## A Survey on Collaborating Small and Large Language Models for Performance, Cost-effectiveness, Cloud-edge Privacy, and Trustworthiness

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### **Abstract**

Large language models (LLMs) have advanced many domains and applications but face high fine-tuning costs, inference latency, limited edge deployability, and reliability concerns. Small language models (SLMs), compact, efficient, and adaptable, offer complementary remedies. Recent work explores collaborative frameworks that fuse SLMs' specialization and efficiency with LLMs' generalization and reasoning to meet diverse objectives across tasks and deployment scenarios. Motivated by these developments, this paper presents a systematic survey of SLM-LLM collaboration organized by collaboration objectives. We propose a taxonomy with four goals: performance enhancement, cost-effectiveness, cloud-edge privacy, and trustworthiness. Within this framework, we review representative methods, summarize design paradigms, and outline open challenges and future directions toward efficient, secure, and scalable SLM-LLM collaboration.

### 1 Introduction

Large language models (LLMs) have profoundly transformed multiple domains, including AI for science (Luo et al., 2022; Al-Lawati et al., 2025; Wang et al., 2024a), programming (Shi et al., 2024), and human-centered interaction (Zhang et al., 2024c), primarily owing to their massive parameter scales. However, such scale also introduces several challenges: (1) fine-tuning is computationally intensive, limiting efficient model adaptation (Thawakar et al., 2025; Liu et al., 2024b); (2) large model size leads to inference latency, constraining real-time applications (Leviathan et al., 2023; Kwon et al., 2023); (3) typical edge devices, such as mobile phones, personal computers, and small servers, lack the capacity to host these models, while cloud-based inference raises privacy and cost concerns (Carlini et al.,

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2021; Xu et al., 2024b); and (4) LLMs exhibit inherent reliability risks, including hallucinations and jailbreak vulnerabilities (Yao et al., 2024; Farquhar et al., 2024). These challenges underscore the increasing need for customizable, cost-efficient, edge-deployable, and trustworthy AI solutions. Small language models (SLMs), characterized by their compact architecture, low computational cost, and adaptability, have emerged as promising counterparts to mitigate these issues, although their general reasoning and knowledge coverage remain more limited than those of LLMs. Consequently, harnessing the complementary strengths of SLMs and LLMs provides a viable pathway toward developing efficient, scalable, and reliable AI systems.

Researchers have proposed diverse approaches for SLM-LLM collaboration, leveraging SLMs' strengths in customization, efficiency, and local deployment alongside LLMs' generalization and reasoning capabilities (Xu et al., 2024a; Chen et al., 2024; Wang et al., 2025b). Despite notable progress, a systematic survey focused on the objectives of SLM-LLM collaboration remains absent. Existing studies largely pursue four objectives. (1) Performance: integrating domain-specific SLMs with general LLMs to improve performance across specialized and general tasks. (2) Costeffectiveness: using SLMs for lightweight processing and invoking LLMs selectively to reduce computational and API costs. (3) Cloud-edge privacy: employing on-device SLMs for private data handling while cloud LLMs offer broader reasoning to balance efficiency and privacy. (4) Trustworthiness: adopting SLMs as safety policy encoders that guide LLMs to produce safer and more reliable outputs. This paper presents the first comprehensive survey around the objectives of SLM-LLM collaboration: performance, cost-effectiveness, cloudedge privacy, and trustworthiness. We propose a taxonomy, summarize representative works (Tab.1 in Appendix), and outline future directions.

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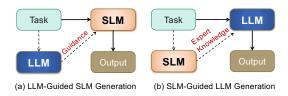


Figure 1: Guidance-Generation Collaboration.

Differences from existing surveys Several surveys have examined SLMs in the LLM era. Wang et al. (2024b, 2025a) provided broad overviews of SLM design, applications, and reliability but mentioned collaboration only briefly. Lu et al. (2024); Van Nguyen et al. (2024); Xu et al. (2024b) analyzed SLM advantages, architectures, and deployment, yet offered limited discussion of collaboration. Existing collaboration surveys, such as Chen and Varoquaux (2024); Niu et al. (2025); Li et al. (2025b), focus on one-way or cloud–edge settings without addressing broader objectives. To fill this gap, we systematically review SLM–LLM collaboration by collaboration objectives, offering key insights to guide future studies.

### 2 Collaboration for Performance

The optimal LLM varies across tasks and queries (Jiang et al., 2023), making single-model solutions suboptimal. Leveraging complementary models is therefore effective. Owing to their customizability, SLMs have produced many domain-specific products, such as SciGLM (Zhang et al., 2024a), Chem-LLM (Zhang et al., 2024b), and Biomistral (Labrak et al., 2024). Hence, SLM-LLM collaboration for performance has been a prevalent strategy. We divide existing works mainly into two paradigms: (1) *Guidance-Generation*, where one model steers another's generation, and (2) *Division-Fusion*, where the SLMs and LLMs leverage their complementary strengths on distinct tasks.

### 2.1 Guidance-Generation Collaboration

Guidance–Generation collaboration involves one assistant model providing guidance based on its strengths to support a backbone model in generation. When one model performs well overall and another excels in a specific aspect, the former serves as the generator while the latter offers complementary guidance. This paradigm generally appears in two forms: (1) LLM-guided SLM generation and (2) SLM-guided LLM generation.

(1) LLM-guided SLM generation. As shown in Fig. 1(a), the LLM uses its semantic understand-

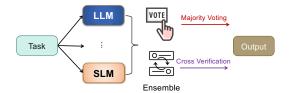


Figure 2: Parallel Ensemble: Collective Intelligence

ing to clarify tasks and provide fine-grained guidance for task-specific SLMs. For example, Syn-CID (Liang et al., 2024) employs LLM-generated task descriptions to guide SLM reasoning.

(2) SLM-guided LLM generation. As shown in Fig. 1(b), the SLM offers domain expertise and cues, while the LLM integrates this information for more accurate and reliable outputs. For instance, SuperICL and its variant (Xu et al., 2024a; Mojarradi et al., 2024) inject SLM predictions and confidence scores into the LLM's context, and LM-Guided CoT (Lee et al., 2024) uses SLM-generated reasoning chains to guide LLM inference.

### 2.2 Division-Fusion Collaboration

Division–fusion collaboration paradigm is preferred when multiple models exhibit heterogeneous capabilities and no single backbone model is suitable. According to different task needs, this paradigm mainly includes (1) *Parallel Ensemble* for collective intelligence and (2) *Sequential Cooperation* for multi-stage workflows.

(1) Parallel Ensemble: Collective Intelligence As shown in Fig. 2, multiple SLMs and LLMs work in parallel, and their outputs are integrated for higher accuracy. Two common strategies are *majority voting*, as in ELM (Gondara et al., 2025), which aggregates outputs by consensus, and *crossverification*, as in CaLM (Hsu et al., 2024), which iteratively refines results until consensus is reached.

# (2) Sequential Cooperation: Division of Labor For multi-stage tasks, subtasks are assigned to suitable models and connected in a pipeline, as shown in Fig. 3. When tasks are explicitly staged, SLMs and LLMs take different roles: SLMs handle precise components (e.g., schema matching in ZeroNL2SQL (Fan et al., 2024) and KDSL (Chen et al., 2025a)), while LLMs manage complex reasoning (e.g., GCIE (Bao and Wang, 2024)). When stages are implicit, the LLM acts as a *planner* and SLMs as *executors*, as in HuggingGPT (Shen et al., 2023) and TrajAgent (Du et al., 2024), which assign subtasks to expert SLMs and integrate them.

### 2.3 Discussion

Current SLM–LLM collaborations for performance highlight the potential of combining specialized and general models but remain limited by fragmented ecosystems and incomplete evaluation standards. Future research should establish open, crossdomain platforms enabling efficient model discovery and integration, alongside collaborative benchmarks that assess structured cooperation, throughput, and cost–performance trade-offs to better capture real-world system efficiency.

### 3 Collaboration for Cost-Effectiveness Trade-off

LLMs deliver advanced performance but face prohibitive costs, including computational expense (FLOPs, GPU hours), high latency, significant communication overhead, large storage footprints, and substantial API spend. Mitigating these costs through isolated model optimization is often inefficient and reaches diminishing returns. SLMs offer a compelling pathway to cost-efficiency by serving as lightweight, specialized collaborators (Wang et al., 2025a). This section targets costeffectiveness in SLM-LLM collaboration frameworks, which are organized across the language modeling lifecycle into three stages: (1) Pretraining Stage: strategies like teacher-guided data curation and co-curricula use LLMs to guide SLM learning for improved compute and data efficiency; (2) Tuning stage: selective knowledge distillation (LLM-SLM) and proxy transfer (SLM-LLM warm-starts or adapters) cut adaptation FLOPs and storage while preserving task quality; and (3) Inference stage, cascade routing, speculative decoding, and compute-optimal test-time scaling allocate just-enough capacity per query to lower latency, communication, and per-call/API cost.

### 3.1 Collaboration During Pre-Training Stage

Pre-training is the most computationally intensive phase of the LLM lifecycle, motivating cost-effective strategies. SLM-LLM collaboration im-

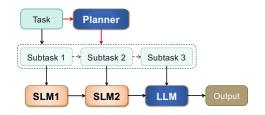


Figure 3: Sequential Cooperation: Division of Labor



(a) SLM selects/Reshape Data and feeds into LLM



(b) Perplexity-based data pruning with SLM

Figure 4: Data Curation.

proves data efficiency and optimizes training via three approaches: (1) data curation, where LLMs refine SLM data (Fig.4a) or SLMs assess LLM data quality (Fig.4b); (2) co-curriculum learning (Fig.5a), which progressively expands model capacity; and (3) pre-training distillation (Fig.5b), transferring knowledge from teacher to student models. (1) Data Curation High-quality data is essential for effective pre-training, yet real-world corpora are often noisy, inflating computational cost and degrading performance. SLM-LLM collaboration addresses this by filtering and refining datasets to improve data efficiency. For example, SALT (Rawat et al., 2024) uses compact models to provide soft labels and select informative samples, accelerating LLM pre-training while reducing FLOPs and energy. Conversely, Ankner et al. (2024) employ perplexity-based pruning with SLM scorers to remove low-yield data, reducing optimization steps and enhancing generalization.

- (2) Co-Curriculum LiGO (Wang et al., 2023) maps small-model parameters to larger ones via a linear growth operator, cutting pre-training compute by up to 50%. Progressive training (Yano et al., 2025) incrementally scales width and depth, saving ~25% compute. HYPERCLONING (Samragh et al., 2024) clones linear layers for stable warm starts and substantial GPU-hour reductions.
- (3) **Pre-Training Distillation** Pre-training distillation (PD) extends classic task-agnostic methods such as DistilBERT, TinyBERT, and MiniLM (Sanh et al., 2019; Jiao et al., 2020;

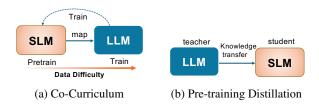


Figure 5: (a) Co-curriculum learning and (b) Knowledge distillation.

Wang et al., 2020), now scaled to LLMs. Recent studies show that larger students can sometimes outperform teachers (Peng et al., 2025) and disentangle PD effects from data confounds (Goyal et al., 2025). MINIPLM (Gu et al., 2025) refines data with teacher inference before student training, enhancing efficiency and diversity.

### 3.2 Collaboration During Tuning Stage

LLM tuning is highly resource-intensive, demanding substantial GPU memory and FLOPs, while SLM tuning distilled from LLMs can suffer from inefficient or low-quality supervision, leading to wasted LLM computation. SLM–LLM collaboration alleviates these by relocating supervision to low-cost venues and compressing guidance: (1) Selective Knowledge Distillation (SLM  $\Leftarrow$  LLM, Fig. 6) distills selective LLM signals to reduce LLM calls; and (2) Proxy Transfer (SLM  $\Rightarrow$  LLM, Fig. 7a, Fig. 7b) generates lightweight, reusable updates for efficient LLM adaptation.

### (1) Selective Knowledge Distillation. Adaptive

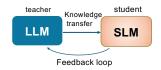


Figure 6: Selective Knowledge Distillation.

selection reduces data and teacher calls (LLKD (Li et al., 2025a), efficiency-oriented KD (Jazbec et al., 2024)); dense supervision uses concise yet rich signals such as contrastive label refinement (SynCID (Liang et al., 2024)), compact CoT (HAWKEYE (She et al., 2025)), and causal explanations (Muhebwa and Osman, 2025); targeted matching focuses on task-relevant features (C2KD (Chen et al., 2025c)). Behavioral KD distills tool-use trajectories (Agent Distillation (Kang et al., 2025)). Applications, e.g., LSC4Rec (Lv et al., 2025), SmallPlan (Pham et al., 2025), and Think (Bergner et al., 2024), show that these strategies jointly cut FLOPs, tokens, and LLM calls while retaining near-LLM performance under tight compute and latency constraints.

(2) Proxy Transfer Models can train parameter updates on a small proxy model and lift them for use in the LLM. LoRAM (Zhang et al., 2025a) trains low-rank adapters on an SLM to locate effective subspaces, later reused in LLMs. Lite-MOE (Zhuang et al., 2024) extracts proxy submodels for on-device tuning, enabling local specializa-

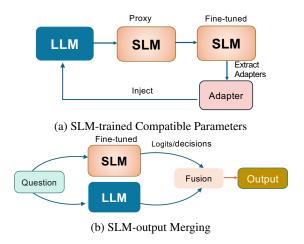


Figure 7: Proxy Transfer.

tion and feedback propagation. GateKeeper (Rabanser et al., 2025) cascades an SLM and LLM to handle easy cases locally and defer harder ones, cutting inference cost, while logit-fusion (Fan et al., 2025c) integrates fine-tuned SLM outputs to refine LLM distributions with minimal updates.

### 3.3 Collaboration During Inference Stage

Inference cost arises from three factors: (i) executing large models for every query (high FLOPs, latency, and API cost), (ii) decoding inefficiency (token-by-token verification by a single heavy model), and (iii) misallocated compute (overspending on easy queries, underspending on hard ones). SLM–LLM collaboration mitigates these through: (1) *Cascade routing*, handling easy queries with an SLM and escalating difficult ones (Fig. 8); (2) *Speculative decoding*, an SLM drafts tokens that a stronger verifier approves in bulk (Fig. 9); and (3) *Compute-optimal test-time scaling*, optimizing model selection and sampling budgets across SLM/LLM under fixed budget (Fig. 10).

(1) Cascade Routing *Query-level routers* route per input using lightweight difficulty predictors (Chen et al., 2024; Ong et al., 2025; Zhang et al., 2024d; Yue et al., 2024; Hao et al., 2024), e.g., SlimPM flags missing LLM knowledge for retrieval (Tan et al., 2024). *Token-level routers* escalate only complex spans to LLMs, improving cost—quality trade-offs (Zheng et al., 2024; Fu et al., 2025a).

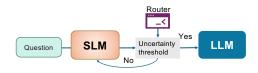


Figure 8: Cascade Routing

Resource-aware routers optimize selection via contextual bandits (Wang et al., 2025c) or MoE-style edge—cloud load balancing (Jin et al., 2025).

- (2) Speculative Decoding Speculative decoding advances focus on (i) decoupled draft-verify architectures, (ii) parallel decoding, and (iii) efficient deployment topologies. Cross-attention drafters (Beagle (Zhong et al., 2025)) simplify verifier fusion; LookAhead Reasoning (Fu et al., 2025b) and Adaptive Parallel Decoding (Israel et al., 2025) improve parallelism; edge-cloud systems (LLM-CAD (Xu et al., 2023), PICE (Zhan et al., 2025), FS-GEN (Zhang et al., 2024e)) reduce verification cost via local drafting and adaptive policies.
- (3) Compute-optimal Test-time Scaling Test-Time Scaling (TTS) increases inference compute to improve performance, while compute-optimal TTS maximizes it under fixed budgets by selecting suitable model sizes and families, representing a form of SLM–LLM collaboration. BestRoute (Ding et al., 2025) optimizes model routing and TTS sampling budgets to reduce cost, and AgentTTS (Wang et al., 2025b) extends this to multi-stage tasks through dynamic model and budget allocation.

### 3.4 Discussion

Existing cost-effectiveness collaborations show clear savings across compute, latency, communication, storage and API spend by coordinating the ML lifecycle, but remain constrained by fragmented pipelines, inconsistent cost reporting and brittle rules for when to hand off to the LLM (Behera et al., 2025). Future work should standardize end-to-end cost-effectiveness metrics and use adaptive routing—paired with compression, bidirectional distillation etc, to deliver reliable savings across SLM-LLM collaboration paradigms.

# 4 Privacy-preserving Cloud-Edge Collaboration

Deploying LLMs on edge devices is limited by storage and computation constraints. A practical alternative is a cloud-edge architecture where lightweight SLMs handle local, context-aware tasks, and cloud-based LLMs provide broader generalization. However, transmitting sensitive data



Figure 9: Speculative Decoding

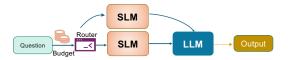


Figure 10: Compute-optimal TTS

from trusted edge SLMs to semi-trusted cloud LLMs raises privacy concerns, as personally identifiable or proprietary information may be logged and leaked for training (Duan et al., 2023), posing long-term security and compliance risks.

To balance privacy and performance, privacy-preserving collaboration has emerged at both the inference and fine-tuning stages. At the inference stage, SLMs act as **Sensitive Information Gate-keepers**, filtering or anonymizing data before sending it to LLMs, or as **All-Information Guardians**, retaining private context locally and integrating it after generation. At the fine-tuning stage, collaboration occurs through **SLMs as Learners** (learning from LLMs via distillation), **LLMs as Learners** (adapting via proxy tuning using SLM signals), or **Collaborative Learners** (jointly improving through federated knowledge transfer).

### 4.1 Inference Stage

During inference, edge user requests often contain sensitive information. Edge SLMs can process them locally but with lower quality than cloud LLMs, while direct cloud LLM use risks data exposure. Thus, privacy-preserving edge-cloud collaboration is needed, based on protection levels, categorized into (1) Sensitive Information Gatekeepers and (2) All-Information Guardians.

- (1) SLMs as Sensitive Information Gatekeepers To protect sensitive information in edge-cloud collaboration, the edge SLM serves as a privacy-preserving filter, for (i) sanitizing sensitive content and (ii) selectively disclosing necessary information before transmitting requests to the cloud.
- (i) Sanitizing sensitive information: Fig.11(a)

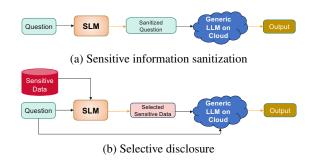


Figure 11: SLMs as Sensitive-Information Gatekeepers.

taining personally identifiable information (PII). Chong et al. (2024) use an SLM to filter PII before cloud transmission, while Papadopoulou et al. (2022) employ SLM probabilities for detection. Uzor et al. (2025) rephrase queries to preserve meaning while removing PII, applied to clinical data (Wiest et al., 2024). Hartmann et al. (2024) further enhance SLMs by masking sensitive data and using LLM-generated in-context examples. (ii) Selective disclosure: Fig. 11(b) illustrates selective disclosure, where the edge SLM shares limited, task-relevant information to reduce privacy risks. Zhang et al. (2024f) share sketches or logits with the LLM, while CORE (Fan et al., 2025a) ranks and filters relevant context. Zhang et al. (2024d) employ a policy network to balance privacy and quality, and Cheng et al. (2025) enforce a differential privacy budget to mathematically bound potential leakage. In sum, these methods shift from full-text disclosure to abstracted representation sharing, mitigating data exposure in SLM-LLM collaboration. (2) SLMs as All-Information Guardians Edge devices often enforce strict privacy rules that prevent PII disclosure. In such settings, SLMs serve as All-Information Guardians, handling sensitive data ondevice while drawing on cloud LLM knowledge, ensuring privacy preservation (Fig. 12). Sketchbased CoGenesis (Zhang et al., 2024f) illustrates this by using cloud LLMs for planning and local SLMs for personalized adaptation. Similar frameworks integrate cloud knowledge with local data for clinical (Zhang et al., 2024g) or retrievalaugmented (Cheng et al., 2025; Hartmann et al., 2024) applications. Industrial systems such as Apple Intelligence (Gunter et al., 2024) follow the same principle, processing sensitive data locally and sharing only abstractions with the cloud.

shows how SLMs remove or rephrase prompts con-

### 4.2 Fine-tuning Stage

During fine-tuning, edge data can enhance both edge and cloud LLMs, though protecting sensitive information remains challenging. Depending on the enhanced target, privacy-preserving edge—cloud frameworks typically adopt three paradigms: (1) SLMs as Learners, gaining knowledge from



Figure 12: SLMs as All-Information Guardians.

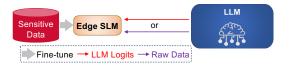


Figure 13: SLMs as Learners.

LLMs through local fine-tuning or distillation; (2) LLMs as Learners, improving via proxy signals from tuned SLMs; and (3) Collaborative Learners, where both models co-evolve through federated or privacy-preserving knowledge exchange.

- (1) SLMs as Learners Fig. 13 shows edge SLMs learning from cloud LLMs to improve their ability and reduce cloud dependence through subsequent local fine-tuning. SLMs can learn via two modes: (i) raw text, such as reasoning traces or samples, and (ii) feedback logits as supervision signals.
- (i) Raw Data: SLMs enhance reasoning by learning from cloud LLM outputs while keeping private data local. The LLM provides interpretable supervision (e.g., responses, reasoning traces) or synthetic samples for SLM fine-tuning. MiniLLM (Gu et al., 2024) and LlamaDuo (Park et al., 2025) distill reasoning traces, while DRAG (Chen et al., 2025b) extends to retrieval-augmented reasoning. Privacyaware frameworks such as HomeLLaMA (Huang et al., 2025b) and Qin et al. (2024) use selective textual supervision to align SLMs with user preferences under strict privacy constraints.
- (ii) Logit-based Learning: SLMs learn from teacher LLMs' numerical outputs, using logits as soft targets to imitate their decision boundaries without accessing raw text. TinyLLM (Tian et al., 2025) distills from multiple teachers for robustness, Mix Distillation (Li et al., 2025d) combines LLM and SLM supervision, and ADPA (Gao et al., 2025) introduces an advantage-based objective for better reasoning alignment, ensuring privacy and efficiency through abstracted signal exchange.
- (2) LLMs as Learners LLMs can be adapted to sensitive data without direct access by leveraging an edge SLM tuned locally. The SLM forwards only supervision signals, such as (i) logits or (ii) LoRA signals, to the LLM, enabling privacy-preserving alignment, as shown in Fig. 14.
- (i) Logit-based Learning: Instead of directly fine-

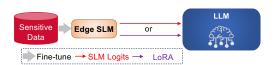


Figure 14: LLMs as Learners.

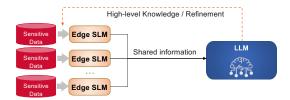


Figure 15: Cloud-Edge Collaborative Learning.

tuning LLMs, Ormazabal et al. (2023) steer them via SLMs trained on private data, exposing only logits for guidance, with later extensions using logit offsets (Liu et al., 2024a; Wang et al., 2025d). Follow-up work addresses training—inference inconsistency (He et al., 2024; Yao et al., 2025) and improves robustness through re-encoding SLM outputs (Fang et al., 2024a), enabling adaptation across SLM–LLM pairs without shared vocabularies while preserving data privacy.

(ii) LoRA-based Learning: Recent work explores using LoRA signals for knowledge transfer. PHLoRA (Vasani et al., 2025) avoids dual logit outputs by computing low-rank adaptations with strong performance gains. LoRASuite (Li et al., 2025c) and LoRA-X (Farhadzadeh et al., 2025) enable cross-version and cross-architecture migration, while Trans-LoRA (Wang et al., 2024c) and Cross-LoRA (Xia et al., 2025) generalize LoRA transfer across heterogeneous models for scalable, privacy-conscious LLM adaptation.

(3) SLMs and LLMs as Collaborative Learners Beyond one-way transfer, collaboration can be bidirectional: SLMs and LLMs co-adapt through shared representations, logits, or adapter weights while preserving privacy (Fig. 15). Edge SLMs train on local data and send abstracted updates (e.g., logits, LoRA signals) for cloud aggregation. CrossLM (Deng et al., 2025) combines private data and LLM-generated samples for co-training, while LSRP (Zhang et al., 2025b) enables mutual retrieval and response refinement. Federated frameworks (Fan et al., 2025b; Gao et al., 2024; Peng et al., 2024; QI et al., 2024; Fang et al., 2024b) aggregate SLM updates to refine central LLMs, with FLoRA (Wang et al., 2024d) enhancing personalization through improved edge aggregation.

### 4.3 Discussion

Current cloud-edge SLM-LLM collaborations face challenges in achieving secure peer-to-peer exchange, effective cold-start learning, formal privacy guarantees, and scalable personalization under strict data protection. Future work should develop

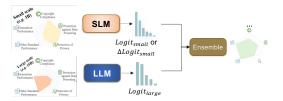


Figure 16: SLM Guided Safe LLM Decoding.

adaptive frameworks enabling privacy-preserving collaboration and lightweight personalization for policy-compliant intelligence in sensitive domains such as healthcare and customer service.

### 5 Collaboration for Trustworthiness

LLMs show strong generative ability but face trust-worthiness issues, including hallucinations, hazards, bias, privacy leaks, and jailbreak. Updating large models for safety is costly and inflexible. As a remedy, SLMs offer lightweight, adaptable external safety control. Recent collaborations adopt two forms: (1) Safety-guided decoding, where SLMs adjust LLM logits during generation, and (2) Guardian—generator, where SLMs filter inputs or outputs, ensuring safer LLM deployment.

### 5.1 Safety-Guided Decoding

Unsafe LLM outputs often emerge during decoding, making token-level safety control essential yet difficult to anticipate. Recent methods use safety-tuned SLMs to guide LLM decoding against jailbreaks, privacy leaks, and bias. As shown in Fig. 16, SLM and LLM logits are fused for safe, high-quality generation via (1) direct logit fusion or (2) offset fusion, where SLM logits steer LLM probabilities toward safer tokens.

(1) **Direct Logit Fusion** The CP- $\Delta$  theory (Vyas et al., 2023) provides an information-theoretic foundation for model fusion, demonstrating that combining the predictive distributions of two models,  $q_1(y|x)$  and  $q_2(y|x)$ , with distinct copyright risks yields a fused distribution  $p(y|x) \propto$  $q_1(y|x)^{\alpha}q_2(y|x)^{1-\alpha}$  that minimizes weighted KL divergence and balances their strengths without retraining, where  $\alpha$  controls each model's contribution. The fused distribution lies closer to both sources than they are to each other, thus achieving a purification effect, retaining desirable properties while reducing copyrighted content. This operation is equivalent to linear weighting in logit space,  $z_p = \alpha z_1 + (1 - \alpha)z_2$ , providing the theoretical foundation for SLM-LLM collaborative logit fusion. Subsequent methods build on this principle:

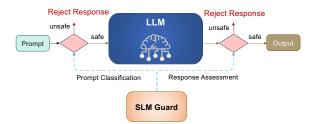


Figure 17: SLM Guardian, LLM Generator

Purifying LLMs (Li et al., 2024) fuses clean SLM and contaminated LLM logits to mitigate copyright, privacy, and backdoor risks, while MOD (Shi et al., 2024) extends fusion to multiple objectives, integrating models optimized for fluency, faithfulness, and safety to enable controllable generation.

(2) Logit Offset Fusion Mitchell et al. (2024) introduced the concept of logit offset fusion by decomposing a fine-tuned model's output into the base model's logits and a behavioral delta. Through an up-scaling strategy, it integrates a large pretrained model's logits with the behavioral delta of a small fine-tuned model, achieving 73% of full large-model fine-tuning helpfulness without retraining. This demonstrates that safety-aligned small models' behavioral deltas can enhance LLM safety when fused at the logit level. Building on this idea, Offset Unlearning (Huang et al., 2025a) trains SLMs to generate targeted logit offsets that suppress sensitive or fabricated knowledge for privacy-preserving unlearning. Conversely, Weakto-Strong Jailbreak (Zhao et al., 2025) reveals that unsafe SLMs can steer safe LLMs toward harmful outputs, implying that the same mechanism can defensively employ safe SLMs to counter jailbreak attacks through safety-guided logit fusion.

### 5.2 SLM as Guardian, LLM as Generator

Guardrail-based approaches enhance LLM safety by placing SLMs before and after generation. In the SLM-as-Guardian and LLM-as-Generator paradigm, as shown in Fig. 17, SLMs, encoding the safety policy, handle input filtering and output auditing, offering configurable, interpretable, and reusable safety control across evolving applications.

Building on the SLM-as-Guardian paradigm, subsequent works further advance safety coverage and efficiency. The Llama Guard series (Inan et al., 2023; Team, 2024; Dubey et al., 2024; Fedorov et al., 2024; Chi et al., 2024; AI, 2025a) evolves from basic LLaMA-based classifiers to multilingual, cross-modal, and domain-adapted guardrails

with fine-grained risk taxonomies. Lightweight filters such as Prompt Guard (AI, 2024, 2025b), ShieldGemma (Zeng et al., 2024, 2025), and WildGuard (Han et al., 2024) improve efficiency and robustness. ThinkGuard (Wen et al., 2025) enhances interpretability, MiniCheck (Tang et al., 2024) supports factual verification, Cascade Guardrails (Nagireddy et al., 2024) introduce hierarchical defenses, and LlamaFirewall (Chennabasappa et al., 2025) enables multi-agent protection.

### 5.3 Discussion

Current SLM-LLM collaborations for trustworthiness face challenges in unifying decoding and guarding, extending safety beyond text, enabling edge deployment, and standard evaluation. Future work should build integrated frameworks with multimodal safety, lightweight edge guardians, and standard evaluation benchmarks.

### **6** Challenges and Future Directions

More future directions are in Appendix A.2.

**Open and Interoperable Ecosystem.** Existing SLM–LLM collaborations are fragmented and task-specific. Future work should build open, cross-domain ecosystems with standardized interfaces and shared repositories to enable model reuse, composition, and joint benchmarking.

Comprehensive Benchmarking. Current evaluations emphasize open-ended performance but neglect structured and system-level metrics. Future benchmarks should assess structured reasoning, modular cooperation, and efficiency indicators such as throughput, latency, and cost–performance. Unified Safety Collaboration. Present safety methods decouple decoding and moderation. Future research should unify them, allowing SLMs to act as safety-aware decoders and guardians for end-to-end, trustworthy generation and interaction.

### 7 Conclusions

In this paper, we present a systematic survey of SLM-LLM collaboration from the perspective of collaboration objectives: performance enhancement, cost-effectiveness, cloud-edge privacy, and trustworthiness. We analyze representative methods showing that most leverage SLMs' lightweight adaptability. We aim to highlight the current research state and provide insights for future work in this promising area of SLM-LLM collaboration.

### Limitations

Although our work introduces a systematic framework for analyzing SLM-LLM collaboration, several limitations remain. First, given the rapid evolution of language model technologies, certain implicit forms of SLM-LLM collaboration may not yet be fully captured, and further insights from the research community are encouraged to complement this study. Second, overlaps exist among several collaboration objectives, for instance, the personalization synergy, while not addressed in this survey, often intersects with cloud-edge collaboration, yet these cross-objective studies remain limited despite their conceptual and practical significance. We expect that addressing these challenges will motivate future comprehensive surveys and deeper investigations into SLM-LLM collaboration.

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### A Appendix

### A.1 Applications

We summarize the representative works in Table 1, detailing their collaboration mechanisms, employed SLMs and LLMs, evaluation datasets, and goals. From these studies, we can summarize the applications under each category.

**Collaboration for performance** In Guidance–Generation, SLMs aid LLMs in reasoning and classification (intent detection, NLI, sentiment,

multi-hop QA). In Division–Fusion, they form pipelines for domains such as clinical analysis, factual verification, NL2SQL, and trajectory modeling, with SLMs handling subtasks and LLMs integrating results.

Collaboration for cost-effectiveness These show stage-specific application preferences. Inference-stage approaches emphasize real-time reasoning and conversational tasks where latency and compute efficiency are critical. Tuning-stage methods focus on intent classification and reasoning transfer, enabling smaller models to inherit LLM capabilities with minimal cost. Pre-training-stage frameworks target corpus construction and scaling efficiency on large datasets, supporting sustainable and scalable model development.

Collaboration for cloud-edge privacy Inferencestage solutions suit end-user scenarios with strict privacy needs, where edge SLMs prevent PII or sensitive context leakage in domains such as healthcare and customer service. Depending on privacy levels, SLMs can act as Sensitive Information Gatekeepers or All-Information Guardians. Meanwhile, proxy tuning enables domain adaptation of cloud LLMs without direct data exposure, offering broader applicability under edge resource limits and SLMs' constrained reasoning capacity.

Collaboration for trustworthiness SLM–LLM collaboration for trustworthiness has been applied in safety-critical and compliance-sensitive contexts. Safe decoding methods mitigate hallucination, privacy, and toxicity risks in code generation, instruction following, and dialogue. Guardian frameworks support moderation, assistants, and fact verification by filtering unsafe inputs and ensuring output integrity. Together, these works show that SLMs function as lightweight, adaptive safety modules, embedded for fine-grained control or external for interactive oversight, enabling scalable, reliable AI deployment.

### **A.2** More Future Directions

### Open and Interoperable SLM-LLM Ecosystem

Current SLM-LLM collaborations remain fragmented, with isolated models and task-specific systems limiting interoperability and reuse. Future research should develop open, cross-domain ecosystems that unify specialized and general models through standardized interfaces and shared repositories, enabling efficient model discovery, seamless composition, and collaborative benchmarking across diverse applications and domains. Benchmark Design for SLM–LLM Collaboration Current SLM–LLM evaluations focus mainly on open-ended tasks and performance, overlooking structured tasks and system-level metrics. Future research should develop diverse benchmarks covering structured reasoning, modular cooperation, and system-level metrics, such as throughput, latency, and cost–performance, to better capture collaborative efficiency and real-world applicability.

Synergistic SLMs as Decoders and Guardians. Current safety mechanisms often separate decoding control from post-hoc moderation, limiting effectiveness in SLM-LLM safety collaboration. Future research should develop unified frameworks where SLMs function simultaneously as safety-aware decoders and guardians, enabling multi-stage, end-toend safety governance that enhances trustworthiness across both generation and interaction phases. Cost-Aware SLM-LLM Collaboration Current SLM-LLM collaboration paradigms mostly prioritize performance gains without a rigorous, comprehensive cost model, potentially leading to inefficient resource allocation where the operational expense negates the utility benefits. Future research can develop intelligent, adaptive orchestration frameworks that dynamically optimize the costperformance trade-off. This includes investigating predictive cost-aware routing to direct queries to the most economically efficient model, designing non-myopic collaboration policies that consider long-term inference budgets, and creating multiobjective optimization techniques that balance accuracy, latency, and financial cost for sustainable and scalable SLM-LLM systems.

Theory for Privacy-Preserving Collaboration Current privacy-preserving SLM-LLM collaborations lack formal theoretical foundations, relying mostly on empirical evaluations without quantifiable privacy assurances. Future research should establish rigorous metrics and provable bounds for information leakage and privacy preservation, enabling verifiable guarantees of data protection and fostering trust in large-scale, privacy-sensitive SLM-LLM systems.

Table 1: Representative works on collaborations across performance, cost-effectiveness, privacy, and trustworthiness.

Collab. Mechanism	Paper	SLM	LLM	Evaluation Dataset	Goal / Contribution
I. Performance Collaboration					
LLM guided SLM SLM guided LLM SLM guided LLM SLM guided LLM Parallel Parallel Sequential Sequential Sequential Sequential	SynCID (2024) SuperICL (2024a) Ensem. SuperICL (2024) LM-Guided CoT (2024) ELM (2025) CaLM (2024) ZeroNL2SQL (2024) KDSL (2025a) HuggingGPT (2023) TrajAgent (2024)	BERT RoBERTa BERT/RoBERTa Flan-T5 ClinicalBERT T5, Flan-T5 T5, BART Qwen2-VL 2B CLIP, BLIP, T5 TrajFormer	GPT-3.5 GPT-3.5/LaMA GPT-3.5/LLaMA ChatGPT GPT-4 Flan-PaLM, GPT-3.5 GPT-3.5/4 Qwen2-VL 7B GPT-3.5 GPT-3.5	Banking 77, CLINC 150 SST-2, MNLI, etc. SST-2, MNLI, etc. SST-2, MNLI, etc. HotpotQA, 2WikiMultiHopQA BCCR Pathology Reports QAGS-CNNDM, Q², etc. Spider, WikiSQL, etc. — ImageNet, COCO, etc. TaxiBJ, Porto, etc.	Refine labels for intent detection Inject SLM predictions and confidence Multi-SLM guidance for LLMs Provide rationales to improve reasoning Aggregate SLM votes; LLM verifies Cross-verification SLM + LLM SLM drafts SQL; LLM finalizes SLM rules; LLM inference LLM orchestrates multimodal SLMs LLM plans; SLMs execute
II. Cost-effective Collaboration					
Cascade Speculative TTS-optimal Selective KD Proxy transfer Data curation Co-curriculum Pre-train distill.	R2R (2025a) Beagle (2025) AgentTTS (2025b) SynCID (2024) LiteMoE (2024) Yano et al. (2025) Peng et al. (2025)	DeepSeek-R1-1.5B LLaMA-68M LLaMA-3-3B BERT Gemma-2B Transformer-1.5B LLaMA-1B GLM-4-1.9B	DeepSeek-R1-32B LLaMA-7B LLaMA-3-70B text-davinci-003 Gemma-7B Transformer-2.8B LLaMA-8B GLM-4-9B	AIME, GPQA ShareGPT HotpotQA, CWQ, etc. BANKING, CLINC MMLU, GSM8K, etc. Pile FineWeb-Ed MMLU, C-Eval, etc.	Token-level routing for efficiency Cross-attention drafting Budget-aware collaboration Latent-space alignment distillation Efficient proxy tuning SLM-guided data selection Joint curriculum design Progressive knowledge transfer
		III. Privacy-av	vare Cloud-Edge Colla	boration	
PII gatekeeper All-info guardian All-info guardian SLM learner LLM learner Co-learners	Uzor et al. (2025) CoGenesis (2024f) Hartmann et al. (2024) MiniLLM (2024) Proxy-tuning (2024a) FDLoRA (2024)	Phi-3.5, Gemma-2 StableLM-Zephyr Gemini 1.0 Nano-2 GPT-2-125M LLaMA-2-7B LLaMA-2-7B	GPT-40 GPT-4-turbo Gemini 1.0 Ultra GPT-2-1.5B LLaMA-2-70B LLaMA-2-7B	HealthTap, MeQSum Avocado Research Email GSM8K DollyEval, SelfInst, etc. GSM, Toxigen, etc. BGL, Spirit, etc.	Rewrite prompts to remove PII Cloud knowledge for edge inference Cloud ICL demos for edge SLM Distill LLM into SLM Steer LLM with private SLM Federated LoRA with sharing
IV. Trustworthiness Collaboration					
Safe decoding Safe decoding Safe decoding Safe decoding SLM guard	MOD (2024) W2S Jailbreaking (2025) Offset Unlearning (2025a) LLM Purifying (2024) LLaMA Guard (2023) Prompt Guard / 2 (2024; 2025b) ShieldGemma / 2 (2024; 2025) STAND-Guard (2024) WildGuard (2024) ThinkGuard (2025) MiniCheck (2024)	Safety branch LLaMA-2-13B LLaMA-2-7B CodeLLaMA-7B LLaMA-2-7B DeBERTa-v2-22M/86M Gemma-2B/9B/27B Mistral-7B Mistral-7B-v0.3 LLaMA-3-8B Flam-T5 / UL2	LLaMA-2-13B/70B LLaMA-2-70B LLaMA-2-13B CodeLLaMA-13B LLaMA-70B LLaMA/GPT-family Any GPT-3.5/4 Any Any GPT-4 / Claude	AdvBench, MaliciousInstruct TOFU HumanEval, LAMBADA, etc. ToxicChat, OpenAI ModEval Red-teaming (multilingual), etc. ToxicChat, OpenAI Mod, etc. BeaverTails, SafeRLHF WildGuardMix BeaverTails, ToxicChat LLM-AggreFact	Logit fusion for safety—utility Analyze SLM logit effects Logit offset for unlearning Logit fusion for clean gen. I/O safety screening Lightweight input filtering Fine-grained moderation Task-adaptive moderation Multi-risk detection Reasoned moderation Fact verification