Secure Multifaceted-RAG for Enterprise: Hybrid Knowledge Retrieval with Security Filtering

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Abstract

Existing Retrieval-Augmented Generation (RAG) systems face challenges in enterprise settings due to limited retrieval scope and data security risks. When relevant internal documents are unavailable, the system struggles to generate accurate and complete responses. Additionally, using closed-source Large Language Models (LLMs) raises concerns about exposing proprietary information. To address these issues, we propose the Secure Multifaceted-RAG (SecMulti-RAG) framework, which retrieves not only from internal documents but also from two supplementary sources: pre-generated expert knowledge for anticipated queries and on-demand external LLM-generated knowledge. To mitigate security risks, we adopt a local open-source generator and selectively utilize external LLMs only when prompts are deemed safe by a filtering mechanism. This approach enhances completeness, prevents data leakage, and reduces costs. In our evaluation on a report generation task in automotive industry, SecMulti-RAG significantly outperforms traditional RAG—achieving 79.3-91.9% win rates across correctness, richness, and helpfulness in LLM-based evaluation, and 56.3-70.4% in human evaluation. This highlights SecMulti-RAG as a practical and secure solution for enterprise RAG.

1 Introduction

Retrieval-Augmented Generation (RAG) (Lewis et al., 2020) has become a powerful tool for AI-driven content generation. However, existing RAG frameworks face significant limitations in enterprise applications. Traditional RAG systems rely heavily on internal document retrieval, which can lead to incomplete or inaccurate responses when relevant information is missing. Moreover, leveraging external Large Language Models (LLMs)

like GPT (OpenAI et al., 2024), Claude (Anthropic, 2024), or DeepSeek (DeepSeek-AI et al., 2025) introduces security risks and high operational costs, making them less viable for enterprise deployment.

To address these challenges, we introduce SecMulti-RAG framework that optimizes information retrieval, security, and cost efficiency. Our approach integrates three distinct sources: (1) dynamically updated enterprise knowledge base, (2) pre-written expert knowledge for anticipated queries, and (3) on-demand external knowledge, selectively retrieved when user prompt is safe. For sercurity, we introduce a filtering mechanism that ensures proprietary corporate data is not sent to external models. Furthermore, instead of relying on powerful closed-source LLMs, we use a local open-source model as the primary generator, selectively invoking external models only when user prompts are non-sensitive.

In this paper, we apply SecMulti-RAG to the Korean automotive industry. Our fine-tuned filter, retriever, and generation models show strong performance, ensuring the reliability of our approach. On the report generation task, our method outperforms the traditional RAG approach in correctness, richness, and helpfulness, as evaluated by both humans and LLMs. We also present adaptable strategies to meet specific environmental needs, emphasizing its flexibility. Our key contributions are:

- Multi-source RAG framework combining internal knowledge, pre-written expert knowledge, and external LLMs to enhance response completeness.
- Confidentiality-preserving filter to prevent exposure of sensitive corporate data to external LLMs.
- · Cost-efficient approach that leverages high-

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quality retrieval to compensate for smaller local generation models.

2 Related Work

Enhancing Retrieval-Augmented Generation Many efforts have been made to enhance RAG systems (Zhou et al., 2024; Gutiérrez et al., 2025). Jeong et al. (2024) classify user prompts based on complexity to determine the optimal retrieval strategy, making their approach relevant to our filtering mechanism for selecting retrieval sources. Meanwhile, Yu et al. (2023) and Wu et al. (2024) replace traditional document retrieval with generative models. In particular, Wu et al. (2024) propose a multi-source RAG (MSRAG) framework that integrates GPT-3.5 with web-based search, making it the most relevant to our work. In contrast, our approach retains internal document retrieval while integrating pre-generated expert knowledge and external LLMs.

Security Risks in LLM As generative models are widely used, concerns about security and privacy risks continue to grow. Many studies have explored methods for detecting and mitigating the leakage of sensitive information (Zhang et al., 2024; Kim et al., 2023; Hayes et al., 2017; Lukas et al., 2023). For example, Chong et al. (2024) present a prompt sanitization technique that enhances user privacy by identifying and removing sensitive information from user inputs before they are processed by LLM services. Our study incorporates a user prompt filtering mechanism, ensuring a more secure retrieval process.

3 Method

As shown in Figure 1, our RAG framework consists of three core components: multi-source retrieval, a confidentiality-preserving filtering mechanism, and local model adaptation. (Appendix A)

1) Multi-Source Retrieval Unlike conventional RAG frameworks that rely solely on internal structured document chunks, our system retrieves information from three distinct sources: (1) internal corporate documents, (2) pre-generated high-quality answers to anticipated queries, and (3) real-time external knowledge generated by closed-source LLMs. This multi-source retrieval strategy improves response completeness and accuracy, especially when internal documents are insufficient.

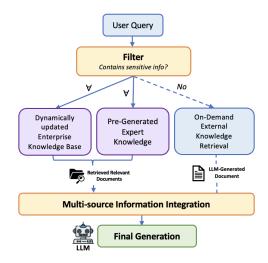


Figure 1: SecMulti-RAG framework

- 2) Confidentiality-Preserving Filtering Mechanism To mitigate the risk of unintended data leakage when interacting with external closed-source LLMs, we introduce a query filtering mechanism that detects security-sensitive content. If a user query is classified as containing confidential information, external retrieval is skipped, and the system generates responses solely based on internal documents and pre-curated expert knowledge. This mechanism ensures data confidentiality while maintaining retrieval quality (Section 4).
- 3) Local Model Adaptation Since enterprises often encounter security and cost limitations when using powerful closed-source LLMs, we use open-source Qwen-2.5-14B-Instruct (Yang et al., 2024) as our primary generation model. We fine-tune this model using domain-specific data to better reflect the language and knowledge of the Korean automotive domain. (Section 6)
- 4) End-to-End RAG Pipeline The final system consists of a multi-stage pipeline where user queries are processed through filtering, retrieval, and generation stages. By integrating high-quality retrieval with local model adaptation, our framework demonstrates that a well-optimized retrieval system can compensate for the limitations of smaller, locally deployed LLMs, making enterprise RAG both scalable and secure.

4 Confidentiality Filter

4.1 Dataset

Security-sensitive and general (non-sensitive) queries were created by Korean automotive engineers with the assistance of the Claude 3.7 Sonnet

Query	Label	Reason	Туре
What is the reason behind the introduction of the IIHS	1	A general question about	General query
small overlap crash test, and how has it influenced ve-		publicly available test stan-	
hicle design?		dards and their impact.	
What is the deformation value in the second-row pas-	0	Contains detailed informa-	Security-sensitive query
senger compartment due to the upper bending near the		tion about structural vul-	with project names
chassis frame fuel tank MTG during HD3 52kph rear		nerabilities.	
evaluation?			
Why is it necessary to change the location of the door	0	Reveals structural design	Security-sensitive query
pushing bracket, and what is the problem with the cur-		weaknesses.	without project names
rent location?			

Table 1: Examples of safe and unsafe queries and their corresponding reasons, translated into English. Label 0 refers to security-sensitive queries, while 1 refers to non-sensitive ones. (Specific vehicle type is anonymized.)

(Anthropic, 2024), accessed through a universityinternal service built on AWS Bedrock¹. This setup provides secure access to Claude without exposing data to external LLM providers². Figure 5 in Appendix B.1 illustrates the prompt template used to construct the guery dataset. The prompts are designed to elicit three types of queries: (1) general queries that do not pose confidentiality risks, (2) security-sensitive queries (easy) containing explicit project names, and (3) securitysensitive queries (hard) that omit project names. Type (3) queries are particularly challenging to classify, even for expert engineers, due to the absence of clear identifiers. In addition to the queries and the binary labels (sensitive or non-sensitive), brief rationales are generated to explain the reasoning behind each label. Table 1 presents example queries, and Table 2 summarizes data statistics.

Set	Safe	Unsafe		Total
		Easy	Hard	
Train	820	800	720	2,340
Validation	102	100	90	292
Test	103	101	90	294

Table 2: Data split for training and evaluation of the filter model.

4.2 Model

For the filter, we fine-tune a lightweight model, Qwen2.5-3B-Instruct (Yang et al., 2024), to classify safe and unsafe queries. The training parameters and the prompt used for the filtering process are detailed in Appendix B.

4.3 Evaluation

As shown in Table 3, we evaluate the filter model on two subsets: Easy-only (queries with explicit project names) and Easy&Hard (both with and without project names). Security-sensitive queries (class 0) are treated as the positive class, making recall critical in preventing information leakage to external LLMs. For easy test cases, the filter achieves 99.01% recall, indicating strong performance with minimal false negatives. When ambiguous queries is included, accuracy drops to 82.31% and recall to 74.35%, while precision remains high (97.93%), meaning that when it does flag a query as sensitive, it is highly likely to be correct. To estimate the upper bound, we conduct human evaluation on the Easy&Hard set. Expert annotator achieves 80.95% accuracy, 92.99% precision, and 76.44% recall, highlighting the intrinsic ambiguity and difficulty of the task.

Method	Test Data	Acc %	Prec	Rec
Filter	Easy-only Easy&Hard	98.04 82.31	97.09 97.93	99.01 74.35
Human	Easy&Hard	80.95	92.99	76.44

Table 3: Evaluation results of the filter model and human annotators on the test set. **Easy-only** includes security-sensitive queries with explicit project names. **Easy&Hard** includes both easy (with project names) and hard (without project names) queries. **Human** shows expert-labeled upper bound performance.

4.4 Application

In practical deployment, constructing a labeled dataset of safe and unsafe queries for filter training can be labor-intensive. To address this, we propose a progressive deployment strategy for the confidentiality filter. Initially, the system oper-

¹https://aws.amazon.com/ko/bedrock/

²All Claude 3.7 Sonnet model used in this study—for data generation and LLM-based evaluation—were accessed exclusively through this secure university-internal service.

ates without filtering or external retrieval, relying only on internal documents and pre-generated expert knowledge. During this phase, real user queries are collected and later labeled to train a filter model, enabling cost-effective integration over time. Alternatively, the filter can perform query rewriting—flagged queries are transformed into safer versions, allowing secure forwarding to external LLMs. This flexible design supports scalable adaptation to organizational privacy and deployment needs.

5 Retrieval

This paper focuses on generating reports for enterprise-level engineering problems. Our retrieval system is built upon 6,165 chunked documents, consisting of 5,625 chunks from the Enterprise Knowledge Base and 540 from Pre-written Expert Knowledge. To prevent data leakage, only the training subset of the 675 Pre-written Expert Knowledge documents is included in the retrieval pool; the remaining 135 keyword–report pairs are reserved for the final evaluation of **SecMulti-RAG** (Section 7). All documents listed in Table 4 are indexed using FAISS (Douze et al., 2025), and our trained retriever retrieves the top five most relevant documents for each query.

Туре	Source	File/Page	Chunks
Enterprise Knowledge Base	Test Report Meeting Report Textbook	1,463 249 404	4,662 882 81
Pre-written Expert Knowledge	Gold Report	-	540
Total			6,165

Table 4: Overview of chunked documents used in SecMulti-RAG retrieval. Traditional RAG retrieves only from the Enterprise Knowledge Base.

5.1 Dataset

5.1.1 Enterprise Knowledge Base

For the Enterprise Knowledge Base dataset, we use the dataset introduced by Choi et al. (2025). It consists of test reports, meeting reports, and text-books, with each document segmented into meaningful units such as slides, chapters, or other relevant sections. QA pairs from the reports and text-book are used to train both retriever and generation model. See Table 7 in Appendix C for details.

5.1.2 Pre-written Expert Knowledge

To construct a high-quality knowledge source, a domain expert in automotive engineering first cu-

rates a list of domain-specific keywords, representing expertise-level problems. Using these keywords, the expert then generates pre-written expert knowledge using Claude (Appendix D.1, D.2). A total of 675 keyword–report pairs are partitioned into training, validation, and test splits in an 8:1:1 ratio.

5.1.3 External Knowledge from LLM

After the user query passes the safety filter and is deemed safe, we use GPT-40³ to provide ondemand external knowledge. Specifically, in this paper, it generates a general-purpose technical background document to assist engineers in drafting formal safety reports. The prompt is illustrated in Appendix E. The generated document is then indexed into the document pool for future retrieval.

5.2 Retriever

We fine-tune BGE-M3 (Chen et al., 2024), a multilingual encoder supporting Korean, using QA and keyword–report pairs (Sections 5.1.1, 5.1.2). Training is done for 10 epochs on $4 \times 48GB$ RTX A6000 GPUs with publicity available code⁴. For evaluation, we use all splits (training, validation, and test) as the chunk pool to ensure sufficient data coverage and mitigate potential biases due to the small size of the test set.

5.3 Retriever Evaluation

The performance of the retriever is evaluated using Mean Average Precision (MAP@k), which calculates the average precision of relevant results up to rank k. As shown in Table 5, fine-tuning BGE-M3 leads to significant improvements, underscoring the importance of task-specific adaptation.

Model	MAP@1	MAP@5	MAP@10
BGE (Vanilla)	0.2855	0.3793	0.3925
BGE (Fine-tuned)	0.5965	0.7027	0.7099

Table 5: Comparison of retrieval performance between the vanilla and fine-tuned models on our test dataset.

5.4 Document Selection Strategy

In this study, we rank candidate documents by semantic similarity and apply a selection constraint: at most one external knowledge is included per query. GPT-generated documents are limited to

³https://platform.openai.com/docs/models/ gpt-4o

⁴https://github.com/FlagOpen/FlagEmbedding

one per query as they provide only general technical background, and excessive reliance on such external content may reduce the factual grounding of responses. Although this constraint is currently implemented via heuristic rules, we aim to develop a learning-based document selection strategy that jointly considers query characteristics and document provenance.

6 Generation

6.1 Generator

We use Qwen-2.5-14B-Instruct (Yang et al., 2024) as our base language model, as it is one of the few multilingual models that officially support Korean while offering a sufficient context length. We fine-tune the model using QA pairs introduced in Section 5.1.1. Hyperparameters, GPU configurations, and the generation prompt are in Appendix F.

6.2 Result

Table 6 summarizes the retrieved document sources and filtering results for the 135 test queries. All queries retrieved pre-generated expert knowledge, while 28.1% and 18.5% also retrieved GPT-generated and internal documents, respectively. Among the test queries, 34 are classified as safe, enabling on-demand GPT generation. Interestingly, the number of queries retrieving GPT-generated documents slightly exceeds the number of safe queries. This is because previously generated external documents remain in the retrieval pool and can still be retrieved for relevant future queries, even if those queries are classified as sensitive. This illustrates a key benefit of our system: as more external knowledge is accumulated over time, the retrieval pool becomes richer, allowing even sensitive queries to benefit from external knowledge without compromising security.

Category	Count (%)
Pre-written knowledge retrieved	135 (100%)
External knowledge retrieved	38 (28.1%)
Internal document retrieved	25 (18.5%)
filter=1 (Safe)	34 (25.2%)
filter=0 (Security-sensitive)	101 (74.8%)

Table 6: Distribution of retrieved document types (appearing at least once among the Top-5 documents) and filtering outcomes in the SecMulti-RAG

7 Evaluation

7.1 Method

To evaluate the effectiveness of our approach, we conduct a qualitative assessment based on three metrics: Correctness, Richness, and Helpfulness. We perform pairwise comparisons using both LLM-as-a-judge (Zheng et al., 2023) and human evaluation, comparing responses generated by Traditional RAG—which retrieves only from the internal knowledge base—with our SecMulti-RAG, which retrieves from the internal knowledge base, pre-generated expert knowledge, and on-demand external knowledge. For each metric, Claude and a human annotator assess which response (A or B) is better and record the outcome as a win, loss, or tie. To mitigate position bias from the judge LLM, we anonymize the response order by randomly assigning either SecMulti-RAG or Traditional RAG as response A or B in half of the cases. The prompt that we use for LLM-based evaluation is in Appendix G.1.

- **Correctness** assesses the factual consistency with the given gold answer. The pre-written reports are provided as gold answers.
- **Richness** evaluates the level of detail and completeness in the response.
- **Helpfulness** measures how clear, informative, and useful the response is.

7.2 Result

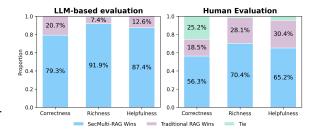


Figure 2: Win rate comparison between SecMulti-RAG and Traditional RAG across evaluation metrics

Figure 2 presents a comparison of win rates between the two systems, evaluated by human annotators and an LLM-based evaluation. Both evaluation sources consistently prefer the outputs of SecMulti-RAG, particularly in the richness metric. There is a substantial agreement between human and LLM evaluations as in Appendix G.2.

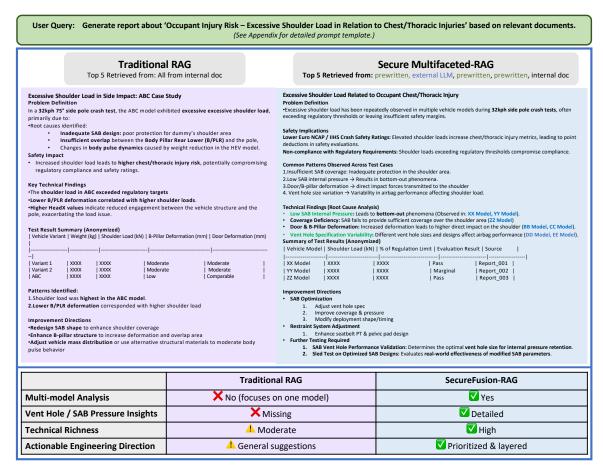


Figure 3: Comparison Between Traditional RAG and SecMulti-RAG (Translated from Korean; Sensitive Information Anonymized)

7.3 Analysis

While human evaluators tend to assign 'tie' labels more frequently than the judge LLM, both clearly favor SecMulti-RAG across all metrics. Figure 3 illustrates an example of reports generated by SecMulti-RAG and Traditional RAG.

As expected, richness is the most notably improved aspect of our framework, reflecting the benefit of incorporating diverse documents from multiple sources. SecMulti-RAG outputs contain significantly more detailed information, such as more diverse test cases and technical findings. In fact, the average length of reports generated by SecMulti-RAG is 2,660.21 tokens, compared to 1,631.84 tokens from Traditional RAG. In terms of correctness, both systems generally produce factually accurate content but occasionally fail to cite the correct source document. For helpfulness, while our approach delivers more comprehensive reports, Traditional RAG may be more favorable when the engineer's intent is to focus on a specific test case, as its responses tend to be more narrowly scoped. This could potentially be mitigated through prompt tuning. One notable issue is the occasional generation of Chinese characters, due to the Qwen model's Chinese-centric pretraining. This problem is likely caused by the longer documents retrieved by SecMulti-RAG, which increase the context length and make the model more vulnerable to generating such errors.

8 Conclusion

In this paper, we present SecMulti-RAG for enterprise that integrates internal knowledge bases, pre-generated expert knowledge, and on-demand external knowledge. Our framework introduces a confidentiality-aware filtering mechanism that protects security-sensitive user prompts by bypassing external augmentation when necessary, mitigating the risk of information leakage to closed-source LLMs. In our experiments on automotive engineering report generation, SecMulti-RAG showed clear improvements over Traditional RAG in terms of correctness, richness, and helpfulness. It achieved win rates ranging from 56.3%

to 70.4%, as evaluated by human evaluators, outperforming traditional RAG across all metrics. Beyond performance gains, our approch is a costefficient, privacy-preserving, and scalable solution, leveraging high-quality retrieval with locally hosted LLMs.

Limitations

Due to the lack of publicly available Koreanlanguage datasets in the automotive domain, our evaluation is limited to the report generation task based on a relatively small amount of data that we have constructed ourselves. While this work is intended for an industry track and demonstrates practical significance, future research could enhance the academic impact by showing the scalability of the SecMulti-RAG framework across a broader range of tasks and domains. In fact, we have conducted preliminary experiments on engineering question answering tasks beyond report generation, and observed that SecMulti-RAG also performs well in those scenarios, indicating its potential. Example responses are provided in Appendix G.3.

Currently, we apply a heuristic selection constraint: at most one external knowledge document is included per query (Section 5.4). This constraint is motivated by our observation that GPTgenerated documents, while useful for providing general technical background or engineering context, may dilute the factual grounding of system responses if overused. However, this rule-based constraint lacks adaptability and may not always yield optimal document combinations tailored to diverse query intents. In future work, we aim to develop a learning-based document selection strategy that jointly considers query characteristics and document sources, allowing the system to automatically re-rank and select optimal document combinations to better match the specific needs of each query and deployment context.

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References

Anthropic. 2024. The claude 3 model family: Opus, sonnet, haiku.

Jianlyu Chen, Shitao Xiao, Peitian Zhang, Kun Luo, Defu Lian, and Zheng Liu. 2024. M3-embedding: Multi-linguality, multi-functionality, multi-granularity text embeddings through self-knowledge distillation. In *Findings of the Association for Computational Linguistics ACL 2024*, pages 2318–2335, Bangkok, Thailand and virtual meeting. Association for Computational Linguistics.

Nayoung Choi, Grace Byun, Andrew Chung, Ellie S. Paek, Shinsun Lee, and Jinho D. Choi. 2025. Trustworthy answers, messier data: Bridging the gap in low-resource retrieval-augmented generation for domain expert systems. *Preprint*, arXiv:2502.19596.

Chun Jie Chong, Chenxi Hou, Zhihao Yao, and Seyed Mohammadjavad Seyed Talebi. 2024. Casper: Prompt sanitization for protecting user privacy in web-based large language models. *Preprint*, arXiv:2408.07004.

DeepSeek-AI, Daya Guo, Dejian Yang, Haowei Zhang, Junxiao Song, Ruoyu Zhang, Runxin Xu, Qihao Zhu, Shirong Ma, Peiyi Wang, Xiao Bi, Xiaokang Zhang, Xingkai Yu, Yu Wu, Z. F. Wu, Zhibin Gou, Zhihong Shao, Zhuoshu Li, Ziyi Gao, Aixin Liu, Bing Xue, Bingxuan Wang, Bochao Wu, Bei Feng, Chengda Lu, Chenggang Zhao, Chengqi Deng, Chenyu Zhang, Chong Ruan, Damai Dai, Deli Chen, Dongjie Ji, Erhang Li, Fangyun Lin, Fucong Dai, Fuli Luo, Guangbo Hao, Guanting Chen, Guowei Li, H. Zhang, Han Bao, Hanwei Xu, Haocheng Wang, Honghui Ding, Huajian Xin, Huazuo Gao, Hui Qu, Hui Li, Jianzhong Guo, Jiashi Li, Jiawei Wang, Jingchang Chen, Jingyang Yuan, Junjie Qiu, Junlong Li, J. L. Cai, Jiaqi Ni, Jian Liang, Jin Chen, Kai Dong, Kai Hu, Kaige Gao, Kang Guan, Kexin Huang, Kuai Yu, Lean Wang, Lecong Zhang, Liang Zhao, Litong Wang, Liyue Zhang, Lei Xu, Leyi Xia, Mingchuan Zhang, Minghua Zhang, Minghui Tang, Meng Li, Miaojun Wang, Mingming Li, Ning Tian, Panpan Huang, Peng Zhang, Qiancheng Wang, Qinyu Chen, Qiushi Du, Ruiqi Ge, Ruisong Zhang, Ruizhe Pan, Runji Wang, R. J. Chen, R. L. Jin, Ruyi Chen, Shanghao Lu, Shangyan Zhou, Shanhuang Chen, Shengfeng Ye, Shiyu Wang, Shuiping Yu, Shunfeng Zhou, Shuting Pan, S. S. Li, Shuang Zhou, Shaoqing Wu, Shengfeng Ye, Tao Yun, Tian Pei, Tianyu Sun, T. Wang, Wangding Zeng, Wanjia Zhao, Wen Liu, Wenfeng Liang, Wenjun Gao, Wenqin Yu, Wentao Zhang, W. L. Xiao, Wei An, Xiaodong Liu, Xiaohan Wang, Xiaokang Chen, Xiaotao Nie, Xin Cheng, Xin Liu, Xin Xie, Xingchao Liu, Xinyu Yang, Xinyuan Li, Xuecheng Su, Xuheng Lin, X. Q. Li, Xiangyue Jin, Xiaojin Shen, Xiaosha Chen, Xiaowen Sun, Xiaoxiang Wang, Xinnan Song, Xinyi Zhou, Xianzu Wang, Xinxia Shan, Y. K. Li, Y. Q. Wang, Y. X. Wei, Yang Zhang, Yanhong Xu, Yao Li, Yao Zhao, Yaofeng Sun, Yaohui Wang, Yi Yu, Yichao Zhang, Yifan Shi, Yiliang Xiong, Ying He,

Yishi Piao, Yisong Wang, Yixuan Tan, Yiyang Ma, Yiyuan Liu, Yongqiang Guo, Yuan Ou, Yuduan Wang, Yue Gong, Yuheng Zou, Yujia He, Yunfan Xiong, Yuxiang Luo, Yuxiang You, Yuxuan Liu, Yuyang Zhou, Y. X. Zhu, Yanhong Xu, Yanping Huang, Yaohui Li, Yi Zheng, Yuchen Zhu, Yunxian Ma, Ying Tang, Yukun Zha, Yuting Yan, Z. Z. Ren, Zehui Ren, Zhangli Sha, Zhe Fu, Zhean Xu, Zhenda Xie, Zhengyan Zhang, Zhewen Hao, Zhicheng Ma, Zhigang Yan, Zhiyu Wu, Zihui Gu, Zijia Zhu, Zijun Liu, Zilin Li, Ziwei Xie, Ziyang Song, Zizheng Pan, Zhen Huang, Zhipeng Xu, Zhongyu Zhang, and Zhen Zhang. 2025. Deepseek-r1: Incentivizing reasoning capability in Ilms via reinforcement learning. *Preprint*, arXiv:2501.12948.

Matthijs Douze, Alexandr Guzhva, Chengqi Deng, Jeff Johnson, Gergely Szilvasy, Pierre-Emmanuel Mazaré, Maria Lomeli, Lucas Hosseini, and Hervé Jégou. 2025. The faiss library. *Preprint*, arXiv:2401.08281.

Bernal Jiménez Gutiérrez, Yiheng Shu, Yu Gu, Michihiro Yasunaga, and Yu Su. 2025. Hipporag: Neurobiologically inspired long-term memory for large language models. *Preprint*, arXiv:2405.14831.

Jamie Hayes, Luca Melis, George Danezis, and Emiliano De Cristofaro. 2017. Logan: Evaluating privacy leakage of generative models using generative adversarial networks. *ArXiv*, abs/1705.07663.

Soyeong Jeong, Jinheon Baek, Sukmin Cho, Sung Ju Hwang, and Jong C. Park. 2024. Adaptiverag: Learning to adapt retrieval-augmented large language models through question complexity. *Preprint*, arXiv:2403.14403.

Siwon Kim, Sangdoo Yun, Hwaran Lee, Martin Gubri, Sungroh Yoon, and Seong Joon Oh. 2023. Propile: Probing privacy leakage in large language models. *Preprint*, arXiv:2307.01881.

Patrick Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, Sebastian Riedel, and Douwe Kiela. 2020. Retrieval-augmented generation for knowledge-intensive nlp tasks. In *Proceedings of the 34th International Conference on Neural Information Processing Systems*, NIPS '20, Red Hook, NY, USA. Curran Associates Inc.

Nils Lukas, Ahmed Salem, Robert Sim, Shruti Tople, Lukas Wutschitz, and Santiago Zanella-Béguelin. 2023. Analyzing leakage of personally identifiable information in language models. *Preprint*, arXiv:2302.00539.

OpenAI, Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, Red Avila, Igor Babuschkin, Suchir Balaji, Valerie Balcom, Paul Baltescu, Haiming Bao, Mohammad Bavarian,

Jeff Belgum, Irwan Bello, Jake Berdine, Gabriel Bernadett-Shapiro, Christopher Berner, Lenny Bogdonoff, Oleg Boiko, Madelaine Boyd, Anna-Luisa Brakman, Greg Brockman, Tim Brooks, Miles Brundage, Kevin Button, Trevor Cai, Rosie Campbell, Andrew Cann, Brittany Carey, Chelsea Carlson, Rory Carmichael, Brooke Chan, Che Chang, Fotis Chantzis, Derek Chen, Sully Chen, Ruby Chen, Jason Chen, Mark Chen, Ben Chess, Chester Cho, Casey Chu, Hyung Won Chung, Dave Cummings, Jeremiah Currier, Yunxing Dai, Cory Decareaux, Thomas Degry, Noah Deutsch, Damien Deville, Arka Dhar, David Dohan, Steve Dowling, Sheila Dunning, Adrien Ecoffet, Atty Eleti, Tyna Eloundou, David Farhi, Liam Fedus, Niko Felix, Simón Posada Fishman, Juston Forte, Isabella Fulford, Leo Gao, Elie Georges, Christian Gibson, Vik Goel, Tarun Gogineni, Gabriel Goh, Rapha Gontijo-Lopes, Jonathan Gordon, Morgan Grafstein, Scott Gray, Ryan Greene, Joshua Gross, Shixiang Shane Gu, Yufei Guo, Chris Hallacy, Jesse Han, Jeff Harris, Yuchen He, Mike Heaton, Johannes Heidecke, Chris Hesse, Alan Hickey, Wade Hickey, Peter Hoeschele, Brandon Houghton, Kenny Hsu, Shengli Hu, Xin Hu, Joost Huizinga, Shantanu Jain, Shawn Jain, Joanne Jang, Angela Jiang, Roger Jiang, Haozhun Jin, Denny Jin, Shino Jomoto, Billie Jonn, Heewoo Jun, Tomer Kaftan, Łukasz Kaiser, Ali Kamali, Ingmar Kanitscheider, Nitish Shirish Keskar, Tabarak Khan, Logan Kilpatrick, Jong Wook Kim, Christina Kim, Yongjik Kim, Jan Hendrik Kirchner, Jamie Kiros, Matt Knight, Daniel Kokotajlo, Łukasz Kondraciuk, Andrew Kondrich, Aris Konstantinidis, Kyle Kosic, Gretchen Krueger, Vishal Kuo, Michael Lampe, Ikai Lan, Teddy Lee, Jan Leike, Jade Leung, Daniel Levy, Chak Ming Li, Rachel Lim, Molly Lin, Stephanie Lin, Mateusz Litwin, Theresa Lopez, Ryan Lowe, Patricia Lue, Anna Makanju, Kim Malfacini, Sam Manning, Todor Markov, Yaniv Markovski, Bianca Martin, Katie Mayer, Andrew Mayne, Bob McGrew, Scott Mayer McKinney, Christine McLeavey, Paul McMillan, Jake McNeil, David Medina, Aalok Mehta, Jacob Menick, Luke Metz, Andrey Mishchenko, Pamela Mishkin, Vinnie Monaco, Evan Morikawa, Daniel Mossing, Tong Mu, Mira Murati, Oleg Murk, David Mély, Ashvin Nair, Reiichiro Nakano, Rajeev Nayak, Arvind Neelakantan, Richard Ngo, Hyeonwoo Noh, Long Ouyang, Cullen O'Keefe, Jakub Pachocki, Alex Paino, Joe Palermo, Ashley Pantuliano, Giambattista Parascandolo, Joel Parish, Emy Parparita, Alex Passos, Mikhail Pavlov, Andrew Peng, Adam Perelman, Filipe de Avila Belbute Peres, Michael Petrov, Henrique Ponde de Oliveira Pinto, Michael, Pokorny, Michelle Pokrass, Vitchyr H. Pong, Tolly Powell, Alethea Power, Boris Power, Elizabeth Proehl, Raul Puri, Alec Radford, Jack Rae, Aditya Ramesh, Cameron Raymond, Francis Real, Kendra Rimbach, Carl Ross, Bob Rotsted, Henri Roussez, Nick Ryder, Mario Saltarelli, Ted Sanders, Shibani Santurkar, Girish Sastry, Heather Schmidt, David Schnurr, John Schulman, Daniel Selsam, Kyla Sheppard, Toki Sherbakov, Jessica Shieh, Sarah Shoker, Pranav Shyam, Szymon Sidor, Eric Sigler, Maddie

Simens, Jordan Sitkin, Katarina Slama, Ian Sohl, Benjamin Sokolowsky, Yang Song, Natalie Staudacher, Felipe Petroski Such, Natalie Summers, Ilya Sutskever, Jie Tang, Nikolas Tezak, Madeleine B. Thompson, Phil Tillet, Amin Tootoonchian, Elizabeth Tseng, Preston Tuggle, Nick Turley, Jerry Tworek, Juan Felipe Cerón Uribe, Andrea Vallone, Arun Vijayvergiya, Chelsea Voss, Carroll Wainwright, Justin Jay Wang, Alvin Wang, Ben Wang, Jonathan Ward, Jason Wei, CJ Weinmann, Akila Welihinda, Peter Welinder, Jiayi Weng, Lilian Weng, Matt Wiethoff, Dave Willner, Clemens Winter, Samuel Wolrich, Hannah Wong, Lauren Workman, Sherwin Wu, Jeff Wu, Michael Wu, Kai Xiao, Tao Xu, Sarah Yoo, Kevin Yu, Qiming Yuan, Wojciech Zaremba, Rowan Zellers, Chong Zhang, Marvin Zhang, Shengjia Zhao, Tianhao Zheng, Juntang Zhuang, William Zhuk, and Barret Zoph. 2024. Gpt-4 technical report. Preprint, arXiv:2303.08774.

Ridong Wu, Shuhong Chen, Xiangbiao Su, Yuankai Zhu, Yifei Liao, and Jianming Wu. 2024. A multi-source retrieval question answering framework based on rag. *Preprint*, arXiv:2405.19207.

An Yang, Baosong Yang, Beichen Zhang, Binyuan Hui, Bo Zheng, Bowen Yu, Chengyuan Li, Dayiheng Liu, Fei Huang, Haoran Wei, et al. 2024. Qwen2. 5 technical report. *arXiv preprint arXiv:2412.15115*.

Wenhao Yu, Dan Iter, Shuohang Wang, Yichong Xu, Mingxuan Ju, Soumya Sanyal, Chenguang Zhu, Michael Zeng, and Meng Jiang. 2023. Generate rather than retrieve: Large language models are strong context generators. *Preprint*, arXiv:2209.10063.

Shuning Zhang, Lyumanshan Ye, Xin Yi, Jingyu Tang, Bo Shui, Haobin Xing, Pengfei Liu, and Hewu Li. 2024. "ghost of the past": identifying and resolving privacy leakage from llm's memory through proactive user interaction. *Preprint*, arXiv:2410.14931.

Lianmin Zheng, Wei-Lin Chiang, Ying Sheng, Siyuan Zhuang, Zhanghao Wu, Yonghao Zhuang, Zi Lin, Zhuohan Li, Dacheng Li, Eric P. Xing, Hao Zhang, Joseph E. Gonzalez, and Ion Stoica. 2023. Judging llm-as-a-judge with mt-bench and chatbot arena. *Preprint*, arXiv:2306.05685.

Yujia Zhou, Zheng Liu, and Zhicheng Dou. 2024. Assistrag: Boosting the potential of large language models with an intelligent information assistant. *Preprint*, arXiv:2411.06805.

A RAG Framework

Figure 4 demonstrates both Traditional RAG and SecMulti-RAG framework.

B Filter

B.1 Query Dataset

Security-sensitive and general (non-sensitive) queries are carefully constructed by Korean automotive engineers with the assistance of Claude. Figure 5 shows the prompt template that the engineers used during data construction, reflecting our efforts to optimize prompt design for query generation.

B.2 Training

Full fine-tuning is performed on Qwen2.5-3B-Instruct (Yang et al., 2024) using a per-device batch size of 2 and a gradient accumulation step of 256, effectively simulating a large batch size. The model is trained for 3 epochs with a learning rate of 8e-6. Training is conducted on $3 \times 48GB$ RTX A6000 GPUs.

B.3 Prompt

Figure 6 provides the prompt that we use to filter out user queries that should not be exposed to closed-source LLM.

C Enterprise Knowledge Base

Table 7 shows the statistics of the Enterprise Knowledge Base dataset. Document chunks and QA pairs are constructed from test reports, meeting reports, and textbook. Refer to Choi et al. (2025) for more details.

Source	Data	Train	Val	Test	Total
Test Report	Chunk	3,729	466	467	4,662
	QA Pair	47,660	5,823	5,919	59,402
Meeting Report	Chunk	705	88	89	882
	QA Pair	6,144	752	800	7,696
Textbook	Chunk	64	8	9	81
Textbook	QA Pair	1,182	162	161	1,505

Table 7: Enterprise Knowledge Base Dataset: Statistics by source, detailing the distribution of chunks and QA pairs.

D Pre-written Expert Knowledge

D.1 Keywords

Below are some of the keywords we use to generate pre-written expert knowledge. Reports re-

SecureFusion-RAG User Query **Traditional RAG** Filter User Query No Dynamically On-Demand Dynamically Enterprise Pre-Generated updated Knowledge Base Expert Enterprise Knowledge Base **Final Generation** Multi-source Information Integration **Final Generation**

Figure 4: Traditional RAG vs SecMulti-RAG

lated to these keywords (main problems) are pregenerated by automotive engineers.

- 1. 차체 구조 및 안전성 관련 이슈 (Vehicle Structural Integrity and Safety Issues)
- 1. 차체 구조 및 구조적 완전성 (Body Structure and Structural Integrity)
- 1.1. 필러(Pillar) 관련 문제 (Pillar-Related Issues)

1.1.1. A필러 문제 (A-Pillar Issues)

A필러 상부 강성 부족 및 변형 (Insufficient upper stiffness and deformation in A-pillar)

A필러 힌지 크랙 발생 (Hinge crack formation in A-pillar)

A필러와 대시 연결부 찢어짐 (Tearing at the connection between the A-pillar and the dashboard)

A필러 변형으로 인한 윈드실드 파손 (Windshield damage due to A-pillar deformation)

A필러 이탈 지연으로 인한 타이어 내측 거동 (Delayed detachment of A-pillar affecting inner tire movement)

1.1.2. B필러 문제 (B-Pillar Issues)

B필러 하단부 강성 부족으로 인한 변형 과다 (Excessive deformation due to insufficient lower stiffness in B-pillar)

B필러 용접부 크랙 및 파단 (Cracks and fractures in B-pillar welding area)

B필러 상단부 꺾임 현상 (Bending at the upper section of the B-pillar)

B필러와 루프라인 연결부 취약성 (Weak connection between B-pillar and roofline)

B필러 변형으로 인한 생존 공간 감소 (Reduction in survival space due to B-pillar deformation)

B필러 부위 접힘 현상 (Folding phenomenon in the B-pillar area) B-PLR INR LWR EXTN 누락 (Omission of B-PLR INR LWR EXTN)

1.1.3. C필러 및 쿼터패널 문제 (C-Pillar and Quarter Panel Issues)

C필러 부위 접힘 현상 (Folding in the C-pillar area)

쿼터패널 측면 파고듦 현상 (Intrusion on the side of the quarter panel)

C필러 트림 파손 (C-pillar trim damage)

쿼터 리테이너 강성 부족 (Insufficient stiffness in quarter retainer)

1.2. 도어 구조 관련 문제 (Door Structure Issues) 1.2.1. 도어 구조체 문제 (Door Frame Issues)

도어 임팩트 빔 마운팅부 파단 및 이탈 (Fracture and detachment of door impact beam mounting)

도어 빔 브라켓 강도 부족 (Insufficient strength in door beam bracket)

도어 힌지 마운팅 볼트 파단 및 뽑힘 (Fracture and detachment of door hinge mounting bolts)

도어 래치 마운팅부 파손 (Breakage in door latch mounting)

도어 변형으로 인한 침입량 증가 (Increased intrusion due to door deformation)

임팩트 빔 꺾임 및 마운팅 용접부 파단 (Bending of impact beam and fracture in mounting weld) 1.2.2. 도어 부품 및 연결부 문제 (Door Compo-

1.2.2. 모여 구름 및 연결구 문제 (Door Components and Connection Issues)

도어 스트라이커 이탈 및 손상 (Detachment and damage of door striker)

도어 인너 판넬 분리 및 파손 (Separation and breakage of door inner panel)

```
Prompt
[Security-sensitive queries without project name]
You are an engineer in charge of vehicle crash safety testing. Based on internal reports, you are tasked with
         generating sensitive security-related queries that should not be exposed to the public. The queries must meet
         the following requirements:
Ouerv Generation Guidelines:

    Query Generation Guidelines:

            Do NOT include any specific project names or test IDs.
            Do NOT ask about exact internal figures or detailed designs directly. Instead, formulate questions that indirectly imply such information through the context.

    Each question should be capable of revealing internal issues or technical weaknesses if exposed externally.
    Vary the length of the queries (mostly short questions, but some longer ones included).
    Generate 50 questions in total.

- Provide a one-line explanation for why each question is considered security-sensitive.
Example Questions:
     What is the root cause of the excessive B-pillar deformation observed in recent tests?" (Indirectly reveals an
        internal issue)
- "What causes the delayed airbag deployment timing?" (Hints at internal system problems)
- "Why is reinforcement needed in the door hinge area?" (Implies structural vulnerability)
- "Why does a specific area repeatedly exhibit excessive deformation in crash tests?" (Reveals unresolved structural
         weaknesses)
Please refer to the examples above and generate 50 diverse security-sensitive questions that indirectly reveal
        sensitive internal information.
Here are the internal reports:
 <Reports>
{reports}
 </Reports>
[Security-sensitive queries with project name]
You are an engineer in charge of vehicle crash safety testing. Based on internal reports, you are tasked with generating security-related queries that include a specific project name but exclude test IDs. The queries must
         meet the following requirements:
Ouerv Generation Guidelines:

    MUST include a specific project name (but do NOT include test IDs).

        most queries, place the project name at the beginning of the sentence, but vary the position in some queries ( middle or end).
2. In most queries
mitude of end).

3. It is acceptable to include sensitive internal figures or specific design information.

4. The queries must be security-sensitive and unsuitable for public exposure.

5. Vary the length of the queries (mostly short, but some longer ones included).

6. Provide a one-line explanation for why each question is considered security-sensitive.

7. Maintain the following consistent output format:
   "Query sentence
(Explanation)
Here are the internal reports:
 <Reports>
{reports}
 </Reports>
______
[General (non-sensitive) queries]
You are an engineer in charge of vehicle crash safety testing. Based on internal reports, generate general queries
         that do not pose any security concerns and can be disclosed publicly. These queries should reflect realistic engineering questions that professionals may encounter in practice. The queries must meet the following
         requirements:
Query Generation Guidelines

    Query Generation Guidelines:
    Do NOT include any specific project names or test IDs.
    Avoid questions about sensitive internal figures or detailed designs. Instead, focus on general technical concepts, practical engineering concerns, and issues that engineers would typically discuss.
    Questions should be centered on issues arising in crash safety testing environments, engineering decision-making,

         and practical field concerns.
4. Vary the length of the queries (mostly short, but some longer ones included).

5. Provide a one-line explanation for why each question is NOT considered security-sensitive.

6. Maintain the following consistent output format:
 - "Query sentence"
(Explanation)
Here are the internal reports:
 <Reports>
{reports}
 </Reports>
```

Figure 5: Prompt used for query data generation (Translated to English)

```
Prompt
You are a classification model for user queries
There are **TWO CLASSES ONLY**:
 => The query may contain internal or sensitive information and is NOT safe.
1 => The query is general and can be safely processed
**IMPORTANT INSTRUCTION**:
- If the query contains any internal project names, testing scores, engineering design details, weakness (defects), and internal solution, you MUST classify as 0.
You must output ONLY one number: either 0 or 1.
    [Example 1] (GPT Not Allowed - Corporate Internal Information) User Question: "Tell me the test results of LX2 P2."
    [Example 2] (GPT Not Allowed - Requesting Internal Evaluation Report for a Specific Vehicle)
    User Question: "Share the internal crash test report of the G70 frontal crash test.
    [Example 3] (GPT Allowed - General Automotive Safety Regulations)
    User Question: "Explain the U.S. Federal Motor Vehicle Safety Standard."
    [Example 4] (GPT Allowed - Structural Improvement Cases for Automotive Components)
                    "Tell me about cases of subframe failure and possible improvements
    [Example 5] (GPT Not Allowed - Confidential Design Information of a Specific Company)
    User Question: "Tell me the key design changes in Hyundai's new engine blueprint.
    [Example 6] (GPT Allowed - General Mechanical Engineering Theory)
                    "What are some methods to increase the rigidity of a car chassis?"
    [Example 7] (GPT Not Allowed - Requesting Internal Test Data)
    User Question: "Tell me the results of the in-house crash tests conducted by HMG."
    [Example 8] (GPT Allowed - Public Data-Based Information)
    User Question: "Explain the European NCAP crash test standards and evaluation criteria."
    Judgment: 1
```

Figure 6: Prompt used for Filtering Progress (Translated to English)

D.2 Pre-written Reports Generation

To generate pre-written expert knowledge, Korean automotive engineers employ the prompt shown in Figure 7, refined through extensive prompt tuning. The generated reports include a structured composition of problem definition, technical analysis, case analysis, improvement suggestions, and relevant references, and are subsequently reviewed by domain experts. The keywords provided in Section D.1 serve as the core problem topics addressed in each report. University-internal Claude service from AWS Bedrock is used for security.

E On-Demand External Knowledge

Once the prompt passes the safety filter and deemed to be safe, we use GPT-40 to provide ondemand external knowledge. Specifically, it generates a general-purpose technical background document to help engineers draft formal safety reports. The prompt used is shown in Figure 8. The GPT-generated document is then indexed into the doc-

ument pool for retrieval.

F Generation

We fine-tune Qwen-2.5-14B-Instruct (Yang et al., 2024) using a Korean question-answering dataset focused on the automobile engineering domain. Full fine-tuning is conducted for the 14B model with a batch size of 2, gradient accumulation steps of 64, a learning rate of 2e-5, and 3 training epochs. $3 \times 80 \text{GB}$ H100 GPUs are used for the training. Figure 9 is the prompt used for report generation of Qwen model.

G Evaluation

G.1 LLM-based Evaluation

Figure 10 is the prompt that we use for LLM-based evaluation.

G.2 Human and LLM evaluation Agreement

Figure 11 demonstrates confusion matrices showing the agreement between LLM and human eval-

```
Prompt
# You are an expert in writing professional engineering reports in the field of automotive crash safety. Based on the given
       problem situation and related report data, you must write a technical report that is useful for field engineers.
1. **Problem Situation**: <Problem> {problem} </Problem>
2. **Reference Reports**: <Reports> {reports} </Reports>
## Output Requirements
     **Title**: A technical title that clearly reflects the problem situation.
2. **Problem Definition**:
    * Detailed description of the problem occurrence.
     * Specification of affected vehicle components.

* Analysis of the impact on safety.

* Identification of common problem patterns observed across multiple cases.
3. **Technical Analysis*:

* Root cause analysis (based on report evidence).

* Summary of related test results and pattern identification.

* Inclusion of measured numerical data (if available).

* Comparative analysis and correlation between multiple tests.
    * Compare and analyze similarities and differences between cases.
* Compare case results in tabular format (recommended).
5. **Improvement Directions**:
     * Summarize all improvement measures mentioned in the reports.
    * Clearly explain the reasons and expected effects of each improvement.
* Provide a prioritization of improvement measures.
     * Identify areas requiring additional testing and justify their necessity.
6. **Conclusion**:
     * Summary of key issues.
* Summary of major findings
     * Comprehensive expected effects of the proposed improvements.
7. **References**:
    * All information sources must be cited in parentheses right after the corresponding content (e.g., "Due to insufficient upper
            A-pillar stiffness, the DASH deformation exceeded the target of 100mm by reaching 128mm (C200728A_CV).")
    \star Arrange citations appropriately to avoid disrupting readability.
## Key Guidelines
1. **Pattern Identification**: Actively identify and analyze recurring problem patterns across different tests and situations.
2. **Data Integration**: Integrate similar data from multiple reports to provide a more comprehensive analysis.

3. **Importance Evaluation**: Assign higher importance to repeated problems and explicitly indicate this.
4. **Flexible Report Structure**: Use the given structure as a starting point but modify, merge, or add sections as needed based
        on data and analysis results.
on data and analysis results.

5. Exclude unnecessary introductions or background explanations and focus on core technical content.

6. Do not make assumptions or use general knowledge to fill in missing report data.

7. Provide specific technical information that engineers can use immediately.

8. Ensure all information can be traced back to its source, but citations should not overshadow the main content.
   Include relevant data, figures, and specific specifications whenever possible. Focus on the methodology applied to solve the problem and the results achieved.
11. Citations should be concise, placed at the end of the sentence or paragraph, and include only the report code in parentheses.
## Citation Examples
  Incorrect: "According to report C200728A_CV, due to insufficient upper A-pillar stiffness..."

Correct: "Due to insufficient upper A-pillar stiffness, the DASH deformation exceeded the target of 100mm by reaching 128mm (
C200728A_CV)."
* Correct:
* Multiple citations: "BrIC is an index developed to assess the risk of brain injury caused by head rotational motion (C200728A_CV , C200730B_NE)."
* Similar issue citation: "The A-pillar deformation issue was consistently observed in three tests (C200728A_CV, C200805B_CV, C200901A_CV), and in all cases, the deformation exceeded the allowable limit by 20-25%."
## Basic Report Structure
    markdown
# Technical Title Based on the Problem Situation
## Problem Definition
– Detailed description of the problem and pattern identification. – Affected vehicle components.
   Safety impact analysis.
  # Technical Analysis
Root cause analysis.
Summary of test results.
   Measurement data.
Case Comparison Analysis
  Test ID | Issue Description | Measured Value | Standard Value | Deviation | Notes |
   TEST-001 | Issue description | 00.0 | 00.0 | 00.0 | Additional info | TEST-002 | Issue description | 00.0 | 00.0 | 00.0 | Additional info |
                                                                                                             | Additional info |
## Improvement Measures and Effects
   Applied solutions.
   Effectiveness measurement results.
   Technical specifications.
## Improvement Directions
- **Priority 1**: [Improvement measure] - [Clear reason and expected effect]
- **Priority 2**: [Improvement measure] - [Clear reason and expected effect]
   **Additional Tests Needed**: [Test details] - [Reason for necessity]
## Conclusion
  Summary of key issues.
Summary of major findings
   Comprehensive expected effects of improvements.
```

Figure 7: Prompt used for generating gold reports. The prompt is originally Korean.

```
Prompt
      You are an expert in automotive crash safety engineering
      You are tasked with generating a general-purpose technical background document **in Korean** that can assist engineers in drafting formal safety reports.
      Only a high-level keyword describing a common engineering issue is provided.
      Based on your expert knowledge, please provide background information and reasonable technical discussion, without fabricating any specific case data, test results, or numeric values that are not grounded in well-known
              general principles.
      Your output should include the following sections:
      1. **Title**: A concise technical title derived from the given keyword.
2. **Issue Overview**:
          - Describe the typical nature of this issue in automotive safety engineering. - Mention which vehicle components are generally involved.
      - Explain how this issue may impact structural integrity or passenger safety. 
 3. **Common Engineering Considerations**:
            - Discuss known design challenges, structural constraints, or typical causes.
- Do NOT include fabricated test results or data.
      - Only refer to general engineering principles or commonly reported concerns in literature. 4. **Improvement Suggestions (General)**:
            - Suggest generic design or material improvements.
- Clarify expected benefits and rationale (without specific test results).
      5. **Conclusion**:
             Summarize key considerations
          \hbox{--} Emphasize that this document provides only general technical guidance, not case-specific findings. \\
      Important:

    Do NOT fabricate test results, measured data, or specific incident cases.
    Only refer to general trends, common engineering knowledge, and design principles.
    This is intended to serve as a general technical reference, not a case analysis.

      kevword: {kevword}
```

Figure 8: Prompt used for generating on-demand external knowledge using GPT-4o.

uations. Each cell contains the count and percentage of cases where Claude (vertical axis) and human evaluators (horizontal axis) made specific judgments about system preference. Darker blue indicates higher frequency. The diagonal cells represent agreement between both evaluators, while off-diagonal cells show disagreement patterns. A large portion of the counts lies along the diagonal, indicating a substantial level of agreement between the two evaluators. Both evaluators show preference for the SecMulti-RAG's generations especially in 'Richness' and 'Overall' metrics.

Table 8 reports the agreement rates and Gwet's AC1 scores. Gwet's AC1 is reported instead of Cohen's Kappa due to the class imbalance in the evaluation results, where SecMulti-RAG is consistently preferred over Traditional RAG. Notably, correctness shows relatively lower agreement, largely due to the LLM's tendency to avoid assigning 'tie' labels, which are more frequently used by human evaluators.

G.3 Task Scalability

In this study, we primarily evaluate our RAG framework on the report generation task. However, in practice, the framework is scalable to various tasks and domains. We conducted a preliminary test with a few engineering questions in the automotive domain, as shown in Figure 12. The

Metric	Agreement (%)	Gwet's AC1
Correctness	56.74%	0.4295
Richness	73.05%	0.6812
Helpfulness	69.50%	0.6264
Overall	72.34%	0.6647

Table 8: Agreement between Claude and Human Evaluation Results

SecMulti-RAG responses include specific injury types, structural causes, and implications for official safety assessments, demonstrating greater richness and helpfulness compared to the Traditional RAG responses.

```
Prompt
You are an expert in writing professional engineering reports in the field of automotive crash safety. Based on the
        given problem description and related report data, you are required to generate a technical report that provides
         practical insights for field engineers.
## Output Requirements
1. **Title**: A technical title that clearly reflects the problem.
2. **Problem Definition**:
    * Describe the situation in which the issue occurred in detail.

* Specify the affected vehicle components.

* Analyze the impact on safety.
* Identify common patterns observed across multiple cases. 
 3. **Technical Analysis**:
    * Analyze the root causes.
* Summarize related test results and identify patterns.
     * Include measured numerical data.
* Compare test results and analyze correlations.
4. **Case Comparison Analysis**:

* List and categorize all cases where similar issues occurred.

* Compare similarities and differences across cases.

* Present comparison of results using tables (recommended).
5. **Improvement Directions**:
     \dot{\star} Summarize all improvement actions mentioned in the reports
    \star Clearly explain the rationale and expected effects of each action. 
 \star Prioritize the improvement directions.
      Identify areas that require additional testing and justify their necessity.
6. **Conclusion**:
    * Summarize the key problems.
    * Recap the main findings.
* Synthesize the expected benefits of the proposed improvements.
7. **References**:
    * Cite all sources immediately after the corresponding information using parentheses.

(e.g., "Due to insufficient upper stiffness of the A-pillar, the DASH deformation exceeded the target value at 128mm compared to the target of 100mm (C200728A_CV).")
    \star Ensure references are properly placed without compromising readability.
Ensure that the report is written in a professional and technically accurate manner according to the guidelines above . All conclusions and improvement directions must be based strictly on evidence extracted from the provided
        reports. Source citations should be placed directly after each statement or piece of information to ensure
        clarity and traceability.
Pay particular attention to identifying recurring patterns observed across multiple tests or cases and include them
        in the report.
                             This is critical for understanding the systematic nature of the problem and for proposing
        effective solutions.
                         content of the report must be optimized so that engineers can clearly understand the issue and
        implement effective solutions. Providing data-driven insights and practical engineering perspectives is key. The conclusion should synthesize the report's core findings and offer clear directions for future development and
        implementation.
```

Figure 9: Prompt used for report generation of Qwen model based on the retrieved documents. The prompt is originally Korean.

```
You are a strict evaluator of AI-generated text for automobile engineering questions.
You must judge two responses, A and B, on the following metrics:

1) Correctness: factual correctness based on the question
2) Richness: level of detail and completeness
3) Helpfulness: clarity, directness, and overall usefulness
Then decide who wins each metric (A/B/tie), and also decide the final overall winner.
Output format strictly:
CorrectnessWINNER: [A/B/tie]
RichnessWINNER: [A/B/tie]
HelpfulnessWINNER: [A/B/tie]
OVERALLWINNER: [A/B/tie]
OVERALLWINNER: [A/B/tie]
No explanations.

Question: {question}
Response A: {answer_a}
Response B: {answer_b}
Please provide the winners in the specified format WITHOUT any numerical scores.
```

Figure 10: Prompt used for LLM-based Evaluation. Pairwise evaluation between Traditional RAG and SecMulti-RAG is conducted using Claude 3.7 Sonnet.

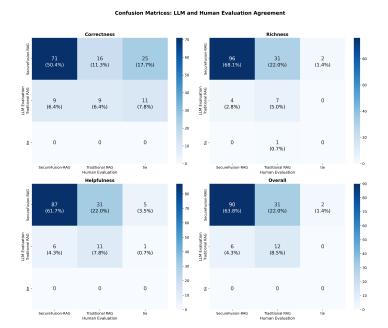


Figure 11: Confusion matrices showing the agreement between LLM and human evaluations. Most counts lie on the diagonal cells, indicating consistent agreement between both evaluators.

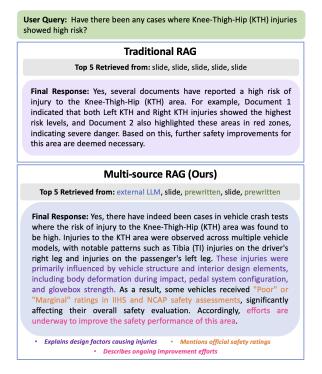


Figure 12: Comparison between Traditional RAG and SecMulti-RAG in QA task (translated from Korean)