightarrow R$
23	Reject	$A \rightarrow R$	Accept	$A \rightarrow R$	Reject	$A \rightarrow R$	$A \rightarrow R$	Reject	Reject

Table 11: The raw data of human study. Each column corresponds to one human annotator. Each row corresponds to one sample and we cluster the samples based on LLM-as-a-Judge's decisions for readability.

## G Prompts Used and Example Artifacts

#### Prompt 1: Fill CR

You are a cellular network protocol expert. Given a segment of the 3GPP specifications, you should envision what bad things may happen when following the statements, and analyze its potential design weakness. Then, you prepare a change request, which should include:

1. REASON FOR CHANGE: Explain why the identified flaws need to be addressed.

2. SUMMARY OF CHANGE: Provide a summary of the necessary changes to the specifications.

3. CONSEQUENCES IF NOT REVISED: Describe potential negative impacts if the proposed changes are not made.

You should avoid missing important statements and try your best to return detailed responses rich in reasoning.

#### **Prompt 2: Rationale Augmentation**

You will be given a task instance composed of TASK INSTRUCTION, USER QUERY, and ASSISTANT RESPONSE. Your task is to revise the ASSISTANT RESPONSE by adding reasoning contents to it. The reasoning contents should explain how the response was generated and act as chain of thoughts for reaching the responses.

Note that

- The task will be related to network protocols, and you should leverage your knowledge in this domain.
- The revised response should be coherent with the original response.
- The revised response should perfectly fit the TASK INSTRUCTION and USER QUERY.
- The revised response should be informative and helpful to the user.
- The revised response should be rich in thoughts and smooth in logic.
- The revised response should be fruitful in educating other assistants.
- You should not alter the original response format.
- You should only return the revised response, which can directly replace the original response.

# TASK INSTRUCTION

{}

{}

# USER QUERY

# ASSISTANT RESPONSE

{}

#### Prompt 3: Evaluating Security Relevance of CR

You will be given a reasoning segment concerning analyzing problems of cellular network protocol. You should determine whether the implied problem is high-risk, meaning that it strongly relates to security, user privacy, attacks, or any threats to normal service. You should meticulously analyze the given task instance and end up with a judgment. If the problem discussed by the instance is high-risk, you should finally respond with 'High-Risk'; otherwise, respond with 'Low-Risk'.

>>> REASON FOR CHANGE

{}
>>> CONSEQUENCES IF NOT REVISED

{}

#### **Prompt 4: Distinguishing Educational Task Instances**

You will be given a task instance concerning analyzing problems of cellular network protocol. The sample is composed of three parts, SYSTEM INSTRUCTION, USER QUERY, and ASSISTANT RESPONSE. You should determine its educational value for a student whose goal is to learn reasoning about the potential flaws in cellular network protocols. You should consider the following aspects:

1. The ASSISTANT RESPONSE is self-contained, meaning that it does not depend on other external information too much and is easy to understand without additional context.

2. The USER QUERY is meaningful and is a suitable analytic target under the SYSTEM INSTRUCTION.

3. The ASSISTANT RESPONSE is logically coherent and conforms well to the requirements of the SYSTEM INSTRUCTION.

4. The ASSISTANT RESPONSE is informative and provides a detailed analysis of the USER QUERY.

You should analyze the given task instance and end up with a judgement. DO NOT make your response too verbose. If it is educational, meaning that it is helpful for a student to learn reasoning about the potential flaws in cellular network protocols, you should finally respond with 'Educational'; otherwise, respond with 'Non-educational'.

# TASK INSTRUCTION

**# USER OUERY** 

# ASSISTANT RESPONSE

{}

{}

₿

#### **Prompt 5: Evaluating Fill CR**

You are given two reports concerning a weakness analysis of the 3GPP protocol: the Reference Report (which should considered \*\*acceptable\*\* in quality of understanding the protocol problems) and the Drafted Report. Both reports aim to explain the weaknesses and reasons for certain revisions. Your task is to evaluate the claim the Drafted Report identifies the hidden problems in the protocol, compared to the Reference Report.

Conclude your evaluation with a judgment score (s) from:

\* \*\*-2 (Strongly Disagree):\*\* The Drafted Report contains significant misunderstandings, misrepresents the issues, or omits critical weaknesses.

\* \*\*-1 (Weakly Disagree):\*\* The Drafted Report shows a partial understanding but includes notable errors or omissions in identifying the weaknesses.

\* \*\*0 (Neutral):\*\* The Drafted Report identifies the main weaknesses correctly but lacks depth or accuracy in some areas.

\* \*\*1 (Weakly Agree):\*\* The Drafted Report largely understands the weaknesses but has minor discrepancies.

\* \*\*2 (Strongly Agree):\*\* The Drafted Report demonstrates a near-perfect understanding of the potential problem, with only trivial deviations from the Reference Report.

Note that:

\* The Reference Report provides a basic understanding of the protocol problems. The Reference Report is not perfect. So the Drafted Report does not need to match exactly with the Reference Report.

\* You should focus on the protocol problems only. Ignore information unrelated to protocol problems in Reference Report, e.g. reference to other documents.

\* Superficial reports, those with speculative analysis, and those that lack focus should be rated lower. In contrast, reports that are decisive, informative, and facilitate further investigation by human experts are preferred.

\* Focus on the content and the understanding of the protocol issues, not on the presentation or formatting.

Do not do anything else other than scoring. Only the final score (x) should be returned in the form of 's: x'.

## Reference Report

{}

## Drafted Report

ť

#### Prompt 6: Weakness-to-Attack Verification

You are an expert in verifying the correctness of a vulnerability analysis. You must be extremely rigorous and thorough in your verification process. Analyze and verify whether a given vulnerability analysis (V) enables an attacker, operating within a specified threat model (T), to execute the described attack (A). In other words, whether  $V + T \rightarrow A$ . Your verification must be comprehensive and consider:

1. Logical completeness - Are all necessary steps and conditions accounted for?

2. Technical accuracy - Are the technical details precise and correct?

3. Exploitability - Can the vulnerability be exploited within the constraints of the threat model?

4. Attack feasibility - Does the analysis conclusively demonstrate the attack's viability?

Note that both T and A are trustworthy and you should evaluate the vulnerability analysis based on them.

1. Vulnerability Analysis (V): Identified weaknesses from the specification

- 2. Threat Model (*T*): Attacker capabilities and assumptions
- 3. Attack Description (A): Attack procedure and implications

ANALYSIS SECTIONS

# Vulnerability Analysis

}

# Threat Model

{}

# Attack Description

{}

OUTPUT FORMAT

Please provide your detailed analysis in the following XML format:

<result>

<correctness\_reason>

Provide a thorough analysis addressing:

1. Logical completeness of the vulnerability analysis

2. Technical accuracy of all claims and assumptions

3. Whether the vulnerability can be exploited given the threat model constraints

4. Clear demonstration of attack feasibility

5. Any gaps or inconsistencies found

Support your conclusion with specific references to the input components.

</correctness\_reason>

<correctness>true/false</correctness>

</result>

Note: Default to false if there is ANY uncertainty or gaps in the logical chain from vulnerability to attack.

#### Example 1: Fill-CR Task Instance in CR-EVAL (Index: 29, CR: S3-190376, Design Flaw), Part: 1/2

#### **Task Instruction**

You are a cellular network protocol expert. Given a segment of the 3GPP specifications, you should envision what bad things may happen when following the statements, and analyze its potential design weakness. Then, you prepare a change request, which should include:

1. REASON FOR CHANGE: Explain why the identified flaws need to be addressed.

2. SUMMARY OF CHANGE: Provide a summary of the necessary changes to the specifications.

3. CONSEQUENCES IF NOT REVISED: Describe potential negative impacts if the proposed changes are not made.

You should avoid missing important statements and try your best to return detailed responses rich in reasoning.

#### **Test Case**

>>> Original Specification Statements:

6.3.3 Authentication and key agreement

The purpose of this procedure is to authenticate the user and establish a new pair of cipher and integrity keys between the VLR/SGSN and the USIM. During the authentication, the USIM verifies the freshness of the authentication vector that is used.

#### Figure 8: Successful UMTS Authentication and Key Agreement

The VLR/SGSN invokes the procedure by selecting the next unused authentication vector from the ordered array of authentication vectors in the VLR/SGSN database. Authentication vectors in a particular node are used on a first-in / first-out basis. The VLR/SGSN sends to the USIM the random challenge RAND and an authentication token for network authentication AUTN from the selected authentication vector.

Upon receipt the user proceeds as shown in Figure 9.

#### Figure 9: User authentication function in the USIM

Upon receipt of RAND and AUTN the USIM first computes the anonymity key AK = f5K (RAND) and retrieves the sequence number SQN = (SQN AK) AK.

Next the USIM computes XMAC = f1K (SQN || RAND || AMF) and compares this with MAC which is included in AUTN. If they are different, the user sends an authentication failure message back to the VLR/SGSN with an indication of the cause and the user abandons the procedure. In this case, VLR/SGSN shall initiate an Authentication Failure Report procedure towards the HLR as specified in section 6.3.6. VLR/SGSN may also decide to initiate a new identification and authentication procedure towards the user, cf. TS 24.008 [35]. Next the USIM verifies that the received sequence number SQN is in the correct range.

If the USIM considers the sequence number to be not in the correct range, it sends synchronisation failure back to the VLR/SGSN including an appropriate parameter, and abandons the procedure.

The synchronisation failure message contains the parameter AUTS. It is AUTS =  $Conc(SQNMS) \parallel MACS$ . Conc(SQNMS) = SQNMS f5\*K(RAND) is the concealed value of the counter SQNMS in the MS, and MACS = f1\*K(SQNMS  $\parallel$  RAND  $\parallel$  AMF) where RAND is the random value received in the current user authentication request. f1\* is a message authentication code (MAC) function with the property that no valuable information can be inferred from the function values of f1\* about those of f1, ..., f5, f5\* and vice versa. f5\* is the key generating function used to compute AK in re-synchronisation procedures with the property that no valuable information can be inferred from the function values of f1, f1\*, f2, ..., f5 and vice versa.

The AMF used to calculate MACS assumes a dummy value of all zeros so that it does not need to be transmitted in the clear in the re-synch message. The construction of the parameter AUTS in shown in the following Figure 10:

#### Figure 10: Construction of the parameter AUTS

If the sequence number is considered to be in the correct range however, the USIM computes RES = f2K (RAND) and includes this parameter in a user authentication response back to the VLR/SGSN. Finally the USIM computes the cipher key CK = f3K (RAND) and the integrity key IK = f4K (RAND). Note that if this is more efficient, RES, CK and IK could also be computed earlier at any time after receiving RAND. If the USIM also supports conversion function c3, it shall derive the 64-bit GSM cipher key Kc from the UMTS cipher/integrity keys CK and IK. UMTS keys are sent to the MS along with the derived 64-bit GSM key for UMTS-GSM interoperability purposes. USIM shall store original CK, IK until the next successful execution of AKA.

Upon receipt of user authentication response the VLR/SGSN compares RES with the expected response XRES from the selected authentication vector. If XRES equals RES then the authentication of the user has passed. The SGSN shall compute the 128-bit GSM ciphering key Kc128 according to annex B.5 if it is to use a 128-bit GSM ciphering algorithm. The VLR/MSC shall compute the 128-bit GSM ciphering key Kc128 according to annex B.5 if it signals a 128-bit GSM ciphering algorithm as a permitted GSM ciphering algorithm to the BSS. The VLR/SGSN also selects the appropriate cipher key CK and integrity key IK from the selected authentication vector. If XRES and RES are different, VLR/SGSN shall initiate an Authentication Failure Report procedure towards the HLR as specified in section 6.3.6. VLR/SGSN may also decide to initiate a new identification and authentication procedure towards the user, cf. TS 24.008 [35].

To be continued in the next page  $\searrow$ 

#### Example 2: Fill-CR Task Instance in CR-EVAL (Index: 29, CR: S3-190376, Design Flaw), Part: 2/2

▶ Continued

Re-use and re-transmission of (RAND, AUTN)

The verification of the SQN by the USIM will cause the MS to reject an attempt by the VLR/SGSN to re-use a quintet to establish a particular UMTS security context more than once. In general therefore the VLR/SGSN shall use a quintet only once.

There is one exception however: in the event that the VLR/SGSN has sent out an authentication request using a particular quintet and does not receive a response message (authentication response or authentication failure) from the MS, it may re-transmit the authentication request using the same quintet. However, as soon as a response message arrives no further re-transmissions are allowed. If after the initial transmission or after a series of re-transmissions no response arrives, retransmissions may be abandoned. If retransmissions are abandoned then the VLR/SGSN shall delete the quintet. At the MS side, in order to allow this re-transmission without causing additional re-synchronisation procedures, the ME shall store for the PS domain (and optionally the CS domain) the last received RAND as well as the corresponding RES, CK and IK. If the USIM returned SRES and Kc (for GSM access), the ME shall store these values. When the ME receives an authentication request and discovers that a RAND is repeated, it shall re-transmit the response. The ME shall delete the stored values RAND, RES and SRES (if they exist) as soon as the 3G security mode command or the GSM cipher mode command is received by the ME or the connection is aborted. If the ME can handle the retransmission mechanism for CS domain then it shall be able to handle the retransmission for both PS and CS domain simultaneously.

#### 6.3.5 Re-synchronisation procedure

A VLR/SGSN may send two types of authentication data requests to the HE/AuC, the (regular) one described in subsection 6.3.2 and one used in case of synchronisation failures, described in this subsection.

Upon receiving a synchronisation failure message from the user, the VLR/SGSN sends an authentication data request with a "synchronisation failure indication" to the HE/AuC, together with the parameters:

- RAND sent to the MS in the preceding user authentication request, and

- AUTS received by the VLR/SGSN in the response to that request, as described in subsection 6.3.3.

An VLR/SGSN will not react to unsolicited "synchronisation failure indication" messages from the MS.

The VLR/SGSN does not send new user authentication requests to the user before having received the response to its authentication data request from the HE/AuC (or before it is timed out).

When the HE/AuC receives an authentication data request with a "synchronisation failure indication" it acts as follows:

1. The HE/AuC retrieves SQNMS from Conc(SQNMS) by computing Conc(SQNMS) f5\*K(RAND).

2. The HE/AuC checks if SQNHE is in the correct range, i.e. if the next sequence number generated SQNHE using would be accepted by the USIM.

3. If SQNHE is in the correct range then the HE/AuC continues with step (6), otherwise it continues with step (4).

4. The HE/AuC verifies AUTS (cf. subsection 6.3.3).

5. If the verification is successful the HE/AuC resets the value of the counter SQNHE to SQNMS.

6. The HE/AuC sends an authentication data response with a new batch of authentication vectors to the VLR/SGSN. If the counter SQNHE was not reset then these authentication vectors can be taken from storage, otherwise they are newly generated after resetting SQNHE. In order to reduce the real-time computation burden on the HE/AuC, the HE/AuC may also send only a single authentication vector in the latter case.

Whenever the VLR/SGSN receives a new batch of authentication vectors from the HE/AuC in an authentication data response to an authentication data request with synchronisation failure indication it deletes the old ones for that user in the VLR/SGSN.

The user may now be authenticated based on a new authentication vector from the HE/AuC. Figure 12 shows how re-synchronisation is achieved by combining a user authentication request answered by a synchronisation failure message (as described in section 6.3.3) with an authentication data request with synchronisation failure indication answered by an authentication data response (as described in this section).

Figure 12: Resynchronisation mechanism

#### **Reference** Answer

#### >>> REASON FOR CHANGE

The calculation of the keystream for concealing SQNMS in the case of re-sychronisation only has RAND as a non-key input and hence the same keystream may be used to protect different SQNMSs if an attacker replays an authentication challenge. This leaks at least the xor between the different SQNMS values and it has been shown how this leak can be used to derive the LSBs of SQNMS.

#### >>> SUMMARY OF CHANGE

Add MAC-S as an input parameter to claculate the keystream at re-synchronisation in order to get a differeent keystream for each SQNMS value.

#### >>> CONSEQUENCES IF NOT REVISED

Keystream is repeated which should be against security design properties.

#### Example 3: Fill-CR Task Instance in CR-EVAL (Index: 145, CR: C1-193185, Under-specification)

#### **Task Instruction**

For display brevity, the repetitive instruction is omitted here.

#### **Test Case**

>>> Original Specification Statements:

5.4.1.2.4.2 EAP message reliable transport procedure initiation by the network

In order to initiate the EAP message reliable transport procedure, the AMF shall create an AUTHENTICATION REQUEST message. The AMF shall set the EAP message IE of the AUTHENTICATION REQUEST message to the EAP-request message to be sent to the UE. The AMF shall set the ngKSI IE of the AUTHENTICATION REQUEST message to the ngKSI value selected in subclause 5.4.1.2.2.2 or subclause 5.4.1.2.3.1. In this release of specification, the AMF shall set the ABBA IE of the AUTHENTICATION REQUEST message with the length of ABBA IE to 2 and the ABBA contents to be 2 octets in length with value 0000H as described in subclause 9.11.3.10. The AMF shall send the AUTHENTICATION REQUEST message to the UE, and the AMF shall start timer T3560 (see example in figure 5.4.1.2.4.2.1).

Figure 5.4.1.2.4.2.1: EAP message reliable transport procedure Upon receipt of an AUTHENTICATION REQUEST message with the EAP message IE, the UE handles the EAP message received in the EAP message IE and the ABBA of the AUTHENTICATION REQUEST message.

#### 5.4.1.3.2 Authentication initiation by the network

The network may initiate a 5G AKA based primary authentication and key agreement procedure for a UE in 5GMM-CONNECTED mode at any time. For restrictions applicable after handover or inter-system change to N1 mode in 5GMM-CONNECTED mode, see subclause 5.4.1.2.3.

The network initiates the 5G AKA based primary authentication and key agreement procedure by sending an AUTHENTICATION REQUEST message to the UE and starting the timer T3560 (see example in figure 5.4.1.3.2.1). The AUTHENTICATION REQUEST message shall contain the parameters necessary to calculate the authentication response (see 3GPP TS 33.501 [24]). This message shall include the ngKSI that will be used by the UE and AMF to identify the KAMF and the partial native security context that is created if the authentication is successful. This message shall also include the ABBA parameter. In this release of specification, the network shall set the length of ABBA IE to 2 and the ABBA contents to be 2 octets in length with value 0000H as described in subclause 9.11.3.10. If an ngKSI is contained in an initial NAS message during a 5GMM procedure, the network shall include a different ngKSI value in the AUTHENTICATION REQUEST message when it initiates a 5G AKA based primary authentication and key agreement procedure. Figure 5.4.1.3.2.1: 5G AKA based primary authentication and key agreement procedure

#### 9.11.3.10 ABBA

The purpose of the ABBA information element is to enable the bidding down protection of security features. The ABBA information element is coded as shown in figure 9.11.3.10.1 and table 9.11.3.10.1. The ABBA is a type 4 information element with a minimum length of 4 octets. 8 7 6 5 4 3 2 1 ABBA IEI octet 1 Length of ABBA contents octet 2 ABBA contents octet 3 octet n Figure 9.11.3.10.1: ABBA information element Table 9.11.3.10.1: ABBA information element ABBA contents (octet 3-n): indicate set of security features defined for 5GS as described in 3GPP TS 33.501 [24].

## **Reference** Answer

#### >>> REASON FOR CHANGE

CT1 sent an LS to SA3 (see C1-191686) asking about the UE behavior when an ABBA parameter with a non-zero value, or with a length that is more than 2 octets, is received in Release 15. This document aims to specify the UE behavior for this case following the LS response from SA3.

#### >>> SUMMARY OF CHANGE

Specify that in case the UE receives an ABBA parameter with - a length of more than 2 octets, - a non-zero value the UE shall use the ABBA as received from the network. Interoperability analysis1) UE compliant with the previous specification version with an AMF that is compliant with this CRIf the UE gets an ABBA parameter with a value that is different from 0000H, the UE will send a 5GMM STATUS message. However, the AMF already handles a 5GMM STATUS message.2) UE compliant with this CR with an AMF that is compliant with the previous specification version the UE gets an ABBA parameter with a value that is different from 0000H, the UE will use the ABBA parameter as it is received. If for some reason the KAMF at the UE and the network is not the same, the integrity check fails during the security mode procedure. However, handling integrity check failures already exists and is not introduced by this CR. If the KAMF at the UE and the network is the same, then no errors will occur. This CR is backwards compatible.

#### >>> CONSEQUENCES IF NOT REVISED

The UE uses an ABBA that is different from what the network has used leading to security failure.

24.301	2871	2 Current version		14.3.0		
Title	Correction of Handling of MO Detach without Integrity Protection			Date		2017-05-19
Category	F (Correction) Release				elease Rel-14	
Reason for change	the integrity check by the protection was to be treated sent by the UE before seed. An additional justification the efforts to listen in ordetaching other subscrift. UE from receiving MT superiodic TAU (or RAU) or Since then, the situation detect and repair the issue - periodic update timer v - some of these devices subut on the other hand the reachable for the applic number per MME), it has random. As there are not so material protection, we suggest the possible. If the authentice reason, the MME may ig MME can attempt to app wait whether the UE is sufficient. When the the following protection: 1) the UE is attached for due to lack of roaming at 2) due to user interaction established; 3) a NAS COUNT wrap at a failing the sufficient of the subscript of the subs	he receiver, CT1 d ated by the MME, b curity can be activation ion was at that the n the NAS signalli- bers. Moreover, in ervices, would be co- or when the UE req n has changed, be- ie, as alues up to 14 days end MO user data was the UEs (e.g. certain ation server. Additi- become easier to p any cases where a be modify the require- cation is not perfor- gnore the Detach H oly additional criter still performing per- ives. ng cases where a emergency bearer greement; an attach procedur- around occurred so possible for the MM the integrity check	me that it did not appear ver ng in a cell and operate a mar the worst case this kind of Do letected and alleviated when th uested some MO service. ecause e.g. for UEs used for a can be negotiated between UE with a frequency of once every metering devices) may be req tionally, due to the higher der berform the attack successfully a UE might rightfully send a ements for the MME: the MME med, e.g. because the detach is Request and remain in state EP ia before marking the subscribe- riodic updating or whether it is UE might rightfully send a eservices and there is no share that the current EPS security of that the current EPS security of the to determine whether any of a is received.)	d Detach R es which "in ry likely th nipulated U oS attack, v he UE perfo MTC/ CIo E and netwo few weeks uired to sta nsity of dev even by pic Detach Ro should auth due to "sw MM-REGIS er as deregi s still respo Detach Ro d EPS secur exchange o context can these cases	Request with a certain site a certain site a certain site a certain site back of the pro- system of the pro- ork, and by attached vices per cacher ing the S- equest wite henticate the itch-off", of TERED. For stered, e.g. nding to pro- equest wite rity context of NAS mess no longer can apply	thout integrity tuations are ne would take the purpose of ild prevent the next normal or take longer to take longer to l in order to be ell (and higher TMSI values at hout integrity ne subscriber if r for any other or this case the the MME may aging when an hout integrity t available, e.g. ssages has been be used. when a Detach
Summary of change	<ul> <li>Rules for the handling of a DETACH REQUEST message failing the integrity check are modified for the case when a current EPS security context exists and the secure exchange of NAS messages has not yet been established:</li> <li>If it is not a detach request due to switch off, and the MME can initiate an authentication procedure, the MME should authenticate the subscriber before processing the detach request any further.</li> <li>If it is a detach request due to switch off, or the MME does not initiate an authentication procedure for an other reason, the MME may ignore the detach request and remain in state EMM-REGISTERED. (The network can attempt to use additional criteria before marking the UE as EMM-DEREGISTERED.)</li> </ul>					
Consequences if not ap- proved	Risk of a DoS attack. UEs	using an extended vithout integrity pr	periodic update timer can beco otection is always accepted wh	me unreach	able for pa	

## Table 12: Meta-information and expert rationales for the example Change Request (C1-172658<sup>11</sup>)

 $<sup>\</sup>fbox{11} https://www.3gpp.org/ftp/tsg_ct/WG1\_mm-cc-sm\_ex-CN1/TSGC1\_104\_Zhangjiajie/Docs/C1-172658.zip$ 

#### Table 13: Specification revisions for the example Change Request (C1-172658)

4.4.4.3 Integrity checking of NAS signalling messages in the MME Except the messages listed below, no NAS signalling messages shall be processed by the receiving EMM entity in the MME or forwarded to the ESM entity, unless the secure exchange of NAS messages has been established for the NAS signalling connection: - EMM messages: - ATTACH REQUEST; - IDENTITY RESPONSE (if requested identification parameter is IMSI); - AUTHENTICATION RESPONSE; - AUTHENTICATION FAILURE; - SECURITY MODE REJECT; - DETACH REQUEST; The remaining unchanged clauses are omitted for brevity. NOTE 2: The DETACH REQUEST message can be sent by the UE without integrity protection, e.g. if the UE is attached for emergency [+] bearer services and there is no shared EPS security context available, or if due to user interaction an attach procedure is cancelled before the secure exchange of NAS messages has been established. For these cases the network can attempt to use additional criteria (e.g. whether the UE is subsequently still performing periodic tracking area updating or still responding to paging) before marking the UE as EMM-DEREGISTERED. All ESM messages are integrity protected except a PDN CONNECTIVITY REQUEST message if it is sent piggybacked in ATTACH REQUEST message and NAS security is not activated. Once a current EPS security context exists, until the secure exchange of NAS messages has been established for the NAS signalling connection, the receiving EMM entity in the MME shall process the following NAS signalling messages, even if the MAC included in the message fails the integrity check or cannot be verified, as the EPS security context is not available in the network: - ATTACH REQUEST; - IDENTITY RESPONSE (if requested identification parameter is IMSI); - AUTHENTICATION RESPONSE; - AUTHENTICATION FAILURE; - SECURITY MODE REJECT; [-] - DETACH REQUEST (if sent before security has been activated); - DETACH REQUEST; [+] - DETACH ACCEPT; - TRACKING AREA UPDATE REQUEST; - SERVICE REQUEST; - EXTENDED SERVICE REQUEST; - CONTROL PLANE SERVICE REQUEST. NOTE 3: These messages are processed by the MME even when the MAC fails the integrity check or cannot be verified, as in certain situations they can be sent by the UE protected with an EPS security context that is no longer available in the network. If an ATTACH REQUEST message fails the integrity check and it is not an attach request for emergency bearer services, the MME shall authenticate the subscriber before processing the attach request any further. For the case when the attach procedure is for emergency bearer services see subclause 5.5.1.2.3 and subclause 5.4.2.5. If a DETACH REQUEST message fails the integrity check, the MME shall proceed as follows: [+] [+] - If it is not a detach request due to switch off, and the MME can initiate an authentication procedure, the MME should authenticate the subscriber before processing the detach request any further. [+] - If it is a detach request due to switch off, or the MME does not initiate an authentication procedure for any other reason, the MME may ignore the detach request and remain in state EMM-REGISTERED. NOTE 4: The network can attempt to use additional criteria (e.g. whether the UE is subsequently still performing periodic tracking area updating or still responding to paging) before marking the UE as EMM-DEREGISTERED. The remaining unchanged clauses are omitted for brevity. [+]

## H Taxonomy of Specification Weaknesses and Existing Attack Vectors

We provide a comprehensive survey of common specification weaknesses (Table 14) reported by previous academic works and their associated attack vectors (Table 15) in cellular networks. Our survey reveals that numerous attacks against cellular networks have been proposed by exploiting unsafe designs and ambiguous drafts. This demonstrates that specification weaknesses, if exploitable, can make significant impacts on cellular networks. However, it would be unfair to place blame solely on specification drafters, given the immense volume and complexity of the cellular network specification system. Rather, it underscores the importance of systematic weakness analysis and motivates automatic tools that help refine cellular specifications.

#### Table 14: Common issues in cellular specifications.

Specification weak- nesses	Related works
Design Flaws	[4, 9, 13, 81-
	83, 95, 98, 100, 102, 112–114]
Underspecification	[4, 12, 97, 101, 115–117]
Undefined Behaviors	[11, 116]
Inconsistencies	[15, 116, 118]

#### Table 15: Reported attacks in cellular networks.

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Attack Effects	Related Works
IMSI/SUPI cracking	[9]
Traffic decryption	[115]
User tracking	[97, 99, 112]
User presence identification	[4, 9, 119, 120]
Device fingerprinting	[100, 112, 116]
Message/Service spoofing	[82, 92, 95, 116] [8]
Traffic fingerprinting	[98, 99]
Denial of service	[4, 9, 81, 82, 101, 113, 114, 117, 118, 120, 121]
Downgrading to insecure versions	[4]
Key re-installation	[96]
Malicious message injection	[5, 112, 113, 120]
Eavesdropping data communication	[82, 115, 116, 122]
Exposing device capabilities	[100]
Content Fingerprinting	[98, 99]
Illegitimate access to services	[92, 101]
Unauthorized entry to secrets	[101]
Phishing legitimate users	[82]
BTS resource depletion	[82]
Free data service	[93, 118]
Signaling storm	[117]