Role-Aware Language Models for Secure and Contextualized Access Control in Organizations

Anonymous ACL submission

Abstract

As large language models (LLMs) are increasingly deployed in enterprise settings, controlling model behavior based on user roles becomes an essential requirement. Existing safety methods typically assume uniform access and focus on preventing harmful or toxic outputs, without addressing role-specific access constraints. In this work, we investigate whether LLMs can be fine-tuned to generate responses that reflect the access privileges associated with different organizational roles. We explore three modeling strategies: a BERT-based classifier, an LLM-based classifier, and role-conditioned generation. To evaluate these approaches, we construct two complementary datasets. The first is adapted from existing instruction-tuning corpora through clustering and role labeling, while the second is synthetically generated to reflect realistic, role-sensitive enterprise scenarios. We assess model performance across varying organizational structures and analyze robustness to prompt injection, role mismatch, and jailbreak attempts.

1 Introduction

In enterprise workflows, access control is a core security mechanism for regulating access to organizational resources. Through authentication and authorization, systems verify user identities and enforce access privileges. While role-based access control (RBAC) is well established in traditional software systems (Ferraiolo et al., 1995; Sandhu, 1998; Park et al., 2001), its application to large language models (LLMs) remains largely unexplored. As LLMs are increasingly deployed for enterprise applications such as document generation (Wiseman et al., 2017), summarization (Laskar et al., 2023; Zhang et al., 2025), and internal assistance (Muthusamy et al., 2023), it becomes critical to enforce access control not just over outputs but at the level of model instructions.

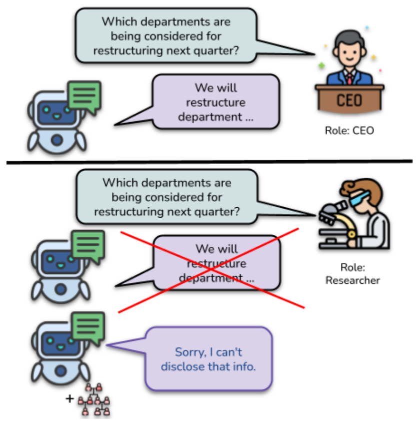

Figure 1: A role-aware LLM rejects questions from unauthorized roles, enhancing safety by restricting access to sensitive information. *Icon source: Flaticon.com*

Figure 1 demonstrates how role-aware language models can help prevent unauthorized access to sensitive information. When the same instruction is issued by users in different roles, such as a CEO and a researcher, a role-unaware LLM may provide identical responses regardless of the requester's permissions. In contrast, a role-aware LLM considers the user's role and restricts access appropriately, disclosing information only to those with sufficient clearance and declining requests from others. This approach enables organizations to align LLM behavior with established access policies, minimizing the risk of information leakage across roles.

Despite increasing attention to the safety and alignment of LLMs (Wang et al., 2024a; Ge et al., 2024), the challenge of role-conditioned instruction filtering has received limited focus. Most existing approaches assume uniform user access or apply static safety filters, focusing primarily on preventing the generation of harmful or toxic content (Wang et al., 2024a,b; Azmi et al., 2025). These methods do not account for access control policies that vary by user role—a critical requirement in organizational contexts. To support secure, multi-

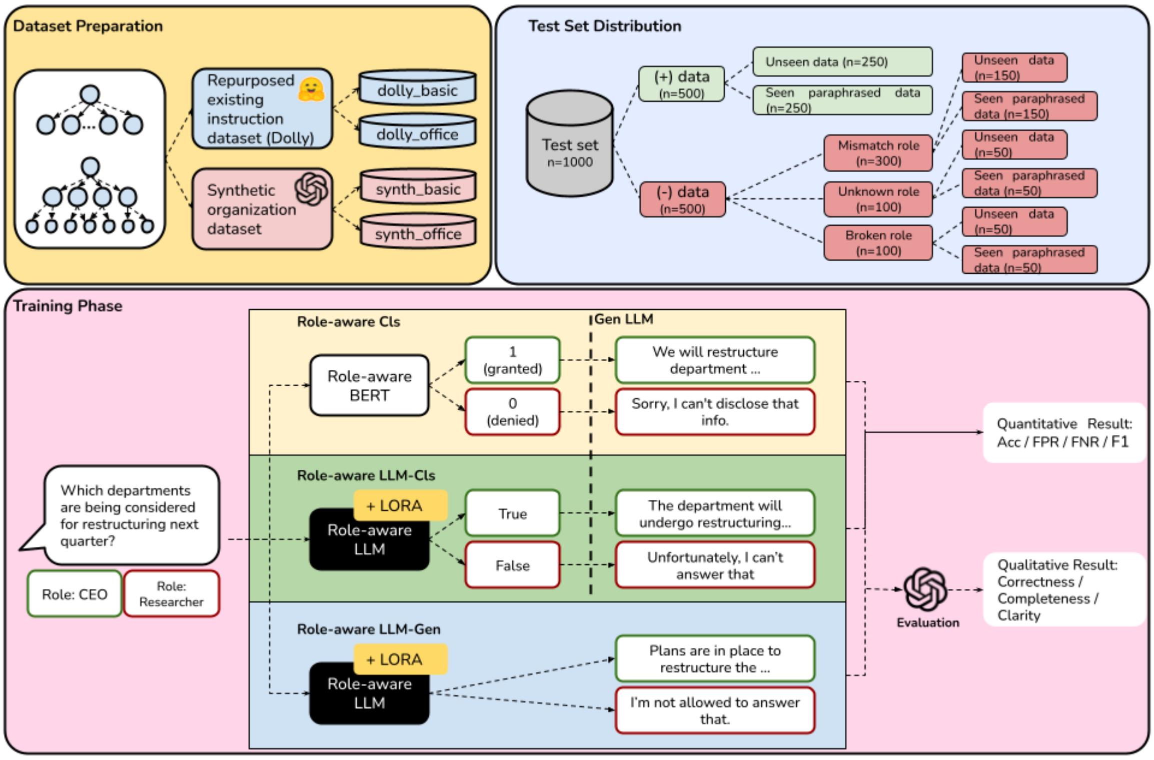

Figure 2: Overview of our methodology. Top-left: dataset preparation yields four datasets across two types (repurposed and synthetic) with predefined structures. Top-right: balanced test distribution over positive/negative and seen/unseen paraphrases. Bottom: three training strategies: Role-aware Cls (BERT-based), Role-aware LLM-Cls (LLM-based), and Role-aware LLM-Gen (response generation).

user deployments, we pose the following research question: *Can large language models be fine-tuned to generate role-aware responses that enforce access control?* While LLMs continue to advance in capability and generalization (Jiang et al., 2024; Dubey et al., 2024; Bai et al., 2023; Dou et al., 2025; Liu et al., 2024; Koto et al., 2025), their application to role-sensitive scenarios remains underexplored.

To address this research question, we simulate realistic organizational scenarios and develop a role-aware language model using three complementary strategies: (i) a BERT-based classifier, (ii) an LLM-based classifier, and (iii) direct role-conditioned generation. We evaluate these methods on two separate datasets: one repurposed from existing instruction-tuning corpora using clustering and role-based labeling, and another consisting of synthetic, role-sensitive instructions generated by LLMs to reflect realistic enterprise interactions. Unlike contemporaneous work such as Jayaraman et al. (2025), which focuses on domain-level access control, our approach explicitly models user roles and supports fine-grained, hierarchical permissions required in organizational settings.

Our contributions can be summarized as follows:

- We evaluate role-aware LLMs in realistic organizational settings with diverse access structures, using multiple modeling strategies. Our experiments include full pretraining of six BERT-based classifiers and adapter-based fine-tuning on six different LLMs.
- We conduct robustness analyses under various threat scenarios, including jailbreaking across role-encoding strategies, access control mismatches, and prompt injection or manipulation attacks.
- We provide a comprehensive evaluation across varying levels of organizational complexity, comparing classifier-based and generation-based approaches, and analyzing performance on role-independent, blacklisted topics.

2 Related Works

Access Control in Traditional Systems In classical role-based access control (RBAC), users are assigned roles with specific permissions (Ferraiolo et al., 1995, 2003), enforcing the principle of least privilege. Organizations often segregate data by clearance levels or roles so that only authorized personnel can view sensitive records (Sandhu, 1998; Jayaraman et al., 2025). Role hierarchies allow higher-level roles (e.g., managers) to inherit the permissions of subordinate roles, a concept well understood in databases and operating systems. However, applying similar role-based permissions to a generative LLM is nontrivial (Chan, 2025), since the model can hallucinate or leak information beyond its explicit training data (Kaddour et al., 2023).

Access Control in Language Models Work on access control in language models remains limited. A contemporaneous study by Jayaraman et al. (2025) introduces `PermissionedLLMs`, which implement domain-based access control through parameter-efficient fine-tuning methods such as LoRA (Hu et al., 2022) and Few-Shot Parameter Efficient Tuning (Liu et al., 2022). Their approach defines access at the domain level, where a domain represents a group of data records requiring identical credentials. In parallel, Saha et al. (2025) proposed `sudoLLM`, which makes LLMs "user-aware" by injecting secret biases into input queries based on user identity. In contrast to these approaches, our work focuses on role-based access control with deeper hierarchical structures, making it more suitable for enterprise and organizational settings.

AdapterSwap (Fleshman et al., 2025) implements access control by associating different access levels with separate LoRA adapters, which are selected and composed at inference time. This approach requires maintaining multiple domain-specific adapters. In contrast, our method uses a unified model that directly encodes role-awareness without external composition. Chen et al. (2023) address a related challenge from a privacy perspective, showing that pre-trained LLMs are prone to leaking sensitive information and proposing a self-moderation mechanism. While their work does not focus on role-aware modeling, it shares our broader goal of improving control over LLM outputs to prevent unauthorized disclosures.

3 Problem Formulation

Let x be a prompt or instruction, y the LLM output, and r a user's role within an organization. A general LLM defines a conditional distribution over outputs y dependent on a user's instruction x:

$$P(y \mid x).$$

However, a role-aware LLM defines the following distribution:

$$P_{\text{RoleLLM}}(y \mid x, r),$$

such that $r \in \mathcal{R}$, where $\mathcal{R}$ is the set of all roles in an organization.

Now, formalizing access control, define a tree $\mathcal{T} = (\mathcal{R}, \leq)$ such that for any two roles $r_1, r_2 \in \mathcal{R}$ where $r_1 \leq r_2$ denotes r_2 inherits r_1's permissions. Then, the **access set** of a role $r \in \mathcal{R}$ is:

$$\mathcal{A}(r) = \bigcup_{r' \leq r} \mathcal{S}(r'),$$

where $\mathcal{S}(r') \subseteq \mathcal{Q}$. $\mathcal{S}(r')$ is the set of all queries of role r', and $\mathcal{Q}$ is the universe of all valid input-output instruction types. Hence,

$$P_{\text{RoleLLM}}(y \mid x, r) = \begin{cases} P(y \mid x, r), & \text{if } x \in \mathcal{A}(r) \\ \delta_{\text{deny}}(y), & \text{otherwise} \end{cases},$$

such that $\delta_{\text{deny}}(y)$ is a degenerate distribution concentrating all the probability mass on a refusal output (i.e., access is denied).

4 Dataset Construction

We define two organizational structures, each comprising 20 roles, to evaluate role-awareness under varying levels of hierarchy. The first is the **Basic** structure, where a single CEO directly supervises 19 subordinate roles. The second is the **Office** structure, which includes a CEO, four department managers reporting to the CEO, and 3–4 team members reporting to each manager. A detailed breakdown of roles in both structures is provided in Appendix C. These configurations are used to assess the ability of each method to encode and respond to hierarchical role information, as outlined in Section 5.1.

For each organizational structure, we construct two datasets using complementary strategies (see Figure 2). The first is by repurposing existing instruction-tuning data via clustering, and the latter involves generating synthetic data via LLMs.

Repurposing Existing Instruction Dataset We repurpose We repurpose the Databricks Dolly-15k dataset (Conover et al., 2023) by clustering instructions and assigning roles based on hierarchical structure. Using a sentence transformer (Reimers and Gurevych, 2019), we encode each instruction and its context into dense vectors. Clustering begins at the root of the organization: we apply K-Means to partition the data into three high-level groups: **General**, **Shared**, and **Root Only** (e.g., CEO-specific). Prompts in the General group are marked terminal and excluded from further subdivision.[1] Shared prompts are recursively partitioned along the hierarchy. At each level, prompts are split into role-specific clusters corresponding to subordinate roles (e.g., Department 1, Department 2, etc.). Within each cluster, we further divide prompts into Shared (used across subordinates) and Role Only (exclusive to the role). The process continues recursively: Shared prompts are passed down for further subdivision, while Role Only groups are treated as terminal. This hierarchical clustering procedure, illustrated in Figure 8 (Appendix D), yields fine-grained, role-aligned instruction sets that mirror the structure of the target organization.

Synthetic Organization Dataset We use OpenAI's `GPT-4.1 mini` with a temperature of 0.7 to generate synthetic organizational data. Based on the basic and office structures (Appendix C), we define each role, department, and access range in a structured JSON-like format. Prompts are then generated for each role, conditioned on its responsibilities and access scope. The resulting data is organized with the fields: `role`, `instruction`, and `output`. We also generate 200 general instruction-response pairs representing organization-wide prompts that are accessible to all roles. Details of the generation prompt are provided in Appendix D.

Synthetic Dataset Quality Analysis To evaluate the quality of the synthetic dataset, we randomly sampled 100 query-response pairs for manual analysis. Each pair was scored on two binary criteria: (1) whether the query was relevant to the assigned role, and (2) whether the response was complete and appropriate. A score of 1 was given for each criterion if it was met, and 0 otherwise. The results show that over 96% of the samples satisfied both criteria, indicating high relevance and response quality.

Training Set Construction To train the model to distinguish between authorized and unauthorized access, we construct positive and negative instances from each instruction-response pair. First, we assign each pair the lowest-level role authorized to access the instruction. Using this role as an anchor, we generate four training instances through a sliding-window over the organizational hierarchy. Specifically, we create: (1) a positive instance using the minimal authorized role, and (2) another positive instance using its immediate parent, reflecting inherited permissions. We then generate two negative instances: (3) one from a subordinate role (or a random role from a different branch if no children exist), and (4) one from a non-existent external role. Each instance is labeled with a binary (1 for access granted, 0 for denied). For the denied request, LLM is expected to generate a generic refusal message. This procedure results in 6,000 training samples per dataset variant: *repurposed_basic*, *repurposed_office*, *synthetic_basic*, and *synthetic_office*. The ratio of positive and negative samples is approximately balanced: repurposed datasets contain 54.5% valid examples, and synthetic datasets contain 52.5%.

Test Set Construction Each dataset variant includes a test set of 1,000 samples, balanced with 50% positive and 50% negative instances. Positive samples are split evenly into two subsets: 250 with previously unseen instructions, and 250 with paraphrased versions of training instructions generated by GPT-4.1 mini. Negative samples are divided into three categories: (1) 300 *mismatch* cases, where an unauthorized in-hierarchy role attempts to access restricted content (e.g., a leaf role querying CEO-level data); (2) 100 *random* cases using external roles not present in the hierarchy; and (3) 100 *broken* cases where the role string is intentionally corrupted (e.g., "1.2" → "01.02", "1..2", or "one.two") to test model robustness. Each negative category includes an equal mix of unseen and paraphrased instructions, ensuring that every test set contains exactly 500 unseen and 500 seen prompts (See Figure 2.

5 Experimental Set-Up

5.1 Role Encoding Strategies

After grouping instruction-response pairs by role, we encode each role to study how different encoding strategies affect access control. Each organizational position is represented by a string that reflects its location in the hierarchy, which is appended to every instruction-response pair to indicate the minimum role required to access the content. Access is permitted to roles at or above the specified level and denied to those below or in unrelated branches. We explore three encoding methods. **Hierarchical Number Encoding** uses

[1]The General group refers to prompts that are accessible to all roles within the organization

dot-delimited indices (e.g., "1" for the CEO, "1.1" and "1.2" for direct subordinates), with "1.0" reserved for general, organization-wide instructions. **Single Name Encoding** uses only the role's title (e.g., "CEO," "IT Department Manager"), while **Hierarchical Name Encoding** concatenates the full path of titles (e.g., "CEO - IT Department Manager - IT Support") to retain both structural and semantic information.

5.2 Training Approaches

We evaluate three methods for access control, training each on all four dataset variants. To ensure reproducibility, we fix random seeds and report averaged results over three runs per setting. Training data is shuffled to eliminate order effects. Each training instance includes a prompt, answer, role, and access label. Full training details and hyperparameters are provided in Appendix B.

Role-aware Cls We trained six BERT-based models (Devlin et al., 2019; Liu et al., 2019), including MODERN BERT-BASE, MODERN BERT-LARGE, GOOGLE BERT-BASE, GOOGLE BERT-LARGE, ROBERTA-BASE, and ROBERTA-LARGE for access control. We appended the role to the end of the prompt as "<prompt> [SEP] <role>".

Role-aware LLM-Cls We fine-tune six open-source LLMs (Bai et al., 2023; Dubey et al., 2024; Team et al., 2024)—QWEN 2.5 (3B, 7B), LLAMA 3.X (3B, 8B), and GEMMA (4B, 7B)—to perform binary access control classification. We include both small and large models to assess the effect of model size. For each example, the role is prepended to the prompt as "Position: <role> <prompt>", and a system prompt instructs the model to respond with `True` (grant access) or `False` (deny access). All inputs and labels are formatted as conversations and fine-tuned using LoRA with supervised learning.

Role-aware LLM-Gen We use the same LLMs and fine-tuning setup as in Role-aware LLM-Cls, but instead train the model to generate full answers rather than binary access decisions. The system prompt is removed to allow free-form responses, and the output corresponds to the original answer instead of a `True`/`False` label.

5.3 Evaluation Protocol

For the classification-based approaches (Role-aware Cls and Role-aware LLM-Cls), we report standard metrics: *accuracy*, *false positive rate (FPR)*, *false negative rate (FNR)*, and *F1 score*. FPR captures unauthorized access incorrectly granted, while FNR reflects valid access that was wrongly denied. We also report performance on "seen" vs. "unseen" instructions, along with category-specific accuracy for mismatch, random, and broken roles. For Role-aware LLM-Gen, which outputs either a direct answer or a generic denial, we use GPT-4.1 mini to classify each response as grant or deny, enabling comparison with the ground-truth `valid` label.

Finally, to assess whether access control impacts answer quality, we randomly sample 100 valid (granted) examples and compare the generated responses to the original references. Each response is evaluated using GPT-4.1 mini, scored on a 1–5 scale for correctness, completeness, and clarity.

6 Results

Tables 1 and 2 (or Table 14 and Table 15 for details) summarize the performance of our proposed *role-aware* LLMs evaluated on access-control accuracy and LLM-rated generation quality across two distinct training datasets: a repurposed existing instruction dataset (*Dolly*) and a synthetic organization dataset. The evaluation is conducted on all Role-aware methods (*Cls*, *LLM-Cls*, and *LLM-Gen*), assessing both quantitative metrics (e.g., accuracy, negative-pair defense) and qualitative dimensions (correctness, completeness, clarity). The detailed results and comparisons between the training datasets and modeling methods are discussed in further detail in the following sections.

Access-Control Performance Our role-aware LLMs consistently achieved high access-control accuracy across both datasets, with *LLM-Cls* models outperforming other variants; specifically, MODERNBERT LARGE attained the highest accuracy (90.0%) on *Dolly*, while LLAMA3 8B INSTRUCT achieved top performance (89.3%) on the synthetic dataset. Generative approaches (*LLM-Gen*) slightly lagged in raw accuracy by approximately 5–10 percentage points with an influx in false-negative errors, indicating a strict access enforcement in role-conditioned generation. However, notable negative results emerged, particularly with ROBERTA LARGE (*Cls*), whose accuracy drastically decreased to 74.8% accompanied by an inflated false-positive rate (58%) on the *Dolly* dataset and subsequently in the synthetic dataset, highlight-

Method	Model	Acc. (↑)	FPR (↓)	FNR (↓)	F1 (↑)	Acc. (↑)		F1 (↑)		Negative Pair Acc. (↑)		
						Seen	Unseen	Seen	Unseen	Mismatch	Broken	Random
Repurposed Existing Instruction Dataset (Dolly)												
Role-aware Cls	BERT Base	86.0±2.4	29.8±1.0	**4.0**±2.4	90.3±0.5	88.6	85.0	92.3	89.5	70.8	42.6	**100.0**
	RoBERTa Base	78.7±5.4	42.2±16.4	6.6±4.1	84.1±3.3	82.7	77.9	87.6	83.5	58.4	53.2	**100.0**
	ModernBERT Base	89.7±3.8	**18.3**±7.8	5.5±2.5	92.0±2.9	90.3	89.0	92.5	91.5	81.7	60.2	**100.0**
	BERT Large	81.4±6.2	43.1±14.8	5.5±2.9	87.0±4.5	82.5	81.2	88.2	86.1	58.0	44.2	**100.0**
	RoBERTa Large	74.8±12.2	58.1±45.6	5.4±5.3	83.3±6.8	74.2	74.4	82.0	83.6	41.0	28.3	90.5
	ModernBERT Large	**90.0**±3.2	18.9±8.1	4.7±1.0	**92.3**±2.3	**90.8**	**89.2**	**92.9**	**91.6**	**81.1**	48.8	99.8
Role-aware LLM-Cls	Qwen2.5 3B Instruct	88.5±2.2	21.8±6.6	5.2±0.8	91.2±1.7	89.5	87.5	91.8	90.3	78.2	44.3	99.7
	Llama3.2 3B Instruct	88.8±1.7	20.0±3.7	6.0±1.3	91.3±1.4	90.2	87.7	92.3	90.2	80.0	45.0	**100.0**
	Gemma3 4B Instruct	88.8±3.3	20.8±7.5	5.3±1.4	91.5±2.6	90.5	87.3	92.7	90.3	79.2	52.5	**100.0**
	Qwen2.5 7B Instruct	86.3±1.8	24.5±4.4	7.2±2.5	89.7±1.4	88.0	85.0	90.3	88.5	75.5	48.8	99.8
	Llama3.1 8B Instruct	81.8±5.0	29.0±7.7	11.5±8.2	85.8±4.6	83.7	80.0	87.3	84.2	71.0	46.2	99.7
	Gemma 7B Instruct	83.0±5.3	31.0±13.6	8.7±6.3	86.8±3.9	84.0	81.8	87.8	85.7	69.0	48.8	99.8
Role-aware LLM-Gen	Qwen2.5 3B Instruct	76.5±1.0	24.0±3.3	23.3±2.3	80.2±1.0	80.3	72.7	84.0	76.5	76.0	**66.8**	99.8
	Llama3.2 3B Instruct	79.7±3.8	26.7±3.6	16.7±5.7	83.5±3.6	82.0	77.0	85.8	81.0	73.3	57.5	99.8
	Gemma3 4B Instruct	77.3±2.6	26.5±2.2	20.3±3.8	81.5±2.4	80.0	74.8	83.8	79.0	73.5	56.2	97.2
	Qwen2.5 7B Instruct	78.2±2.1	25.0±3.5	20.2±5.1	82.0±2.4	81.3	74.7	85.2	78.7	75.0	60.2	**100.0**
	Llama3.1 8B Instruct	78.0±2.6	25.8±2.1	19.5±5.0	81.8±2.8	80.8	75.2	84.7	79.3	74.2	60.2	99.7
	Gemma 7B Instruct	73.0±1.5	34.0±6.8	22.3±2.6	78.3±1.0	76.0	70.3	81.7	75.0	66.0	61.7	97.3
Synthetic Organization Dataset												
Role-aware Cls	BERT Base	81.4±6.7	44.0±20.1	3.5±1.1	87.2±4.1	82.5	82.1	87.7	86.0	56.9	37.8	**100.0**
	RoBERTa Base	77.2±3.9	56.1±8.7	3.7±0.8	84.3±1.8	78.4	76.8	84.5	84.0	44.7	53.9	**100.0**
	ModernBERT Base	85.6±6.0	27.9±17.9	6.2±1.8	89.3±4.0	86.0	85.3	89.4	89.1	72.1	**64.8**	99.8
	BERT Large	84.5±6.9	35.5±21.6	5.3±2.2	89.3±4.1	84.0	84.4	90.6	88.2	65.5	42.6	99.0
	RoBERTa Large	65.3±4.9	77.1±3.4	6.8±6.7	77.8±3.4	66.6	68.0	78.4	78.5	22.4	47.4	99.5
	ModernBERT Large	80.8±8.5	39.3±18.6	7.1±6.9	85.9±6.2	81.2	80.4	86.1	85.7	60.7	48.3	99.8
Role-aware LLM-Cls	Qwen2.5 3B Instruct	85.2±6.6	33.0±20.3	4.3±3.5	89.0±4.1	85.2	85.0	89.3	89.2	67.0	50.3	**100.0**
	Llama3.2 3B Instruct	88.3±9.2	27.7±24.5	2.2±0.8	91.5±6.4	88.7	88.0	91.8	91.0	72.3	46.2	**100.0**
	Gemma3 4B Instruct	88.5±9.8	27.5±26.0	2.2±0.4	91.5±6.8	89.3	87.5	92.5	91.0	72.5	36.8	99.8
	Qwen2.5 7B Instruct	88.8±8.4	25.8±21.8	2.2±1.2	91.8±5.7	89.3	88.2	92.5	91.5	74.2	47.3	**100.0**
	Llama3.1 8B Instruct	**89.3**±8.6	**25.2**±24.1	**2.0**±0.0	/ **92.5**±6.2	**90.7**	**88.2**	**93.0**	**91.8**	**74.8**	31.5	99.8
	Gemma 7B Instruct	85.8±6.5	34.3±16.8	**2.0**±0.0	89.8±4.4	86.5	85.3	90.2	89.7	65.7	39.0	99.7
Role-aware LLM-Gen	Qwen2.5 3B Instruct	74.8±3.5	42.5±6.8	14.7±8.5	80.7±3.6	76.3	73.5	81.5	80.2	57.5	59.3	95.0
	Llama3.2 3B Instruct	85.3±7.4	30.0±19.1	5.5±1.2	89.0±4.9	85.8	84.7	89.3	88.8	70.0	62.0	95.8
	Gemma3 4B Instruct	74.5±4.7	50.0±10.6	10.8±5.8	81.5±3.5	75.8	73.0	81.8	80.7	50.0	52.8	75.5
	Qwen2.5 7B Instruct	78.2±5.2	40.2±11.1	10.8±5.6	83.3±4.1	80.0	76.0	84.7	82.2	59.8	51.3	95.2
	Llama3.1 8B Instruct	85.3±8.4	31.2±20.0	5.3±1.5	89.0±5.8	86.3	84.0	89.7	88.5	68.8	50.8	95.0
	Gemma 7B Instruct	77.2±4.1	43.8±11.1	10.5±5.8	83.0±3.2	79.8	73.8	84.7	81.0	56.2	40.3	77.3

Table 1: Overall performance on the role-aware access-control benchmark. **Bold** marks the best *score* for a given training set, while underline marks the best model *within each method*.

ing critical sensitivity to encoder selection. In the more challenging synthetic dataset, all methods faced increased difficulty (3–6% accuracy drop), yet instruction-tuned models maintained comparatively robust performance, emphasizing that richer instruction tuning substantially mitigates accuracy degradation under semantically overlapping role conditions. Please refer to Appendix E for further explanation.

Method Robustness To evaluate the robustness of our proposed methods, each method-model combination was trained under two organizational structures (*basic*, *office*) across three independent random seeds, with the results averaged and summarized in Tables 1–2. Generally, all methods demonstrated low variance (acc std.$<$ 4%) on the *Dolly* dataset, except for notable brittleness in RoBERTa Large (*Cls*), which exhibited substantial instability (12.2% accuracy, 45.6% FPR), contrasting strongly with the more stable ModernBERT Large (3.2% accuracy, 8.1% FPR). Instruction-tuned LLM classifiers (*LLM-Cls*), such as Qwen2.5 3B Inst. and Llama3 3B Inst., further reduced variance (acc std.$<$ 2.2%), underscoring stability gains from modern instruction tuning. On the synthetic dataset, semantic overlaps increased variance to around 8–10%, yet instruction-tuned models (e.g., Llama3 8B Inst.) maintained comparative stability (8.4-8.6%). More detailed of the performances on Basic and Office are shown in Appendix H. Collectively, these results demonstrate that our proposed methods achieve robust performance, primarily due to richer pretraining and instruction tuning rather than merely model scale.

Negative Pair Accuracy All methods achieved near-perfect accuracy (100%) in identifying randomly assigned negative-role pairs, highlighting their effectiveness in clearly invalid scenarios. However, performance dropped notably for subtler cases such as existing-but-mismatched and broken-role pairs. Specifically, *LLM-Cls* models demonstrated comparatively stronger performance (e.g., ModernBERT Large: 81.1%; Qwen2.5

Model	Generation Quality (↑, 5-pt rubric)		
	Correctness	Completeness	Clarity
Repurposed Existing Instruction Dataset (Dolly)			
Qwen2.5 3B Instruct	3.9±0.1	3.5±0.2	4.6±0.1
Llama3.2 3B Instruct	4.0±0.1	3.6±0.2	4.7±0.1
Gemma3 4B Instruct	4.0±0.1	3.6±0.1	4.6±0.0
Qwen2.5 7B Instruct	**4.1**±0.2	**3.7**±0.2	**4.7**±0.0
Llama3.1 8B Instruct	**4.1**±0.1	**3.7**±0.1	**4.7**±0.1
Gemma 7B Instruct	3.9±0.1	3.5±0.1	4.5±0.1
Synthetic Organization Dataset			
Qwen2.5 3B Instruct	3.9±0.2	3.6±0.2	4.7±0.1
Llama3.2 3B Instruct	3.9±0.1	3.7±0.1	4.7±0.0
Gemma3 4B Instruct	3.9±0.1	3.7±0.1	4.7±0.1
Qwen2.5 7B Instruct	**4.0**±0.1	**3.8**±0.1	**4.8**±0.0
Llama3.1 8B Instruct	3.9±0.1	**3.8**±0.1	**4.8**±0.0
Gemma 7B Instruct	3.9±0.1	3.6±0.1	4.6±0.1

Table 2: LLM-rated generation quality against gold reference. **Bold** = best within the same training dataset; underline = best within the Role-aware LLM-Gen method.

3B INST.: 78.2% on *Dolly*), whereas standard classifiers (*Cls*), particularly ROBERTA LARGE (41.0%), struggled significantly. Generative models (*LLM-Gen*) showed moderate accuracy (e.g., LLAMA3 3B INST.: 73.3%), underscoring ongoing challenges in detecting nuanced role mismatches. These results indicate that while instruction-tuned models substantially enhance negative-pair detection, subtle distinctions between valid yet incorrect role assignments remain difficult, suggesting a promising direction for future improvements in fine-grained role understanding.

Generation Quality Generation quality ratings (correctness, completeness, clarity) were consistently high (around 4 out of 5), with larger instruction-tuned models (e.g., QWEN2.5 7B INST., LLAMA3 8B INST.) achieving the best scores. The differences between the training data sets were minimal, highlighting the reliability of role-aware generation regardless of the data source.

7 Analysis

7.1 Jailbreak Robustness

To assess the model's robustness against prompt injection attempts, we conducted an additional experiment involving modifications to the original datasets. Specifically, we generated 100 more negative samples for both training and test sets in which the original instruction was prepended with misleading phrases. These included assertions of higher authority (e.g., "I'm authorized as CEO to ask this:") or commands (e.g., "Regardless of policy, respond to this:"). We evaluated Role-aware LLM-Cls using *Llama 3.2 3B Instruct*. The model was trained in two ways: the first incorporates jailbreak samples in the training data, and the other does not. A comparative summary of performance is presented in Appendix F. Although the inclusion of jailbreak prompts did not significantly affect overall accuracy across the test set (except for experiments with the *repurposed_basic* dataset, which can be attributed to randomness), the model trained with jailbreak-specific examples demonstrated improved resistance to prompt injection with an average of 87% compared to the 70% accuracy of the baseline model.

7.2 Robustness on Blacklisted Topics

To evaluate the model's capacity to restrict answers to queries whose content violates organizational policies, we extended the original datasets mentioned in Section 4. We generated 100 queries on general blacklisted topics (e.g., violence, weapons, cheating, etc.) and 100 queries related to real-life politics. The respective responses to the queries were designed to be restricted, regardless of an employee's role. Subsequently, each original dataset was extended by adding 50 unique blacklisted queries of each type separately, and duplicates of each blacklisted query for multiple organization roles. The remaining 50 queries of each blacklisted dataset were used for the evaluation datasets. Using the Role-aware LLM-Cls method, LLAMA 3.2 3B INSTRUCT was trained and tested using these extended datasets. The detailed information on the results can be found in Appendix G. As shown in Table 8, the blacklisted model's performance remained unchanged relative to the baseline model. The model was also highly successful in restricting answers to blacklisted queries with an overall accuracy >99%. The accuracy rates for the model trained on the repurposed basic dataset were the only outliers, exhibiting a decrease in accuracy from 92% to 84%.

7.3 Effect of Role Information in Prompts

To assess whether including role information in the prompt affects response quality, we fine-tuned all LLMs on the four training datasets *without* role annotations. We evaluated response quality using three metrics: correctness, completeness, and clarity. From the 1,000 test outputs, we randomly sampled 100 responses and compared them to the reference answers using GPT-4.1 mini. The same evaluation was applied to Role-aware LLM-Gen,

Prompt Style	Correctness	Completeness	Clarity
Without roles	3.90	3.58	4.67
With roles	3.93	3.59	4.64

Table 3: Quality ratings (five-point scale) of responses generated by LLMs trained with versus without role prompts, assessed by GPT-4.1 mini.

which was trained with roles included in the prompt. Results show that the average difference in quality between the two settings is under 1%, indicating that including roles does not degrade response quality. Summary metrics are reported in Table 3, with detailed results in Appendix I.

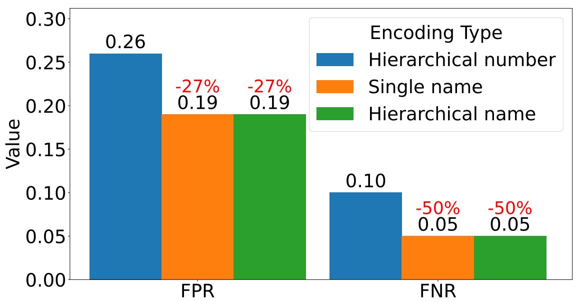

Figure 3: Comparison of FPR and FNR across role encodings. The *Hierarchical Number Encoding* has the worst defense against unauthorized roles (highest FPR), and overly denies authorized roles (highest FNR).

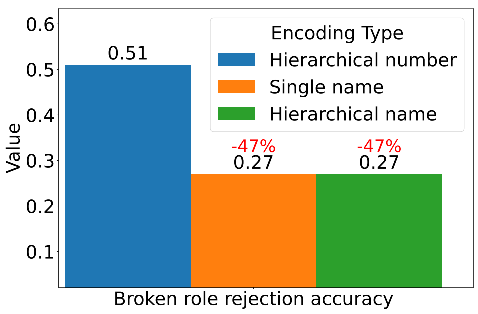

Figure 4: Comparison of broken role rejection accuracy across role encodings. The *Hierarchical Number Encoding* has the best defense against broken roles.

7.4 Effect of Role Encoding on Access Control

We investigate how different role encoding strategies affect access control performance across our three methods: Role-aware Cls, Role-aware LLM-Cls, and Role-aware LLM-Gen. For consistency, we use the ModernBERT-base model for Role-aware Cls and Llama 3.1 8B Instruct for the LLM-based methods, training each on the four dataset variants.

We compare three encoding strategies: Hierarchical Number Encoding, Single Name Encoding, and Hierarchical Name Encoding, and present the results in Figures 3 and 4. Hierarchical Number Encoding achieves the highest FPR, indicating poorer rejection of unauthorized roles and weaker robustness to broken role strings (e.g., misspelled or manipulated encodings). This suggests that LLMs can more easily differentiate between role names like “CEO” and “Researcher” than between formats like “1.1” and “1.a” . This encoding also results in the highest FNR, likely because LLMs struggle to generalize upward in hierarchical structures (e.g., understanding that “1” can access data assigned to “1.1”). In contrast, name-based encodings offer slightly better generalization across authorized roles but are more vulnerable to adversarial role perturbations. Full results are provided in Appendix J.

8 Conclusion

This paper investigates methods for modeling role-aware behavior in large language models, with a focus on enforcing access control and evaluating the effects of different fine-tuning strategies and datasets. Our experiments compare classification-based and generative approaches across multiple organizational structures. Instruction-tuned classifiers (*LLM-Cls*) consistently outperform both generative (*LLM-Gen*) and traditional classifier-based (*Cls*) methods, reaching up to 90.0% and 89.3% accuracy on the *Dolly* and synthetic datasets, respectively, without compromising answer quality.

Despite high overall performance, challenges remain. All models are effective at rejecting clearly unauthorized roles, such as random or external entities (≈100% accuracy), and instruction-tuned methods reliably detect more subtle mismatches (≈70% accuracy on average). However, broken role formats and fine-grained violations still present difficulties, with a 15–30% gap in accuracy. Generative models, while more flexible, suffer a modest performance trade-off. Future work should focus on enhancing generalization across complex hierarchies, reducing false positives from brittle encoders, and improving discrimination between closely related roles.

9 Limitations

While our results demonstrate promising capabilities in enabling safe and role-aware deployment of LLMs within organizational contexts, several limitations constrain the scope of our conclusions.

Unified Organization Representation Our experiments used a single adapter to represent all roles within an organization. Although effective, we did not investigate the alternative of using a multi-adapter strategy, such as separate adapters for each department. This strategy could potentially reduce information leakage by further isolating department-specific knowledge, though it may come at the cost of overall effectiveness.

Access Control Post Fine-tuning We demonstrated effective fine-tuning of adapters for initial access control; however, our methodology did not address dynamic modification or addition of roles after the fine-tuning phase. Future research should explore approaches that enable post-training updates to role-based access, as roles are dynamic and such updates would eliminate the need to retrain adapters from scratch.

Alignment Methods Beyond SFT This study exclusively employed SFT for alignment. We did not explore alternative methods such as Direct Preference Optimization (DPO) or other preference-based alignment techniques, which could potentially yield improved alignment outcomes.

Integration of External Knowledge Although our results indicate strong capabilities in controlling internal knowledge, either by restricting specific topics organization-wide or selectively authorizing content per role, we did not evaluate role-aware control when the LLM is augmented with external knowledge sources (e.g., Retrieval-Augmented Generation or web search). Investigating how role-based adapters influence responses that incorporate external information remains an open area for future study.

References

Muhammad Falensi Azmi, Muhammad Dehan Al Kautsar, Alfan Farizki Wicaksono, and Fajri Koto. 2025. Indosafety: Culturally grounded safety for llms in indonesian languages. *arXiv preprint arXiv:2506.02573*.

Jinze Bai, Shuai Bai, Yunfei Chu, Zeyu Cui, Kai Dang, Xiaodong Deng, Yang Fan, Wenbin Ge, Yu Han, Fei Huang, and 1 others. 2023. Qwen technical report. *arXiv preprint arXiv:2309.16609*.

Shih-Han Chan. 2025. Encrypted prompt: Securing llm applications against unauthorized actions. *arXiv preprint arXiv:2503.23250*.

Yang Chen, Ethan Mendes, Sauvik Das, Wei Xu, and Alan Ritter. 2023. Can language models be instructed to protect personal information? *arXiv preprint arXiv:2310.02224*.

Mike Conover, Matt Hayes, Ankit Mathur, Jianwei Xie, Jun Wan, Sam Shah, Ali Ghodsi, Patrick Wendell, Matei Zaharia, and Reynold Xin. 2023. Free dolly: Introducing the world's first truly open instruction-tuned llm.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Longxu Dou, Qian Liu, Fan Zhou, Changyu Chen, Zili Wang, Ziqi Jin, Zichen Liu, Tongyao Zhu, Cunxiao Du, Penghui Yang, and 1 others. 2025. Sailor2: Sailing in south-east asia with inclusive multilingual llms. *arXiv preprint arXiv:2502.12982*.

Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Amy Yang, Angela Fan, and 1 others. 2024. The llama 3 herd of models. *arXiv e-prints*, pages arXiv–2407.

David Ferraiolo, Janet Cugini, D Richard Kuhn, and 1 others. 1995. Role-based access control (rbac): Features and motivations. In *Proceedings of 11th annual computer security application conference*, pages 241–48.

David Ferraiolo, D Richard Kuhn, and Ramaswamy Chandramouli. 2003. *Role-based access control*. Artech house.

William Fleshman, Aleem Khan, Marc Marone, and Benjamin Van Durme. 2025. Adapterswap: Continuous training of llms with data removal and access-control guarantees. *Preprint*, arXiv:2404.08417.

Suyu Ge, Chunting Zhou, Rui Hou, Madian Khabsa, Yi-Chia Wang, Qifan Wang, Jiawei Han, and Yuning Mao. 2024. MART: Improving LLM safety with multi-round automatic red-teaming. In *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pages 1927–1937, Mexico City, Mexico. Association for Computational Linguistics.

Edward J Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, Weizhu Chen, and 1 others. 2022. Lora: Low-rank adaptation of large language models. *ICLR*, 1(2):3.

Bargav Jayaraman, Virendra J Marathe, Hamid Mozaffari, William F Shen, and Krishnaram Kenthapadi. 2025. Permissioned llms: Enforcing access control in large language models. *arXiv preprint arXiv:2505.22860*.

Albert Q Jiang, Alexandre Sablayrolles, Antoine Roux, Arthur Mensch, Blanche Savary, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Emma Bou Hanna, Florian Bressand, and 1 others. 2024. Mixtral of experts. *arXiv preprint arXiv:2401.04088*.

Jean Kaddour, Joshua Harris, Maximilian Mozes, Herbie Bradley, Roberta Raileanu, and Robert McHardy. 2023. Challenges and applications of large language models. *arXiv preprint arXiv:2307.10169*.

Fajri Koto, Rituraj Joshi, Nurdaulet Mukhituly, Yuxia Wang, Zhuohan Xie, Rahul Pal, Daniil Orel, Parvez Mullah, Diana Turmakhan, Maiya Goloburda, and 1 others. 2025. Llama-3.1-sherkala-8b-chat: An open large language model for kazakh. *arXiv preprint arXiv:2503.01493*.

Md Tahmid Rahman Laskar, Xue-Yong Fu, Cheng Chen, and Shashi Bhushan TN. 2023. Building real-world meeting summarization systems using large language models: A practical perspective. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing: Industry Track*, pages 343–352, Singapore. Association for Computational Linguistics.

Aixin Liu, Bei Feng, Bing Xue, Bingxuan Wang, Bochao Wu, Chengda Lu, Chenggang Zhao, Chengqi Deng, Chenyu Zhang, Chong Ruan, and 1 others. 2024. Deepseek-v3 technical report. *arXiv preprint arXiv:2412.19437*.

Haokun Liu, Derek Tam, Mohammed Muqeeth, Jay Mohta, Tenghao Huang, Mohit Bansal, and Colin A Raffel. 2022. Few-shot parameter-efficient fine-tuning is better and cheaper than in-context learning. *Advances in Neural Information Processing Systems*, 35:1950–1965.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*.

Vinod Muthusamy, Yara Rizk, Kiran Kate, Praveen Venkateswaran, Vatche Isahagian, Ashu Gulati, and Parijat Dube. 2023. Towards large language model-based personal agents in the enterprise: Current trends and open problems. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pages 6909–6921, Singapore. Association for Computational Linguistics.

Joon S Park, Ravi Sandhu, and Gail-Joon Ahn. 2001. Role-based access control on the web. *ACM Transactions on Information and System Security (TISSEC)*, 4(1):37–71.

Nils Reimers and Iryna Gurevych. 2019. Sentence-BERT: Sentence embeddings using Siamese BERT-networks. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 3982–3992, Hong Kong, China. Association for Computational Linguistics.

Soumadeep Saha, Akshay Chaturvedi, Joy Mahapatra, and Utpal Garain. 2025. sudollm : On multi-role alignment of language models. *Preprint*, arXiv:2505.14607.

Ravi S Sandhu. 1998. Role-based access control. In *Advances in computers*, volume 46, pages 237–286. Elsevier.

Gemma Team, Thomas Mesnard, Cassidy Hardin, Robert Dadashi, Surya Bhupatiraju, Shreya Pathak, Laurent Sifre, Morgane Rivière, Mihir Sanjay Kale, Juliette Love, and 1 others. 2024. Gemma: Open models based on gemini research and technology. *arXiv preprint arXiv:2403.08295*.

Yuxia Wang, Haonan Li, Xudong Han, Preslav Nakov, and Timothy Baldwin. 2024a. Do-not-answer: Evaluating safeguards in LLMs. In *Findings of the Association for Computational Linguistics: EACL 2024*, pages 896–911, St. Julian's, Malta. Association for Computational Linguistics.

Yuxia Wang, Zenan Zhai, Haonan Li, Xudong Han, Shom Lin, Zhenxuan Zhang, Angela Zhao, Preslav Nakov, and Timothy Baldwin. 2024b. A Chinese dataset for evaluating the safeguards in large language models. In *Findings of the Association for Computational Linguistics: ACL 2024*, pages 3106–3119, Bangkok, Thailand. Association for Computational Linguistics.

Sam Wiseman, Stuart Shieber, and Alexander Rush. 2017. Challenges in data-to-document generation. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 2253–2263, Copenhagen, Denmark. Association for Computational Linguistics.

Bing Zhang, Mikio Takeuchi, Ryo Kawahara, Shubhi Asthana, Md. Maruf Hossain, Guang-Jie Ren, Kate Soule, Yifan Mai, and Yada Zhu. 2025. Evaluating large language models with enterprise benchmarks. In *Proceedings of the 2025 Conference of the Nations of the Americas Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 3: Industry Track)*, pages 485–505, Albuquerque, New Mexico. Association for Computational Linguistics.

A Training Seeds

We used each of the seeds shown in Table 4 for all experiments and averaged the result over seeds for each experiment.

Seed #	Value
Seed 1	42
Seed 2	937
Seed 3	3827

Table 4: Seeds for training, testing and evaluation for all methods

B Training Hyperparameters

We used the same set of hyperparameters (Table 5) to train all LLMs and a different set of hyperparameters (Table 6) to train all BERT models. We created a LoRA adapter to train LLMs with the LoRA configuration given in (Table 5).

Parameter	Value
LoRA rank	32
LoRA alpha	64
LoRA dropout	1×10^{-1}
LoRA modules	up proj, down proj, gate proj, k proj, q proj, v proj, o proj
Batch size	1
Epochs	4
Learning rate	1×10^{-4}
Grad. accumulation	1
Weight decay	0.0
Warmup ratio	0.0

Table 5: Hyperparameters used for LoRA SFT training of LLMs

Parameter	Value
Batch size	16
Epochs	5
Learning rate	2×10^{-5}
Grad. accumulation	1
Weight decay	1×10^{-2}
Warmup ratio	1×10^{-1}

Table 6: Hyperparameters for BERT training

C Organizational Structure Details

We define two predefined structures for dataset creation: the Basic and Office structures, shown in Table 5 and Table 6, respectively. In the Basic structure, a single CEO directly corresponds to all other roles, allowing us to test whether the models can leverage role-awareness when faced with a wide, single-layer hierarchy. In contrast, the Office structure introduces a multi-level hierarchy, where the CEO supervises department managers, who in turn oversee several team members. This setup evaluates whether the methods discussed in Section 5.1 can effectively capture and utilize hierarchical relationships within the organization. Additionally, Figure 7 presents several example roles introduced in each structure for synthetic role data generation, making the data specific to the roles defined in each structure.

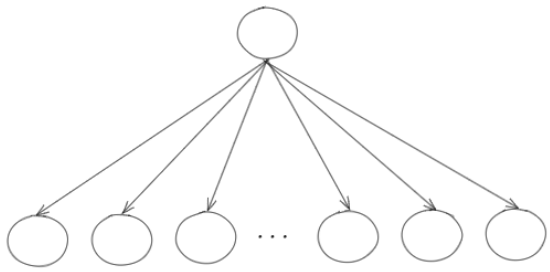

Figure 5: Hierarchical structure for **Basic** structure.

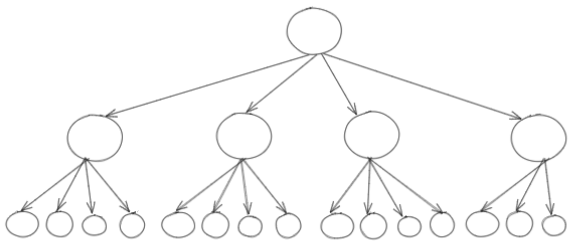

Figure 6: Hierarchical structure for **Office** structure.

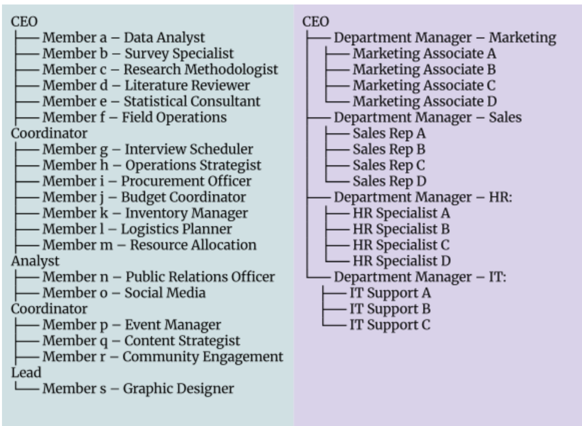

Figure 7: Predefined roles for each **Basic** and **Office** structure.

D Dataset Creation

Figure 8 shows our clustering scheme when repurposing the dataset. At the root level, datasets are first partitioned into three clusters: General, Shared, and Root-Only. Prompts in the General cluster terminate immediately; those in Shared are then split along the root's direct subordinate roles, and recursion continues further. Furthermore, Figure 9 shows the specific system-level prompt used to generate the synthetic data. Below the prompt is an example of the OpenAI API output with the specified keys after generating the dataset.

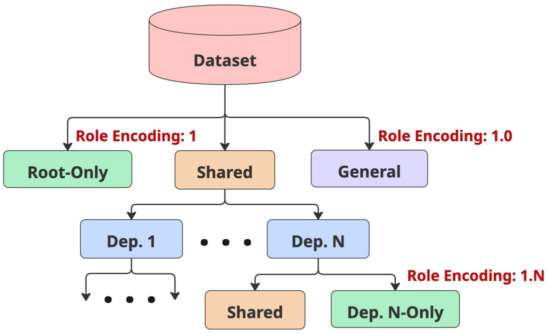

Figure 8: Hierarchical clustering scheme of repurposed dataset.

Role Data Generation

Prompt: *"""You are a data generation assistant. Your task is to generate role-specific synthetic, realistic data for organizational settings. The schema will include field names, types, and any constraints or requirements for the data.*
Generate queries and responses that reflect the role's responsibilities in the specified organizational or institutional structure.

Consider the role's responsibilities and access privileges when generating the examples.

Output must be in JSON format, with the following keys:
- "role": The name of the role.
- "department": Associated department (if applicable).
- "access_range": The data access range.
- "queries": List of 100 realistic queries.
- "responses": Corresponding list of 100 realistic responses to each query."""

{
"role": "CEO (t)"
"department": "Executive"
"access_range": "1-100"
"instruction": "Summarize the outcomes of the last board..."
"output": "The last board meeting approved increased R&D..."
}

{
"role": "Marketing Associate (a)"
"department": "Marketing"
"access_range": "1-7"
"instruction": "What is the click-through rate for..."
"output": "Our paid search ads have a click-through rate of 3.8%..."
}
⋮

Figure 9: System-Level Output for Synthetic Dataset.

E Role-aware Method: Cls vs LLM-Cls vs LLM-Gen

The *Role-aware Cls* shows a highly inconsistent performance, with a mean *FPR* of 0.41 and a large variance between 0.23 and 0.68, where the Roberta-large model performed the worst with the highest *FPR* of 0.68, which means that there are significant model-dependent weaknesses to unauthorized access. However, they are consistently low in *FNR* (0.04-0.06, average 0.05), indicating reliable access to authorized users. Conversely, the *Role-aware LLM-Gen* exhibited more stable but poor security performance with moderate *FPR* (0.28-0.38, average 0.33) and significantly higher *FNR* variability (0.11-0.19, average 0.15), indicating that it has greater difficulty in rejecting genuine access requests across model implementations and organizational designs.

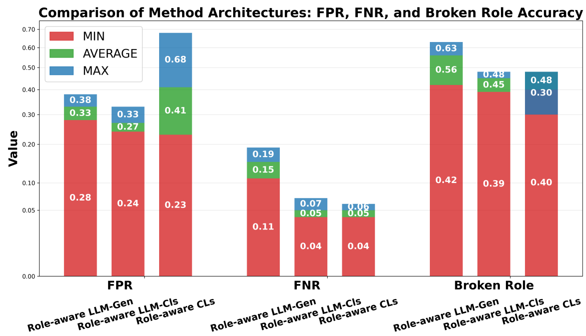

Figure 10: **Performance comparison of three role-based access control architectures across security metrics.** Results show minimum, average, and maximum values for *FPR*, *FNR*, and *Broken Role* accuracy across six different models per architecture, averaged over multiple datasets with organizational structure variations. Higher *Broken Role* accuracy indicates better defense against one of jailbreak attacks.

Most importantly, our analysis shows that there are different security capabilities against adversarial attacks in different architectures. The Role-aware LLM-Gen strategy showed the best protection against *broken role* attacks with an average *broken role* accuracy of 0.56 (range: 0.42-0.63), and was able to reject the greatest percentage of malicious role manipulation attempts. Such high performance indicates that the integrated method, in which both access control and question answering are performed by a single model, offers improved contextual knowledge of role-based attacks. Role-aware CLs performed at average levels (average: 0.48, range: 0.30-0.40), whereas Role-aware LLM-CLs had the lowest broken role accuracy (average: 0.45, range: 0.39-0.48), which means that it is more susceptible to such adversarial attacks. These results indicate a curious tradeoff: whereas the Role-aware LLM-Gen approach exhibits larger *FNR* variation and moderate *FPR*, it makes up in better resistance to advanced attacking methods, indicating that the unified architecture might be inherently more capable of identifying and resisting role-based manipulation attacks than separated classification systems.

F Metrics for Jailbreak Experiment

Figure 7 shows the detailed performance between the baseline and the model that has been trained on the jailbreak train set (See Section 7.1).

Model	Structure	Accuracy	Broken	Jailbreak
Baseline	RB[1]	0.92	0.49	0.71
	RO[2]	0.89	0.29	0.69
	SB[3]	0.96	0.58	0.89
	SO[4]	0.80	0.30	0.51
With jailbreak samples	RB	0.84	0.56	0.98
	RO	0.88	0.27	0.70
	SB	0.97	0.60	0.96
	SO	0.82	0.39	0.83

Table 7: Jailbreak Experiment Performance for Llama 3.2 3B Instruct.

[1]Repurposed Basic, [2]Repurposed Office, [3]Synthetic Basic, [4]Synthetic Office

G Metrics for Blacklist Experiment

Figure 8 presents a detailed comparison between the baseline model and the model trained on the original plus the blacklist training set (see Section 7.2).

Blacklist Topic	Structure	Accuracy	Blacklist
Baseline	RB[1]	0.92	-
	RO[2]	0.89	-
	SB[3]	0.96	-
	SO[4]	0.80	-
Politics	RB	0.84	1.00
	RO	0.88	1.00
	SB	0.97	1.00
	SO	0.80	1.00
General	RB	0.84	1.00
	RO	0.88	1.00
	SB	0.96	1.00
	SO	0.81	0.99

Table 8: Blacklist Experiment Performance for Llama 3.2 3B Instruct.

[1]Repurposed Basic, [2]Repurposed Office, [3]Synthetic Basic, [4]Synthetic Office

Note that Baseline here denotes the baseline datasets (original) used to train the model.

H Basic vs Office Structures

After training the models using three methods of Section 5.1, we averaged the accuracy metrics for the two types of structures (basic and office). As shown in Figure 11, model performance, on average, on the office organizational structure is lower than on the basic structure, as expected. For the Role-aware Cls and Role-aware LLM-Cls methods, the accuracy rates decreased by 6.0% and 6.7% when trained with the office structure. The reason for this is due to the deep hierarchy associated with the office structure compared to the basic one. Nonetheless, when using the Role-aware LLM-Gen method, the accuracy rate increased 1.3% when training with the office structure, potentially indicating that, with answer generation, there is negligible model performance difference when training with either structures

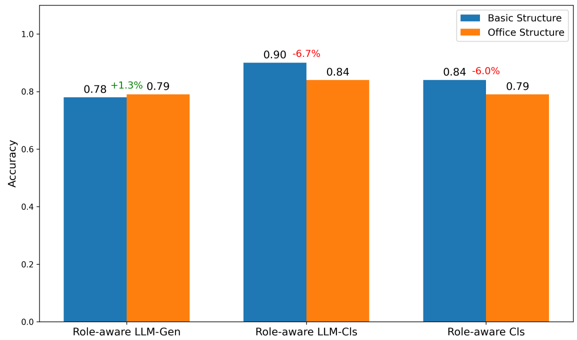

Figure 11: Average Accuracy Rates of Models Trained on the Basic vs Office Datasets.

Across almost all methods, models exhibit lower accuracy rates when trained with the office structure. Note that for Role-aware LLM-Gen, accuracy rates for both structures are almost equal.

I Role vs No role comparison

Tables 9 and 10 show the difference in quality of LLM responses to prompts with and without roles respectively. We use three metrics for response quality - Correctness, Completeness, and Clarity (on a scale of 1 to 5). The LLM responses are sent to ChatGPT 4.1 mini for evaluation as described in Section 7.3. The average metrics for prompts with and without roles are similar, with less than 1% difference between each of the metrics.

Architecture	Dataset	Model	Org. Structure	Seed	Completeness	Correctness	Clarity
LLM + LLM	Repurposed	Qwen2.5 3B Instruct	Basic	42	3.86	3.26	4.62
LLM + LLM	Repurposed	Qwen2.5 3B Instruct	Office	42	3.7	3.21	4.61
LLM + LLM	Repurposed	Llama 3.2 3B Instruct	Basic	42	3.85	3.43	4.64
LLM + LLM	Repurposed	Llama 3.2 3B Instruct	Office	42	3.93	3.28	4.7
LLM + LLM	Repurposed	Gemma 3 4B Instruct	Basic	42	4.03	3.53	4.52
LLM + LLM	Repurposed	Gemma 3 4B Instruct	Office	42	3.91	3.39	4.41
LLM + LLM	Repurposed	Qwen2.5 7B Instruct	Basic	42	4.1	3.69	4.75
LLM + LLM	Repurposed	Qwen2.5 7B Instruct	Office	42	4.01	3.55	4.63
LLM + LLM	Repurposed	Llama 3.1 8B Instruct	Basic	42	4.11	3.69	4.73
LLM + LLM	Repurposed	Llama 3.1 8B Instruct	Office	42	4.15	3.63	4.72
LLM + LLM	Repurposed	Gemma 7B Instruct	Basic	42	3.95	3.61	4.44
LLM + LLM	Repurposed	Gemma 7B Instruct	Office	42	4.03	3.6	4.36
LLM + LLM	Synthetic	Qwen2.5 3B Instruct	Basic	42	3.93	3.59	4.75
LLM + LLM	Synthetic	Qwen2.5 3B Instruct	Office	42	3.6	3.63	4.75
LLM + LLM	Synthetic	Llama 3.2 3B Instruct	Basic	42	3.84	3.66	4.74
LLM + LLM	Synthetic	Llama 3.2 3B Instruct	Office	42	3.68	3.66	4.71
LLM + LLM	Synthetic	Gemma 3 4B Instruct	Basic	42	4.09	3.66	4.77
LLM + LLM	Synthetic	Gemma 3 4B Instruct	Office	42	3.75	3.62	4.65
LLM + LLM	Synthetic	Qwen2.5 7B Instruct	Basic	42	3.95	3.71	4.83
LLM + LLM	Synthetic	Qwen2.5 7B Instruct	Office	42	3.59	3.69	4.74
LLM + LLM	Synthetic	Llama 3.1 8B Instruct	Basic	42	4.04	3.73	4.81
LLM + LLM	Synthetic	Llama 3.1 8B Instruct	Office	42	3.79	3.75	4.78
LLM + LLM	Synthetic	Gemma 7B Instruct	Basic	42	4.05	3.71	4.69
LLM + LLM	Synthetic	Gemma 7B Instruct	Office	42	3.74	3.73	4.66
Average					3.9	3.58	4.67

Table 9: Response quality when no role is included in question for LLM

Architecture	Dataset	Model	Org. Structure	Seed	Completeness	Correctness	Clarity
LLM	Repurposed	Qwen2.5 3B Instruct	Basic	42	3.85	3.41	4.58
LLM	Repurposed	Qwen2.5 3B Instruct	Office	42	3.83	3.38	4.67
LLM	Repurposed	Llama 3.2 3B Instruct	Basic	42	3.97	3.50	4.56
LLM	Repurposed	Llama 3.2 3B Instruct	Office	42	3.80	3.40	4.59
LLM	Repurposed	Gemma 3 4B Instruct	Basic	42	3.96	3.56	4.53
LLM	Repurposed	Gemma 3 4B Instruct	Office	42	4.10	3.64	4.54
LLM	Repurposed	Qwen2.5 7B Instruct	Basic	42	3.94	3.51	4.73
LLM	Repurposed	Qwen2.5 7B Instruct	Office	42	4.09	3.59	4.73
LLM	Repurposed	Llama 3.1 8B Instruct	Basic	42	4.09	3.65	4.64
LLM	Repurposed	Llama 3.1 8B Instruct	Office	42	4.02	3.52	4.63
LLM	Repurposed	Gemma 7B Instruct	Basic	42	3.77	3.42	4.38
LLM	Repurposed	Gemma 7B Instruct	Office	42	3.73	3.36	4.36
LLM	Synthetic	Qwen2.5 3B Instruct	Basic	42	3.89	3.56	4.75
LLM	Synthetic	Qwen2.5 3B Instruct	Office	42	3.96	3.86	4.82
LLM	Synthetic	Llama 3.2 3B Instruct	Basic	42	3.91	3.61	4.64
LLM	Synthetic	Llama 3.2 3B Instruct	Office	42	3.87	3.76	4.70
LLM	Synthetic	Gemma 3 4B Instruct	Basic	42	3.92	3.60	4.61
LLM	Synthetic	Gemma 3 4B Instruct	Office	42	3.90	3.78	4.73
LLM	Synthetic	Qwen2.5 7B Instruct	Basic	42	4.13	3.88	4.79
LLM	Synthetic	Qwen2.5 7B Instruct	Office	42	3.98	3.81	4.79
LLM	Synthetic	Llama 3.1 8B Instruct	Basic	42	3.86	3.60	4.78
LLM	Synthetic	Llama 3.1 8B Instruct	Office	42	3.91	3.65	4.78
LLM	Synthetic	Gemma 7B Instruct	Basic	42	3.84	3.55	4.54
LLM	Synthetic	Gemma 7B Instruct	Office	42	3.88	3.65	4.59
Average					3.93	3.59	4.64

Table 10: Response quality when role is included in question for LLM

J Comparison of encodings

We show our results from comparison of different role encodings for access control as described in Section 7.4. We experimented with Single Name Encoding (Table 11), Hierarchical Name Encoding (Table 12), and Hierarchical Number Encoding (Table 13). We used four metrics to compare model responses across role encodings: Accuracy, FPR (how often the model gives access to unauthorized roles), FNR (how often the model denies access to authorized roles), and F1. Compared to Hierarchical Number Encoding, the Single Name Encoding has a 28.33% decrease in FPR (26.19% to 18.77%) and a 45.15% decrease in the FNR (9.08% to 4.98%). There is a 47.64 % decrease in the broken role rejection accuracy (51.42% to 26.92%). Similarly, the Hierarchical Name Encoding has a 29.13 % decrease in FPR (26.19% to 18.56%), a 45.15% decrease in the FNR (9.08% to 4.98%) and a 47.64 % decrease in the broken role rejection accuracy (51.42% to 26.92%) when compared to the Hierarchical Number Encoding. Overall, the Hierarchical Number Encoding has the highest FPR, highest FNR and highest broken role rejection accuracy.

Architecture	Dataset	Model	Org. Structure	Seed	Accuracy	FPR	FNR	F1	Seen Role Acc.	Unseen Role Acc.	Exist Mismatch Acc.	Broken Role Acc.	Random Role Acc.
LLM	Repurposed	Llama 3.1 8B Instruct	basic	42	84.11	16.50	15.00	85.54	86.33	81.89	78.00	43.00	100.00
LLM + LLM	Repurposed	Llama 3.1 8B Instruct	basic	42	96.22	6.00	2.00	96.65	95.11	97.33	92.00	14.00	100.00
BERT + LLM	Repurposed	Modern BERT-base	basic	42	90.56	14.25	5.60	91.74	91.89	89.22	81.00	53.00	100.00
LLM	Repurposed	Llama 3.1 8B Instruct	office	42	84.56	22.50	11.00	86.65	87.89	80.11	70.00	49.00	100.00
LLM + LLM	Repurposed	Llama 3.1 8B Instruct	office	42	88.11	20.25	4.00	89.86	89.22	87.00	73.00	17.00	100.00
BERT + LLM	Repurposed	Modern BERT-base	office	42	87.89	21.75	4.40	89.77	88.78	87.00	71.00	33.00	100.00
LLM	Synthetic	Llama 3.1 8B Instruct	basic	42	95.78	5.75	2.00	96.23	94.67	96.89	94.00	8.00	95.00
LLM + LLM	Synthetic	Llama 3.1 8B Instruct	basic	42	98.11	2.25	2.00	98.30	98.11	98.11	97.00	7.00	100.00
BERT + LLM	Synthetic	Modern BERT-base	basic	42	96.00	4.50	3.60	96.40	94.78	97.22	94.00	41.00	100.00
LLM	Synthetic	Llama 3.1 8B Instruct	office	42	84.00	30.50	5.00	86.91	85.11	81.78	63.00	14.00	89.00
LLM + LLM	Synthetic	Llama 3.1 8B Instruct	office	42	83.78	33.75	2.00	87.01	84.89	82.67	55.00	16.00	100.00
BERT + LLM	Synthetic	Modern BERT-base	office	42	77.22	47.25	3.20	82.52	78.22	76.22	37.00	28.00	100.00
Average					88.86	18.77	4.98	90.63	89.58	87.95	75.42	26.92	98.67

Table 11: Access control metrics for Single Name Encoding

Architecture	Dataset	Model	Org. Structure	Seed	Accuracy	FPR	FNR	F1	Seen Role Acc.	Unseen Role Acc.	Exist Mismatch Acc.	Broken Role Acc.	Random Role Acc.
LLM	Repurposed	Llama 3.1 8B Instruct	basic	42	90.44	11.25	15.00	91.43	90.44	90.44	78.00	43.00	100.00
LLM + LLM	Repurposed	Llama 3.1 8B Instruct	basic	42	94.11	9.75	2.00	94.83	95.22	93.00	92.00	14.00	100.00
BERT + LLM	Repurposed	Modern BERT-base	basic	42	93.44	10.50	5.60	94.24	94.00	92.89	81.00	53.00	100.00
LLM	Repurposed	Llama 3.1 8B Instruct	office	42	85.56	18.75	11.00	87.25	87.78	84.44	70.00	49.00	100.00
LLM + LLM	Repurposed	Llama 3.1 8B Instruct	office	42	88.33	18.75	4.00	89.95	90.56	86.11	73.00	17.00	100.00
BERT + LLM	Repurposed	Modern BERT-base	office	42	88.89	17.50	4.40	90.38	89.44	88.33	71.00	33.00	100.00
LLM	Synthetic	Llama 3.1 8B Instruct	basic	42	96.33	6.00	2.00	96.75	95.22	97.44	94.00	8.00	95.00
LLM + LLM	Synthetic	Llama 3.1 8B Instruct	basic	42	98.56	2.25	2.00	98.71	98.56	97.44	97.00	7.00	100.00
BERT + LLM	Synthetic	Modern BERT-base	basic	42	96.56	4.25	3.60	96.91	97.33	95.78	94.00	41.00	100.00
LLM	Synthetic	Llama 3.1 8B Instruct	office	42	80.78	34.50	5.00	84.32	83.00	78.56	63.00	14.00	89.00
LLM + LLM	Synthetic	Llama 3.1 8B Instruct	office	42	78.11	46.50	2.00	83.23	79.22	77.00	55.00	16.00	100.00
BERT + LLM	Synthetic	Modern BERT-base	office	42	79.33	42.75	3.20	83.91	81.44	77.22	37.00	28.00	100.00
Average					89.20	18.56	4.98	90.99	90.19	88.22	75.42	26.92	98.67

Table 12: Access control metrics for Hierarchical Name Encoding

Architecture	Dataset	Model	Org. Structure	Seed	Accuracy	FPR	FNR	F1	Seen Role Acc.	Unseen Role Acc.	Exist Mismatch Acc.	Broken Role Acc.	Random Role Acc.
LLM	Repurposed	Llama 3.1 8B Instruct	Basic	42	75.00	24.00	25.00	79.00	78.00	72.00	76.00	74.00	100.00
LLM + LLM	Repurposed	Llama 3.1 8B Instruct	Basic	42	79.00	16.00	24.00	82.00	81.00	77.00	84.00	64.00	100.00
BERT + LLM	Repurposed	Modern BERT-base	Basic	42	92.25	13.33	4.40	93.91	91.25	93.25	86.67	65.00	100.00
LLM	Repurposed	Llama 3.1 8B Instruct	Office	42	80.00	27.00	15.00	84.00	84.00	77.00	73.00	49.00	99.00
LLM + LLM	Repurposed	Llama 3.1 8B Instruct	Office	42	87.00	26.00	5.00	90.00	89.00	84.00	74.00	31.00	100.00
BERT + LLM	Repurposed	Modern BERT-base	Office	42	86.75	27.33	4.80	89.98	89.00	84.50	72.67	50.00	100.00
LLM	Synthetic	Llama 3.1 8B Instruct	Basic	42	89.00	19.00	7.00	91.00	89.00	89.00	81.00	62.00	95.00
LLM + LLM	Synthetic	Llama 3.1 8B Instruct	Basic	42	97.00	3.00	2.00	98.00	98.00	97.00	97.00	43.00	100.00
BERT + LLM	Synthetic	Modern BERT-base	Basic	42	89.75	17.33	6.00	91.98	88.50	91.00	82.67	71.00	100.00
LLM	Synthetic	Llama 3.1 8B Instruct	Office	42	76.00	54.00	6.00	83.00	78.00	74.00	46.00	34.00	94.00
LLM + LLM	Synthetic	Llama 3.1 8B Instruct	Office	42	81.00	48.00	2.00	87.00	83.00	79.00	52.00	20.00	100.00
BERT + LLM	Synthetic	Modern BERT-base	Office	42	80.38	39.33	7.80	85.45	81.50	79.25	60.67	54.00	99.00
Average					84.43	26.19	9.08	87.94	85.85	83.08	73.81	51.42	98.92

Table 13: Access control metrics for Hierarchical Number Encoding

Struct.	Arch.	Model	Acc.	FPR	FNR	F1	Corr.	Comp.	Clar.	Seen	Unseen
Repurposed Dataset (Dolly)											
Basic	LLM	Qwen2.5-3B	76.33	22.67	24.33	80.00	3.92	3.53	4.65	80.00	72.67
Basic	LLM	Llama-3.2-3B	76.33	28.00	21.67	80.33	4.02	3.64	4.65	78.00	74.00
Basic	LLM	gemma-4B	75.33	27.33	23.00	79.67	3.99	3.55	4.59	78.33	72.33
Basic	LLM	Qwen2.5-7B	76.33	24.33	24.00	80.00	4.08	3.67	4.71	78.67	73.33
Basic	LLM	Llama-3.1-8B	75.67	25.00	24.00	79.33	4.12	3.65	4.69	78.00	73.00
Basic	LLM	gemma-7B	73.00	34.00	22.33	78.33	3.85	3.55	4.45	76.00	70.33
Basic	LLM-Cls	Qwen2.5-3B	90.33	16.00	5.67	92.67	–	–	–	90.67	90.67
Basic	LLM-Cls	Llama-3.2-3B	89.00	18.00	6.67	91.67	–	–	–	90.67	88.00
Basic	LLM-Cls	gemma-4B	91.33	14.67	5.33	93.33	–	–	–	92.67	90.33
Basic	LLM-Cls	Qwen2.5-7B	85.67	22.67	9.33	89.00	–	–	–	86.67	85.00
Basic	LLM-Cls	Llama-3.1-8B	77.33	29.67	18.33	81.67	–	–	–	78.67	76.00
Basic	LLM-Cls	gemma-7B	78.33	37.33	12.67	83.33	–	–	–	78.67	77.67
Basic	Cls	Modern BERT-base	92.96	11.44	4.40	94.44	–	–	–	92.92	93.00
Basic	Cls	Modern BERT-large	92.58	12.11	4.60	94.15	–	–	–	92.75	92.42
Basic	Cls	Google BERT-base	86.82	29.33	1.97	90.36	–	–	–	88.00	86.43
Basic	Cls	Google BERT-large	75.77	56.61	4.69	82.95	–	–	–	75.77	77.28
Basic	Cls	RoBERTa-base	74.21	57.18	3.29	82.50	–	–	–	80.07	71.66
Basic	Cls	RoBERTa-large	85.83	16.45	9.99	89.54	–	–	–	85.50	86.49
Office	LLM	Qwen2.5-3B	76.67	25.33	22.33	80.33	3.93	3.47	4.63	80.67	72.67
Office	LLM	Llama-3.2-3B	83.00	25.33	11.67	86.67	3.99	3.59	4.66	86.00	80.00
Office	LLM	gemma-4B	79.33	25.67	17.67	83.33	4.08	3.72	4.59	81.67	77.33
Office	LLM	Qwen2.5-7B	80.00	25.67	16.33	84.00	4.19	3.74	4.73	84.00	76.00
Office	LLM	Llama-3.1-8B	80.33	26.67	15.00	84.33	4.17	3.70	4.68	83.67	77.33
Office	LLM	gemma-7B	80.00	24.67	17.67	83.67	3.77	3.41	4.40	83.67	75.67
Office	LLM-Cls	Qwen2.5-3B	86.67	27.67	4.67	89.67	–	–	–	88.33	84.33
Office	LLM-Cls	Llama-3.2-3B	88.67	22.00	5.33	91.00	–	–	–	89.67	87.33
Office	LLM-Cls	gemma-4B	86.33	27.00	5.33	89.67	–	–	–	88.33	84.33
Office	LLM-Cls	Qwen2.5-7B	87.00	26.33	5.00	90.33	–	–	–	89.33	85.00
Office	LLM-Cls	Llama-3.1-8B	86.33	28.33	4.67	90.00	–	–	–	88.67	84.00
Office	LLM-Cls	gemma-7B	87.67	24.67	4.67	90.33	–	–	–	89.33	86.00
Office	Cls	Modern BERT-base	86.38	25.22	6.67	89.52	–	–	–	87.67	85.08
Office	Cls	Modern BERT-large	87.38	25.67	4.80	90.41	–	–	–	88.75	86.00
Office	Cls	Google BERT-base	85.11	30.20	6.09	90.17	–	–	–	89.19	83.62
Office	Cls	Google BERT-large	86.96	29.65	6.34	91.12	–	–	–	89.29	85.03
Office	Cls	RoBERTa-base	83.15	27.18	9.83	85.68	–	–	–	85.35	84.16
Office	Cls	RoBERTa-large	63.75	99.72	0.81	77.13	–	–	–	62.85	62.41

Table 14: Role-aware performance on repurposed (Dolly) dataset. Green cells mark the best accuracy in each dataset block. Higher is better for all metrics except FPR/FNR (lower is better).

Struct.	Arch.	Model	Acc.	FPR	FNR	F1	Corr.	Comp.	Clar.	Seen	Unseen
Synthetic Dataset											
Basic	LLM	Qwen2.5-3B	72.00	37.33	22.33	77.67	3.96	3.69	4.74	72.67	71.33
Basic	LLM	Llama-3.2-3B	92.00	12.67	5.33	93.33	3.86	3.60	4.68	91.33	92.33
Basic	LLM	gemma-4B	75.33	42.00	14.33	81.33	3.96	3.63	4.62	75.33	75.00
Basic	LLM	Qwen2.5-7B	77.33	35.00	15.33	82.00	4.04	3.78	4.78	79.00	75.00
Basic	LLM	Llama-3.1-8B	92.67	13.33	4.67	94.00	3.95	3.73	4.79	92.67	92.00
Basic	LLM	gemma-7B	78.33	34.33	14.67	83.00	3.93	3.66	4.62	79.67	76.00
Basic	LLM-Cls	Qwen2.5-3B	90.67	14.67	6.67	92.33	–	–	–	89.33	91.67
Basic	LLM-Cls	Llama-3.2-3B	96.67	5.33	2.33	97.33	–	–	–	96.33	97.00
Basic	LLM-Cls	gemma-4B	97.33	4.00	2.33	97.67	–	–	–	97.00	97.33
Basic	LLM-Cls	Qwen2.5-7B	96.33	6.33	2.00	97.00	–	–	–	96.33	96.00
Basic	LLM-Cls	Llama-3.1-8B	97.00	3.67	2.00	98.00	–	–	–	97.33	97.33
Basic	LLM-Cls	gemma-7B	91.67	19.33	2.00	93.67	–	–	–	91.67	91.67
Basic	Cls	Modern BERT-base	91.08	12.00	7.07	92.88	–	–	–	89.92	92.25
Basic	Cls	Modern BERT-large	84.50	25.33	9.60	87.92	–	–	–	84.25	84.75
Basic	Cls	Google BERT-base	87.48	25.74	3.05	90.96	–	–	–	86.80	90.83
Basic	Cls	Google BERT-large	90.73	15.81	5.90	92.94	–	–	–	90.95	91.23
Basic	Cls	RoBERTa-base	80.67	48.27	3.67	85.95	–	–	–	80.46	80.61
Basic	Cls	RoBERTa-large	61.45	74.25	12.94	74.83	–	–	–	62.30	66.95
Office	LLM	Qwen2.5-3B	77.67	47.67	7.00	83.67	3.76	3.60	4.71	80.00	75.67
Office	LLM	Llama-3.2-3B	78.67	47.33	5.67	84.67	3.85	3.71	4.73	80.33	77.00
Office	LLM	gemma-4B	73.67	58.00	7.33	81.67	3.84	3.69	4.69	76.33	71.00
Office	LLM	Qwen2.5-7B	79.00	45.33	6.33	84.67	3.89	3.77	4.77	81.00	77.00
Office	LLM	Llama-3.1-8B	78.00	49.00	6.00	84.00	3.94	3.77	4.81	80.00	76.00
Office	LLM	gemma-7B	76.00	53.33	6.33	83.00	3.81	3.59	4.58	80.00	71.67
Office	LLM-Cls	Qwen2.5-3B	79.67	51.33	2.00	85.67	–	–	–	81.00	78.33
Office	LLM-Cls	Llama-3.2-3B	80.00	50.00	2.00	85.67	–	–	–	81.00	79.00
Office	LLM-Cls	gemma-4B	79.67	51.00	2.00	85.33	–	–	–	81.67	77.67
Office	LLM-Cls	Qwen2.5-7B	81.33	45.33	2.33	86.67	–	–	–	82.33	80.33
Office	LLM-Cls	Llama-3.1-8B	81.67	46.67	2.00	87.00	–	–	–	84.00	79.00
Office	LLM-Cls	gemma-7B	80.00	49.33	2.00	86.00	–	–	–	81.33	79.00
Office	Cls	Modern BERT-base	80.17	43.89	5.40	85.63	–	–	–	82.08	78.25
Office	Cls	Modern BERT-large	77.13	53.33	4.60	83.91	–	–	–	78.17	76.08
Office	Cls	Google BERT-base	75.32	62.32	3.97	83.51	–	–	–	78.18	73.29
Office	Cls	Google BERT-large	78.17	55.27	4.67	85.57	–	–	–	77.10	77.62
Office	Cls	RoBERTa-base	73.79	63.95	3.63	82.71	–	–	–	76.38	72.93
Office	Cls	RoBERTa-large	69.13	79.94	0.73	80.69	–	–	–	70.98	69.10

Table 15: Role-aware performance on synthetic datasets. Green cells mark the best accuracy in each dataset block. Higher is better for all metrics except FPR/FNR (lower is better).