CIRCUIT-LEVEL STEERING FOR PERSONALIZED KNOWLEDGE INJECTION IN LANGUAGE MODELS

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ABSTRACT

As large language models (LLMs) become central to user-facing applications, effective personalization, adapting models to individual users' evolving facts and contexts, has become crucial. However, existing approaches struggle with **mutable personal knowledge**: finetuning can embed static user information but is costly and prone to catastrophic forgetting, while knowledge editing methods rely on pre-cached representations from large corpora like Wikipedia, which are unavailable or unsuitable for personal domains due to data scarcity and privacy concerns. We formalize updating the fact-level personalization with mutable knowledge as a new task, constructing synthetic Personal Knowledge Graphs (PKGs) that capture user information across time points to evaluate models' ability to incorporate updates without degrading existing knowledge. Drawing on insights from mechanistic interpretability, we discover that personal facts are encoded in localized circuits within LLMs. We propose **SPIKE** (Steering for Personalized Knowledge Injection), which combines adapter modules with steering-based activation injection, targeting identified personal knowledge circuits. This approach enables the precise integration of new user-specific facts, including previously unseen triples, while maintaining the integrity of prior knowledge. Our experiments demonstrate that SPIKE effectively balances the accuracy of incorporating new facts with the preservation of existing knowledge, offering a practical solution for continual personalization in settings where user information evolves frequently.

1 INTRODUCTION

As large language models (LLMs) become increasingly integrated into user-facing applications, **personalization**, which adapts the model to reflect the facts, contexts, and preferences of individual users, has emerged as a critical direction for practical AI. Current LLM personalization techniques mainly focus on aspects such as persona modeling or writing style adaptation (Jiang et al., 2024; Liu et al., 2025; Li et al., 2025; Zhang et al., 2025). However, these methods may fall short when it comes to reasoning over *grounded, user-specific **factual** knowledge*, such as "Mike started commuting by bike instead of taking the subway." or "Jack transitioned from being a programmer to working as a product manager.". Addressing personalized factual knowledge is essential to advance LLMs toward the role of personal agents. For example, an LLM capable of accurately answering (reasoning) a user's waking preferences could autonomously set individualized alarms. Consequently, it becomes necessary to explore approaches that **internalize** such knowledge within the LLM itself, enabling reasoning that is both accurate and contextually aligned with the user.

Personal factual knowledge, however, poses unique challenges: it is inherently **mutable**, reflecting changes such as job transitions, address updates, or evolving daily routines, and also comes with natural privacy concerns. One approach to integrate *mutable personal factual knowledge* into LLMs is to *finetune* them on personal data (Dutt et al., 2022; Salemi et al., 2024), embedding user-specific information directly into model parameters. While this can embed personal knowledge, the approach is computationally costly and risks **catastrophic forgetting**, potentially degrading the model's global capabilities (Dou et al., 2024). Another line of research, *knowledge editing* methods such as ROME (Meng et al., 2022) or MEMIT (Meng et al., 2023), updates facts in the model by leveraging pre-cached representations obtained from large-scale corpora like Wikipedia. However, this assumption does not hold in the personal domain: for each individual, there is no large corpus

from which to derive such pre-cached structures, and even if available, repeated extraction of sensitive user data would pose serious privacy concerns. These limitations highlight the need for new strategies to effectively internalize mutable personal factual knowledge.

In this work, we formalize *fact-level personalization with mutable knowledge* as a new LLM task, aiming to effectively internalize mutable personal knowledge in LLMs, updating changed facts while preserving unchanged personal knowledge.

We first assume that the original personal information to be internalized is stored as a Personalized Knowledge Graph (PKG). This aligns with recent work using KGs as external memory due to their **modular, interpretable, and easily updatable** nature (Dutt et al., 2022; Wang et al., 2024; Prahlad et al., 2025). However, rather than relying on external memory, we aim to *internalize* the KG into the LLM model. To effectively internalize personal information into LLMs, two key objectives must be clearly defined: (i) where within the model's parameter space the modifications should occur, and (ii) how those parameters should be updated.

For the first objective, our insight is based on the concept of **knowledge circuits** (Yao et al., 2024), which posits that different domains of knowledge are handled by different components in an LLM. We show that *personal facts are encoded in localized circuits*, and propose a **circuit-aware injection strategy** that targets only the relevant substructures. Empirical analysis on personalized questions indicates that adjusting the parameters of attention heads provides a more effective means of updating knowledge than modifying the FFN (Feed Forward Neural Networks) parameters.

For the second objective, we construct a representation that captures the discrepancy between the updated information and its initial information, which is incorporated through the identified personal knowledge circuits. Unlike existing editing methods that rely on pre-cached representations from large corpora, our approach derives this signal directly from the structured personal knowledge itself. This design minimizes unnecessary parameter changes and mitigates unintended side effects, while enabling precise integration of user-specific information. This method, which we refer to as circuit-level **S**teering for **P**ersonal**I**zed **K**nowledge inj**E**ction in language models (**SPIKE**), enables precise and efficient integration of user-specific updates directly into the relevant model circuits. Our method strikes a balance between **accurately integrating new facts** (accuracy) and **preserving the integrity of prior knowledge** (locality). Furthermore, our method extends beyond conventional knowledge editing settings by enabling LLMs to incorporate *unseen updated triples* without disrupting existing knowledge. Our main contributions are summarized as follows:

- We introduce a new task setting for LLM personalization that models **updates of user-specific knowledge** over time in the form of changing knowledge graph triples.
- We leverage insights from mechanistic interpretability to identify and target the **responsible circuits for personal knowledge**, enabling effective and localized editing within the LLM.
- We propose a method that allows the LLM to integrate updated triples, **reflecting new user-specific facts without compromising prior knowledge**.

2 Related Work

2.1 Knowledge Editing Methods

Knowledge editing methods modify LLM parameters without full re-training, but this risks side effects such as forgetting or distortion (Gupta et al., 2024). Many approaches also assume access to pre-cached representations from large corpora (e.g., Wikitext), an assumption that fails in the personal domain due to data scarcity and privacy concerns. Representative methods include ROME (Meng et al., 2022), which edits FFN parameters as key–value memories, MEMIT-Merge (Dong et al., 2025) extending MEMIT (Meng et al., 2023) to support batch edits for the same subject, and AlphaEdit (Fang et al., 2025), which preserves unrelated knowledge through a projection step. These illustrate the potential of editing but also its limitations for adapting LLMs to evolving personalized KGs.

2.2 CIRCUIT FINDING

Recent efforts to interpret Transformer-based large language models (LLMs) have focused on identifying compact subgraphs of the model that are responsible for specific behaviors. These subgraphs, known as circuits, typically consist of a small set of attention heads and MLPs that strongly influence the output. Automated Circuit Discovery (ACDC) (Conmy et al., 2023) formalizes circuit extraction as a subgraph selection problem, where nodes are LLM components and edges denote their connections. By progressively removing low-impact edges, it produces compact, interpretable circuits, but at a high computational cost since each edge requires a separate forward pass. Edge Attribution Patching (EAP) (Syed et al., 2024) mitigates this with a gradient-based approximation. HeadMap (Wang et al., 2025) instead ranks attention heads by their contribution, retaining only the most influential ones for fine-tuning. This reduces overhead, avoids unnecessary updates, and maintains interpretability, making it a practical alternative to full-model tuning.

3 PRELIMINARIES

3.1 TASK FORMULATION

Personal factual knowledge is not static: individuals frequently change their occupations, addresses, or daily routines. A practical system must not only reflect newly updated information but also preserve consistency with personal knowledge that remain unchanged. Motivated by this scenario, we formulate a fact-level personalization task that explicitly models updates in personal knowledge graphs (PKGs). We assume access to two versions of a PKG, which serves as a minimal and structured interface to personal information: the initial KG ($\mathbf{KG}^{\text{init}}$) and the updated KG ($\mathbf{KG}^{\text{upd}}$). The initial KG contains user-specific facts that have already been internalized into the LLM via fine-tuning. The updated KG reflects changes that occur over time (modeled here as a single update for simplicity), such as a new workplace or altered daily routine (See Appendix A.2 for the formal formulation).

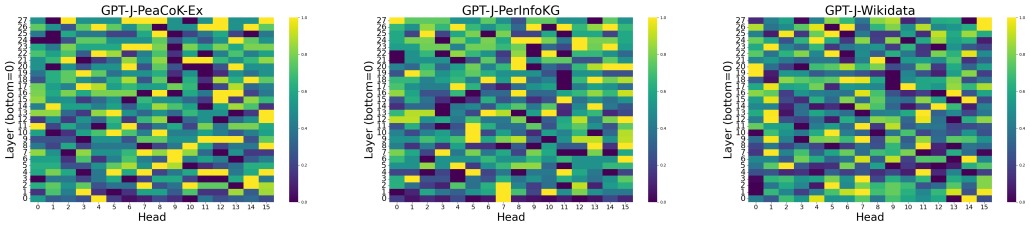
A practical example of our task is as follows: When the KG itself contains sensitive individual-level information (e.g., medical histories or financial transactions), external retrieval from the KG poses direct privacy risks. Even partial disclosure may expose identifiable attributes of individuals (e.g., Patient C) and breach confidentiality. By internalizing the personalized KG into the LLM through fine-tuning or adaptation, the model can answer personal queries without exposing raw records at *inference time*. This makes internalization an effective mechanism for safeguarding privacy while enabling personalized responses.

3.2 PERSONAL KNOWLEDGE GRAPH CONSTRUCTION

To experiment with the task formulation introduced earlier, we construct two personalized KG datasets, **PeaCoK-Ex** (Extended) and **PerInfoKG**.

PeaCoK-Ex extends the original PeaCoK (Gao et al., 2023) (based on commonsense knowledge), adding relations for personal attributes (e.g., `experience`, `routine_habit`, `characteristics`) and introducing 822 synthetic individuals, each linked to a single occupation. The resulting KG contains 105K triples, 49K entities, and 18 relations. To build $\mathbf{KG}^{\text{upd}}$, we modify 20 % of the person–occupation pairs while keeping other attributes fixed.

PerInfoKG is a dataset we create by defining 23 personal information fields for each of 2,000 fictitious individuals, resulting in 46K triples and 2,134 entities in total. For every individual, we partition the 23 fields into 17 *mutable* attributes used for editing and 6 *immutable* attributes reserved for evaluating locality, so that each individual contributes to both edit and locality evaluation. We prepare two versions of this dataset: (i) an **edit setting** where 200 individuals are randomly sampled and the required update triples are directly provided as supervision for injection (editing), and (ii) an **unseen test setting** (Section 5.3.1) where all 2,000 individuals are used to train the alignment module, and generalization is evaluated on previously unseen cases.



(a) GPT-J - PeaCoK-Ex (b) GPT-J - PerInfoKG (c) GPT-J - Wikidata

Figure 1: Heatmap visualizations of important components identified in GPT-J (Wang & Komatsuzaki, 2021) across PeaCoK-Ex, PerInfoKG, and Wikidata (Meng et al., 2022) (i.e., *Known1000* dataset). Each plot shows attention heads (x-axis) by layers (y-axis). The similarity is highest when comparing personal knowledge datasets.

4 METHODOLOGY

4.1 CIRCUIT ANALYSIS FOR PERSONAL INFORMATION LOCALIZATION

To efficiently reflect updated personal information in large language models (LLMs) while minimizing side effects such as unintended changes to unrelated knowledge, we adopt a circuit-level analysis approach inspired by mechanistic interpretability. This perspective enables us to identify and intervene on a sparse subset of components that are causally linked to personal knowledge, thereby avoiding the need for full-model fine-tuning.

We first investigate which components of LLMs, attention heads or FFNs, are more effective targets for updating personal knowledge. To this end, we extend HeadMap (Wang et al., 2025), which quantifies the importance of attention heads by masking their outputs and measuring the induced loss, to FFNs using the same strategy. Based on these scores, we select a limited number of parameters (heads or FFNs across layers) for selective fine-tuning with personal knowledge from PeaCoK-Ex. On GPT2-Large (Radford et al., 2019), fine-tuning only 3 important layers of FFNs (4.3% of total parameters) yields just 27.47% accuracy, while finetuning a similar number of parameters corresponding to important attention heads, which involves 3 heads per layer across all layers (4.6% of total parameters), the model achieves 99.75% accuracy (See Table 1). These results demonstrate a clear distinction: FFNs appear to require broad, costly intervention to be effective, whereas attention heads enable efficient and accurate updates when targeted selectively in personalized factual queries.

Table 1: Selective Finetuning Results

Target	**Ratio (%)**	**Acc (%)**
FFN	4.3	27.47
Heads	4.6	99.75

Based on this finding, we focus our circuit discovery efforts solely on attention heads. We identify circuits responsible for personalization based on importance scores of attention heads and present a heatmap visualization of layer-wise attention head importance scores for GPT-J (Wang & Komatsuzaki, 2021) in Figure 1. For GPT-J, the similarity between the personal information datasets PerInfoKG and PeaCoK-Ex is 0.6242, which is higher than the similarity between PerInfoKG and Wiki-based general knowledge (Wikidata, 0.5335), suggesting the presence of circuits dedicated to personal information. Detailed procedures for computing similarity, as well as additional results on Qwen, are provided in Appendix A.4.

4.2 PERSONAL INFORMATION INJECTION MODULE

Building on the circuit identified in Section 4.1, we propose a steering mechanism (Rimsky et al., 2024) that enables an LLM to reflect updates from $\mathbf{KG}^{\text{upd}}$ while preserving previously encoded knowledge. The key idea is to align structured user-profile facts (represented as triples) with internal LLM representations and steer the model by intervening on a sparse set of attention heads (we select the top-k most important heads based on importance scores for each layer), rather than modifying all parameters.

Figure 2 provides an overview of this pipeline and visually illustrates the update process. The following update scenario can illustrate the overall process. From the initial KG, the occupation

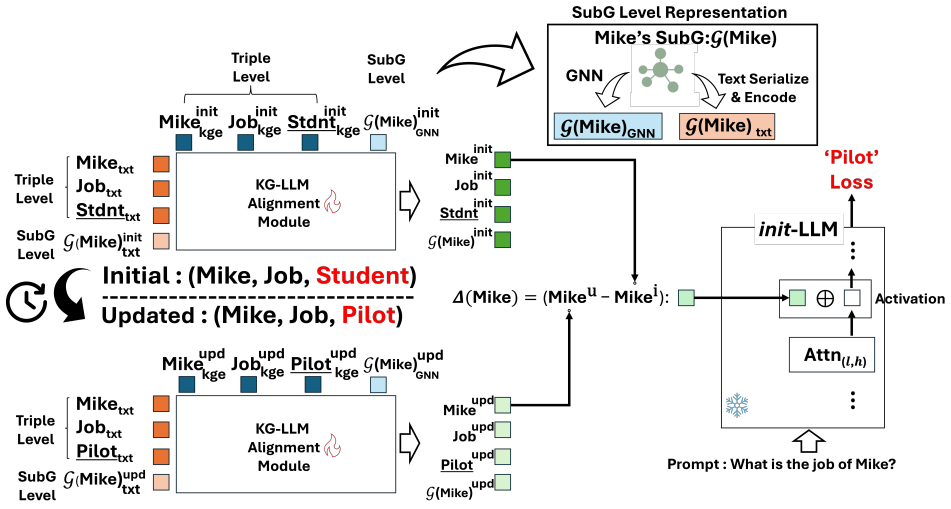


Figure 2: Illustration of our knowledge injection process when `(Mike, Job, Student)` triple is updated to `(Mike, Job, Pilot)`.

of a person `Mike` is `Student`, which is later updated to `Pilot`. To incorporate this change, we analyze the difference between the two triples (`(Mike, Job, Student)` vs. `(Mike, Job, Pilot)`), obtain their textual representations through the alignment procedure (Section 4.2.1), and use the resulting difference to steer the outputs of the attention heads identified by our circuit analysis (Section 4.1). This circuit-guided intervention allows the LLM to behave as if it had internalized the updated information (Section 4.2.2). Since the steering signal is derived from the difference between $\mathbf{KG}^{\text{init}}$ and $\mathbf{KG}^{\text{upd}}$, knowledge that remains unchanged exerts little or no influence on the model's behavior.

4.2.1 KG-LLM Alignment Module

When updates occur in the profile, the KG-LLM Alignment Module aligns the two representation spaces so that the LLM can generate responses consistent with the modified information.

The alignment is performed at two levels. The first is **triple-level alignment**, which focuses on local updates of individual triples (e.g., `(Mike, Job, Student)` $\rightarrow$ `(Mike, Job, Pilot)`). The second is **subgraph-level alignment**, which captures broader structural changes within the local subgraph centered on the updated entity $\mathcal{G}$(`Mike`). The motivation for separating the two levels is that triple-level updates alone cannot capture higher-order differences that arise in the overall subgraph structure (Wang et al., 2020).

The inputs to the alignment module consist of two modalities: structural representations from the KG and textual representations from the LLM. On the KG side, we include both triple-level embeddings extracted from a pretrained KG embedding model Bordes et al. (2013); Trouillon et al. (2016) and subgraph-level embeddings obtained from a GNN encoder (Wang et al., 2020) over the local subgraph centered on the updated entity. On the LLM side, we obtain textual representations by serializing the triple or subgraph into natural language and encoding them with the LLM.

The alignment module follows an attention-based structure, where textual representations serve as queries, structural embeddings as keys, and values:

$$\mathbf{Q_{txt}}, \mathbf{K_{kge}}, \mathbf{V_{kge}} = \mathbf{H_{txt}}\mathbf{W_Q}, \mathbf{H_{kge}}\mathbf{W_K}, \mathbf{H_{kge}}\mathbf{W_V}, \tag{1}$$

where $\mathbf{W_Q}, \mathbf{W_K}, \mathbf{W_V} \in \mathbb{R}^{D\times d}$. Here, $\mathbf{H_{txt}}$ and $\mathbf{H_{kge}}$ are defined as:

$$\mathbf{H_{txt}} = [\mathbf{h}_{txt}, \mathbf{r}_{txt}, \mathbf{t}_{txt}, \mathbf{h}^{\mathcal{G}(h)}_{txt}] \in \mathbb{R}^{4\times D}, \ \mathbf{H_{kge}} = [\mathbf{h}_{kge}, \mathbf{r}_{kge}, \mathbf{t}_{kge}, \mathbf{h}^{\mathcal{G}(h)}_{kge}] \in \mathbb{R}^{4\times D}. \tag{2}$$

Here, $\mathbf{h}_{txt}, \mathbf{r}_{txt}, \mathbf{t}_{txt}$ correspond to the textual embeddings of the head(h), relation(r), and tail(t) of given knowledge graph, while $\mathbf{h}^{\mathcal{G}(h)}_{txt}$ denotes the subgraph textual embedding of head(h). Simi-

larly, $\mathbf{h}_{kge}, \mathbf{r}_{kge}, \mathbf{t}_{kge}$ correspond to the KG embeddings of the triple, and $\mathbf{h}_{kg}^{\mathcal{G}(h)}$ denotes the GNN-encoded subgraph embedding.

The alignment process is then performed as:

$$\hat{\mathbf{H}}'_{\mathbf{txt}} = \text{Softmax}(\mathbf{Q_{txt}}\mathbf{K_{kge}}^T/\sqrt{d})\mathbf{V_{kge}}, \quad \hat{\mathbf{H}}_{\mathbf{txt}} = MLP_{up}(\hat{\mathbf{H}}'_{\mathbf{txt}}), \tag{3}$$

where d denotes the dimensionality of the queries, and MLP_{up} denotes a linear transformation. For both initial and updated KG settings, we obtain aligned textual representations $\hat{\mathbf{H}}^{\text{init}}_{\mathbf{txt}}, \hat{\mathbf{H}}^{\text{upd}}_{\mathbf{txt}} \in \mathbb{R}^{(4\times D)}$. The first embedding vector of each corresponds to the aligned representation of the updated entity in the textual space (i.e., $\hat{\mathbf{H}}^{\text{init}}_{\mathbf{txt}}[0,:]$ and $\hat{\mathbf{H}}^{\text{upd}}_{\mathbf{txt}}[0,:]$, respectively). These correspond to **Mike**$^{\text{init}}$ and **Mike**$^{\text{upd}}$ in Figure 2, respectively.

4.2.2 Updated Knowledge Adaptation via LLM Steering

The representation difference is computed as the change in the head entity's embedding (position [0]) extracted from the alignment module, and this difference is used to steer the LLM's behavior. Specifically, we compute the difference vector between the two time points, $\Delta = \sigma(\hat{\mathbf{H}}^{\text{upd}}_{\mathbf{txt}}[0,:] - \hat{\mathbf{H}}^{\text{init}}_{\mathbf{txt}}[0,:])$, and inject it into the output of the attention heads identified during circuit discovery. Here, σ denotes the sigmoid function. Importantly, knowledge injection is applied only at the heads previously identified as responsible for personal information processing (Section 4.1).

Let d_{head} denote the dimensionality of a single head output and N is the number of selected heads. The output dimensionality of the alignment module is set to $d_{\text{head}} \times N$, which is partitioned into N segments, each added to the corresponding head output. This design enables us to selectively control the internal activations of the LLM, allowing a model to respond to the updated information.

As a result, our method achieves personalized knowledge updates and generation without requiring full fine-tuning, relying instead on activation steering. In addition, since the alignment module is trained to convert updated triples into LLM representations and inject them into intermediate activations to steer the model's behavior, our approach naturally extends to unseen settings, where updates for previously unseen triples (with seen entities and relations) can still be incorporated effectively (Figure 3a).

4.2.3 Optimization

The alignment module is trained so that the injected difference vector accurately transforms the activation from the initial timestamp into a representation consistent with the updated knowledge. Given a pair of initial triple $((s_i, r_i, o_i^{\text{init}}))$ and updated triple $((s_i, r_i, o_i^{\text{upd}}))$, the negative log-likelihood loss is defined as $\mathcal{L}_{\text{NLL}} = -\sum_i \sum_{t=1}^{|o_i^{\text{upd}}|} \log\ p\Big(o_{i,t}^{\text{upd}} \mid o_{i,<t}^{\text{upd}},\, g_{+\Delta}^{\text{init}}(s_i, r_i)\Big)$, where $g_{+\Delta}^{\text{init}}$ denotes the *init-LLM* steered by the difference vector $\Delta = \sigma\big(f_\phi((s_i, r_i, o_i^{\text{upd}})) - f_\phi((s_i, r_i, o_i^{\text{init}}))\big)$, and f_ϕ is the alignment module parametrized by ϕ.

To ensure that knowledge unrelated to the updates remains intact, we introduce a KL divergence loss between the output distributions of the LLM before and after steering, obtained by feeding the subject into the model: $\mathcal{L}_{\text{KL}} = D_{\text{KL}}\big(\text{softmax}\big(g^{\text{init}}(s_i)\big) \,\big\|\, \text{softmax}\big(g_{+\Delta}^{\text{init}}(s_i)\big)\big)$. Furthermore, to prevent the steering vector (Δ) from deviating excessively from the initial representation $f_\phi((s_i, r_i, o_i^{\text{init}}))$, we add a norm-based penalty: $\mathcal{L}_{\text{norm}} = \frac{\|\Delta\|_2}{\|f_\phi((s_i, r_i, o_i^{\text{init}}))\|_2}$. Finally, the overall training objective is

$$\mathcal{L} = \mathcal{L}_{\text{NLL}} + \lambda_1 \cdot \mathcal{L}_{\text{KL}} + \lambda_2 \cdot \mathcal{L}_{\text{norm}}, \tag{4}$$

where λ_1 and λ_2 are scaling factors. The learnable parameters include those of the KG–LLM alignment module (ϕ) and the GNN encoder responsible for subgraph-level representations.

5 Experiment

5.1 Experimental Setup

Our problem setting (Section 3.1) considers the scenario in which an LLM, initially fine-tuned on the initial personal knowledge graph $\mathbf{KG}^{\text{init}}$, is subsequently updated with the modified knowledge

contained in $\mathbf{KG}^{\text{upd}}$. To simulate an LLM that already encodes prior personal information, we first inject $\mathbf{KG}^{\text{init}}$ through supervised fine-tuning, resulting in what we refer to as the *init-LLM*. Since all personal information constructed in Section 3.2 is represented as triples (e.g., (`Mike`, `Medical_Condition`, `Hypertension`)), we design prompt templates for each relation type (e.g., `Medical_Condition`: "{Subject} suffers from") and fine-tune the model to predict the correct tail entity given the head and relation. To ensure reliability, the resulting *init-LLM* is trained until it achieves over 99% accuracy on $\mathbf{KG}^{\text{init}}$ triples, guaranteeing that the initial personal knowledge is fully encoded before conducting update experiments with $\mathbf{KG}^{\text{upd}}$.

Although one could assume a separate personalized LLM per individual, this is computationally prohibitive as it would require storing a distinct model for every user. Instead, our *init-LLM* is trained to encode the collective personal knowledge of all users. During evaluation, when updating to $\mathbf{KG}^{\text{upd}}$, we inject the changes corresponding to a specific individual, measure performance (Table 2), and then reload the original $init$*-LLM* before repeating the process for another individual.

It should be noted that in our experimental setup, updates from $\mathbf{KG}^{\text{upd}}$ are applied exclusively through the modified triple set; triples that remain unchanged relative to $\mathbf{KG}^{\text{init}}$ are not re-injected.

5.1.1 DATASETS

We evaluate our approach on two personalized knowledge graph (KG) datasets, PeaCoK-Ex and PerInfoKG, constructed in Section 3.2. Each dataset consists of two temporal snapshots: an initial KG (i.e., $\mathbf{KG}^{\text{init}}$) containing both unchanged and updated personal facts, and an updated KG (i.e., $\mathbf{KG}^{\text{upd}}$) reflecting changes to a subset of those facts. The update set corresponds to triples that differ between $\mathbf{KG}^{\text{init}}$ and $\mathbf{KG}^{\text{upd}}$, while the remaining triples stay unchanged and serve as the basis for evaluating *locality*. We inject only the modified triples when updating from $\mathbf{KG}^{\text{init}}$ to $\mathbf{KG}^{\text{upd}}$.

In the PeaCoK-Ex dataset, the only updated personal field is `Job`, the tail entity of a triple where the relation is `has_a_job_of`. Once a person's job changes, there are no other unchanged attributes left for that individual, so locality cannot be directly assessed on the same person. Instead, we evaluate locality using the information of other individuals whose facts remain unchanged. In contrast, the PerInfoKG dataset contains 23 personal fields. Thus, even if one field, such as job information, is updated, many other fields for the same person remain intact, allowing locality to be measured directly on that individual by relying on the unaffected fields. Detailed dataset statistics are provided in the Appendix A.3.

5.1.2 BASELINES

We compare our approach against several representative baselines for predicting the correct tail entity in $\mathbf{KG}^{\text{upd}}$. These include: (i) full-model fine-tuning (FT), which updates all parameters of the LLM; (ii) circuit-selective fine-tuning (FT-C), which only fine-tunes the personal-knowledge circuit identified in Section 4.1; and (iii) knowledge editing methods that modify parameters in specific layers to update factual knowledge. Among editing methods, we consider four representative approaches. ROME (Meng et al., 2022) treats FFN modules as key–value memories and directly alters them to inject new facts. MEMIT-Merge (Dong et al., 2025) extends MEMIT by merging edits for overlapping subjects, making it effective in batch editing scenarios. Finally, AlphaEdit (Fang et al., 2025) projects updates to avoid interference with preserved knowledge, explicitly supporting *locality*.

5.2 MAIN RESULTS

The performance on the two datasets, PeaCoK-Ex and PerInfoKG, is presented in Table 2. Each dataset exhibits distinct characteristics: the number of updated triples per subject is fixed to 1 in PeaCoK-Ex, whereas it is 17 in PerInfoKG. Consequently, as shown in the table, most baselines achieve relatively high accuracy on PeaCoK-Ex. In contrast, certain approaches, such as finetuning and LoRa, demonstrate weaker performance in terms of Locality. Furthermore, editing-based approaches generally perform well on the PeaCoK-Ex dataset, since it still contains a large amount of commonsense knowledge and thus remains aligned with the pre-cached representations obtained from large-scale corpora like Wikipedia.

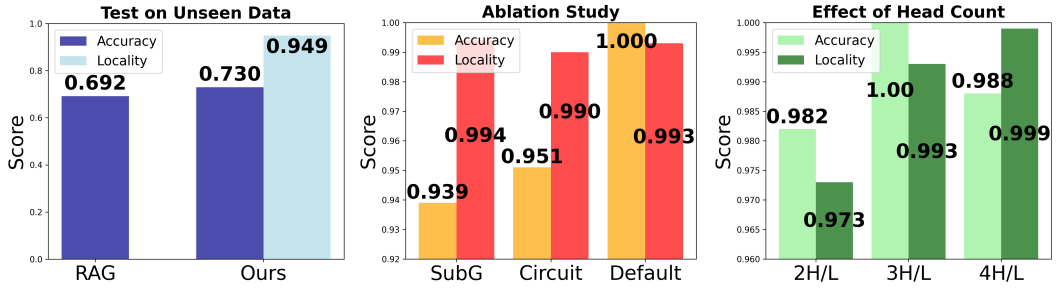
Table 2: Performance comparison of injecting updated personal information into LLMs. **Accuracy** denotes whether the model outputs the correct tail entities for updated facts. **Locality** checks the accuracy for unchanged facts, and **Total Score** (the harmonic mean of Accuracy and Locality).

Method	LLM Model	PeaCoK-Ex			PerInfoKG		
		Acc. (%)	Loc. (%)	Total Score	Acc. (%)	Loc. (%)	Total Score
FT	GPT-J (6B)	**100.00**	64.04	78.08	**100.00**	82.61	90.48
FT-Circuit		98.78	35.26	51.97	**100.00**	82.38	90.34
LoRA		91.58	65.54	76.40	94.20	70.55	80.68
ROME		93.53	95.81	94.66	62.24	66.24	64.18
MEMIT-Merge		71.90	88.89	79.50	47.82	71.80	57.41
AlphaEdit		**100.00**	**99.96**	**99.98**	22.30	43.40	29.46
Ours		**100.00**	99.30	99.65	94.38	**96.34**	**95.35**
FT	Qwen2.5-7B-Instruct	**100.00**	32.90	49.51	**100.00**	67.74	80.77
FT-Circuit		98.78	67.82	80.42	**100.00**	83.17	90.81
LoRA		91.00	68.04	77.86	99.41	69.55	81.84
ROME		81.57	90.00	85.58	56.31	47.58	51.58
MEMIT-Merge		67.88	80.96	73.85	65.96	74.12	69.80
AlphaEdit		99.39	**99.98**	99.68	18.42	77.62	29.77
Ours		**100.00**	99.39	**99.69**	95.44	**95.26**	**95.35**

Our experiments reveal a more specific limitation of existing editing models when compared in multiple update scenarios (e.g., PerInfoKG dataset). Most knowledge editing baselines (ROME, AlphaEdit) fail to achieve good performance on both performance measures. One possible candidate reason for this observation is that many editing methods assume access to pre-cached representations derived from large general-domain corpora (e.g., Wikipedia) to guide and stabilize edits. Such representations are unavailable in the personal domain due to both data scarcity and privacy considerations, making these approaches ill-suited for handling mutable personal knowledge.

Another reason relates to structural limitations in handling multiple correlated updates. While several methods allow batch editing across different facts, they do not natively support simultaneous updates to multiple facts tied to the same subject (with the exception of MEMIT-Merge (Dong et al., 2025), which explicitly merges edits for the same subject). For example, when both (s_1, r_1, o_1) and (s_1, r_2, o_2) must be modified together, these models typically treat each edit independently and fail to maintain consistency across correlated attributes. Since current editing approaches lack mechanisms to coordinate within-subject edits, they produce conflicts and degraded performance (Duan et al., 2025).

Full fine-tuning (FT) unsurprisingly achieves high accuracy, since all parameters are supervised, but its locality performance is consistently poor. This weakness is particularly evident on PeaCoK-Ex, where each subject contains only a single fact and the model tends to overfit to that fact, yielding worse locality compared to PerInfoKG. FT-Circuit, which tunes only a small portion of parameters, also achieves high accuracy, but its performance exhibits large variance across models and datasets, suggesting that circuit-only supervision is unstable and requires more principled methods. LoRA yields reasonably strong performance overall, demonstrating its robustness as a lightweight alternative. ROME performs competitively on PeaCoK-Ex, where the setting aligns with its design of editing a single fact per subject, but it degrades substantially on PerInfoKG, where multiple facts for the same subject must be updated jointly. MEMIT-Merge, in principle, should be better suited to multi-fact updates, yet its performance remains suboptimal in our setting. AlphaEdit achieves strong performance and ranks second overall, but it still struggles on PerInfoKG, again reflecting the challenge of handling multiple fact updates per subject. In contrast, our method consistently delivers both high accuracy and strong locality across datasets, showing stable performance with low variance and outperforming all baselines.



(a) Evaluation on unseen test data using GPT-J.

(b) Ablation study on GPT-J.

(c) Effect of head number on GPT-J.

Figure 3: (a) Evaluation of our align module against RAG on GPT-J using the test split of PerInfoKG data. (b) Ablation study on GPT-J with PeaCoK-Ex: `SubG` denotes the variant without subgraph representations ($\mathbf{h}_{txt}^{\mathcal{G}(h)}, \mathbf{h}_{kge}^{\mathcal{G}(h)}$), and `Circuit` denotes the variant using *low-importance heads*. (c) Experiments varying the number of heads per layer when applying knowledge injection.

5.3 Extended Experimental Results

5.3.1 Unseen Triples

To assess the generalization ability of our approach, we test whether the align module can apply updates to triples outside its training supervision. The idea is that once trained on multiple (initial, updated) triple pairs, it should be able to inject new updates into the LLM even for unseen triples. Using the dataset split in Section 3.2, where for each of the 2,000 individuals we partition the 23 fields into 17 mutable attributes (for editing) and 6 immutable attributes (for evaluating locality), the module is trained on the resulting 32,952 update instances in the train split and evaluated on 500 unseen instances each in the validation and test splits. As shown in Figure 3a, our method achieves 73% accuracy with 94.9% locality, demonstrating strong generalization. Notably, this accuracy surpasses a retrieval-augmented generation (RAG) baseline (Baek et al., 2023), which scored 0.692 accuracy under 100% retrieval success, showing that our approach incorporates new knowledge effectively without direct supervision while preserving prior knowledge.

5.3.2 Contribution Analysis

Ablation Study. We evaluated the effect of circuits by replacing important heads with low-importance ones (i.e., heads with the lowest importance scores across layers), and assessed the contribution of subgraph representations by removing the subgraph features from both KG and LLM (Figure 3b). Both ablations led to performance degradation, with the subgraph removal causing the larger drop. This indicates that subgraph information captures higher-order structure beyond triples, while circuit-level steering also contributes to effective personal information update.

Head Count. We next varied the number of heads per layer that constitute the circuit. Using three or four heads yields better performance than using only two, although four does not consistently outperform three (Figure 3c). Interestingly, locality degrades when the circuit contains only two heads. A possible explanation is that, with fewer heads in the circuit, the parameter update for each head increases, causing each steering vector to grow larger in magnitude compared to the three- or four-head cases, which in turn amplifies unintended side effects, particularly the reduction of locality.

6 Conclusion

In this work, we introduced a new setting for LLM personalization, where mutable personal knowledge in knowledge graphs must be reflected in the model. We defined a fact-level personalization task and proposed a circuit-level steering method that, unlike finetuning or editing approaches reliant on pre-cached corpora, integrates updates while preserving unchanged personal facts. Our experiments show strong performance, demonstrating effective personalization with minimal forgetting.

Ethics Statement

All authors have read and will adhere to the ICLR Code of Ethics. Our experiments use only synthetic personal-knowledge datasets (PeaCoK-Ex and PerInfoKG), comprising fictitious individuals and knowledge graph triples; no real human-subject or personally identifiable data were collected, and IRB approval was not applicable. Our method (SPIKE) internalizes updates by steering a sparse set of attention heads rather than retrieving external records, which reduces exposure of raw records but does not by itself ensure legal compliance; any deployment with real data should include consent, access control, auditing, and revocation mechanisms. We note possible dual-use risks, such as injecting false personal facts, and potential biases inherited from backbone LLMs; conflicts of interest and funding sources will be disclosed through the conference system.

Reproducibility Statement

We will release code in `https://anonymous.4open.science/r/SPIKE-F4B6/readme.md`, configuration files, and Dockerized environments to reproduce all results, along with datasets. The repository will include the full training pipeline to create the init-LLM, evaluation scripts for Accuracy, Locality, and the Total Score. Default hyperparameters are reported in Appendix A.6. Hardware and environment details will be documented, and all code, data, and prompts will be released under a permissive license.

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A APPENDIX

A.1 LLM USAGE

We used a large language model (LLM) solely as a writing assistant. Its role was strictly limited to checking grammar, word choice, and stylistic consistency in the manuscript. All aspects of research ideation, experimental design, analysis, and substantive content generation were carried out independently by the authors.

A.2 TASK FORMULATION & METRICS

We measure the success of knowledge injection using an accuracy metric on the method in Section 5.1.2. Specifically, for each updated triple, accuracy is defined as whether all tokens of the gold tail entity are contained in the model's generated output, and we report the average over all updated triples. As described in Section 3.2, $\mathcal{T}^{\text{init}} = \{(s_1, r_1, o_1^{\text{init}}), \ldots, (s_n, r_n, o_n^{\text{init}})\}$ denotes the triples in $\mathbf{KG}^{\text{init}}$ and $\mathcal{T}^{\text{upd}} = \{(s_1, r_1, o_1^{\text{upd}}), \ldots, (s_n, r_n, o_n^{\text{upd}})\}$ denotes the triples in $\mathbf{KG}^{\text{upd}}$, where n is the number of personal factual triples. For PeaCoK-Ex, $\mathbf{KG}^{\text{upd}}$ is obtained by modifying 20% of the person–occupation pairs while keeping other attributes fixed. The set of modified pairs of triples is given by $\mathcal{C} = \{\big((s_i, r_i, o_i^{\text{init}}), (s_i, r_i, o_i^{\text{upd}})\big) \mid i \in [n],\ o_i^{\text{init}} \neq o_i^{\text{upd}}\}$, and accuracy is computed with respect to $\mathcal{C}$. Locality is defined analogously to accuracy, except that it is measured on the set of non-modified triples $\mathcal{R} = \{\big((s_i, r_i, o_i^{\text{init}}), (s_i, r_i, o_i^{\text{upd}})\big) \mid i \in [n],\ o_i^{\text{init}} = o_i^{\text{upd}}\}$. Given $|\mathcal{C}| = m$ and $|\mathcal{R}| = (n - m)$, locality assesses whether the model continues to correctly reproduce the gold tail entities for facts that remain unchanged after the update.

For PerInfoKG, we take a simpler setup: each individual has 23 fields, of which 17 mutable attributes are updated to form $\mathbf{KG}^{\text{upd}}$, while the remaining 6 immutable attributes are left unchanged and used to evaluate locality.

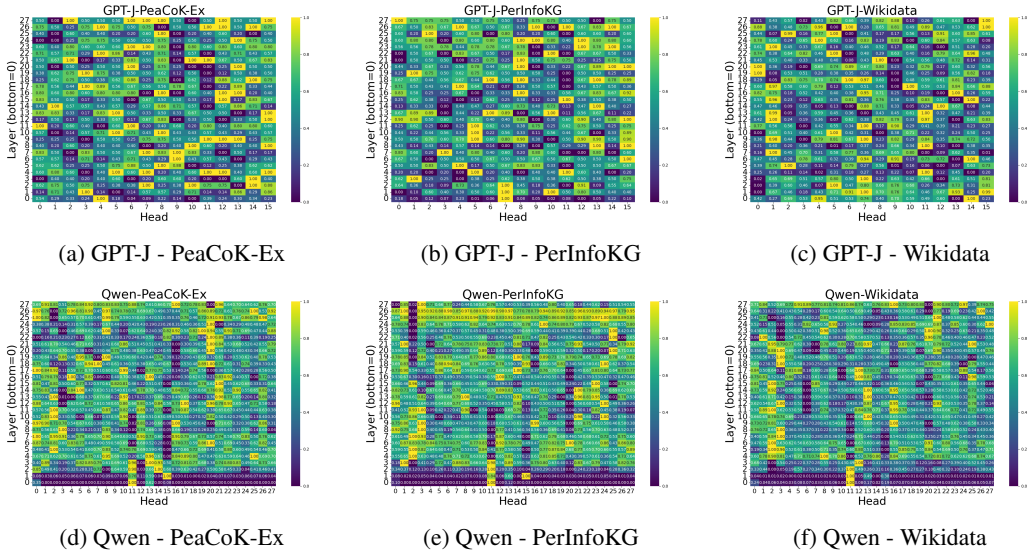
A.3 DATASET CONSTRUCTION & STATISTICS

PeaCoK-Ex (Extended) is derived from PeaCoK Gao et al. (2023), which itself extends commonsense KGs such as ATOMIC Sap et al. (2019). We select relations describing personal attributes (`experience`, `routine_habit`, `characteristics`, `goal_plan`) as well as their social counterparts (`relationship_experience`, `relationship_routine_habit`, `relationship_characteristics`, `relationship_goal_plan`).

To incorporate explicitly personal information, we introduce 822 synthetic person entities, each connected to exactly one job entity via the `has_a_job_of` relation. This construction yields 1,644 person–job triples (including reverse relations), in addition to a large number of job-related attribute triples inherited from the original PeaCoK schema.

The final graph contains 105,258 triples, 49,818 entities, and 18 relation types (counting reverse relations). We regard this graph as the initial snapshot $\mathbf{KG}^{\text{init}}$. To simulate temporal evolution, we generate $\mathbf{KG}^{\text{upd}}$ by modifying 20% of the person–occupation pairs, while leaving other attributes intact. This design produces a realistic setting where part of a subject's personal information changes over time, providing a controlled benchmark for evaluating methods' ability to incorporate updates while preserving unaffected knowledge. Table 3 summarizes the key statistics of the dataset.

PerInfoKG is a synthetic dataset constructed over 2,000 fictitious individuals and 23 personal information fields. For each individual, we partition the 23 fields into 17 *mutable* attributes used for editing and 6 *immutable* attributes reserved for evaluating locality, ensuring that every individual contributes to both edit and locality evaluation. The dataset contains 2,134 entities and 46,000 triples at $\mathbf{KG}^{\text{init}}$, with 33,952 update instances used to derive $\mathbf{KG}^{\text{upd}}$. We split these instances into 32,952 for training and 500 each for validation and test. This split is designed to evaluate the model's capacity to generalize to *unseen updated triples*, i.e., new user-specific facts that were not observed during training, thereby testing the adaptability of our alignment module.



(a) GPT-J - PeaCoK-Ex (b) GPT-J - PerInfoKG (c) GPT-J - Wikidata

(d) Qwen - PeaCoK-Ex (e) Qwen - PerInfoKG (f) Qwen - Wikidata

Figure 4: Heatmap visualizations of important components identified in GPT-J (Wang & Komatsuzaki, 2021) and Qwen (Yang et al., 2024) across PeaCoK-Ex, PerInfoKG, and Wikidata (Meng et al., 2022) (*Known1000*). Each plot shows attention heads (x-axis) by layers (y-axis). The similarity is highest when comparing personal knowledge datasets.

A.4 Visualization

In this section, we visualize and analyze the circuits identified in Section 4.1. Figure 4 presents the min–max normalized importance scores of attention heads across layers for each LLM (Wang & Komatsuzaki, 2021; Yang et al., 2024) and personal information dataset (PeaCoK-Ex, PerInfoKG).

A.5 Circuit Structure Analysis

Overall, models of the same architecture exhibit highly consistent circuit structures across personal information datasets. Interestingly, Qwen shows a clear and consistent pattern: head 11 dominates in the early layers, heads 2 and 3 are salient in layers 4–11, head 20 becomes prominent in deeper layers, and importance gradually dissipates toward the final layers. In contrast, GPT-J does not display dominance of specific heads but instead distributes importance across multiple heads within each layer, suggesting a more diffuse circuit structure for handling personal data.

Top-k Circuit Similarity Analysis. To further examine the specialization of circuits for personal information processing, we conduct a top-k analysis that focuses only on the most critical attention heads within each layer. Specifically, for each layer ℓ, we identify the k highest-scoring heads based on importance scores and construct a binary mask $\mathbf{M}_\ell \in \{0,1\}^H$, where H is the number of heads. The masked importance matrix is then obtained as $\mathbf{S}^{(k)} = \mathbf{S} \odot \mathbf{M}$, where $\mathbf{S}$ is the original importance

Table 3: Statistics of the extended PeaCoK-Ex dataset.

#Entities	49,818
#Relations	18 (including reverse)
#Triples	105,258
#Synthetic person entities	822
#Person–job triples	1,644
Update ratio	20% of person–occupation pairs

Table 4: Top-8 circuit similarity analysis across datasets and models.

Dataset Pair	GPT-J	Qwen
PeaCoK-Ex vs. PerInfoKG	**0.6242**	**0.4754**
PeaCoK-Ex vs. Known1000	0.5774	0.4375
PerInfoKG vs. Known1000	0.5335	0.4100

score matrix and $\odot$ denotes element-wise multiplication. Circuit similarity is then measured as the cosine similarity between the flattened masked matrices.

Table 4 presents pairwise cosine similarities with k=8 (top-8 heads per layer). The results reveal a clear pattern: personal information datasets (PeaCoK-Ex and PerInfoKG) consistently show higher similarity to each other than to general Wiki-based knowledge data (Known1000).

For GPT-J, the similarity between PeaCoK-Ex and PerInfoKG reaches 0.6242, notably higher than the cross-domain similarities of 0.5774 (PeaCoK-Ex vs. Known1000) and 0.5335 (PerInfoKG vs. Known1000). Qwen shows the same trend, with 0.4754 (PeaCoK-Ex vs. PerInfoKG) exceeding 0.4375 and 0.4100 for cross-domain pairs.

Implications for Personal Information Processing. These findings provide strong evidence for the existence of specialized neural circuits for personal information processing in large language models. The consistently higher intra-domain similarity (personal vs. personal) compared to cross-domain similarity (personal vs. general) suggests that LLMs recruit distinct computational pathways for handling personal information queries. This specialization has important implications for both interpretability and privacy: identifying dedicated personal circuits enables targeted interventions such as selective parameter editing or circuit-level privacy protection. Moreover, the contrast between GPT-J's diffuse attention patterns and Qwen's concentrated head dominance indicates that circuit specialization strategies may differ across architectures, highlighting an avenue for future research.

A.6 Hyperparameter Setting

As shown in Eq. 4, our objective consists of three components: the negative log-likelihood term $\mathcal{L}_{\text{NLL}}$ that enforces the updated KG to be reflected in the initial LLM, the KL divergence term $\mathcal{L}_{\text{KL}}$ that preserves knowledge unrelated to the updates, and the norm-based penalty $\mathcal{L}_{\text{norm}}$ that prevents the steering vector from deviating excessively from the LLM representation. The additional terms are controlled by the hyperparameters $\lambda_1, \lambda_2 \in \{0.0, 0.1, \ldots, 0.5\}$ to find the optimal configuration. Moreover, we treat the number of intervened attention heads k as a hyperparameter, setting $k = 2$ for the PeaCoK-Ex dataset and $k = 3$ for the PerInfoKG dataset. The best-performing settings are $\lambda_1 = 0.1, \lambda_2 = 0.2$ on the PeaCoK-Ex dataset and $\lambda_1 = 0.0, \lambda_2 = 0.0$ on the PerInfoKG dataset, consistently across LLM backbones.

A.7 LLM Personalization

Wang et al. (2024) proposed EMG-RAG, which addresses personalized question answering by extracting personal memories from smartphone conversations and app screenshots. Their approach introduces an Editable Memory Graph (EMG) that supports dynamic memory operations, including insertion, deletion, and replacement of personal information. The system employs reinforcement learning to train an agent for adaptive memory selection, moving beyond fixed Top-K retrieval methods to handle complex queries requiring diverse memory combinations. While their work focuses on memory retrieval and selection for downstream tasks such as QA and form autofill, our approach tackles a different challenge: efficiently incorporating updated knowledge graph information into LLM behavior without full model retraining.

A line of research (Prahlad et al., 2025) has explored personalization approaches for LLMs by structuring personal data from applications such as calendars, conversational chats, and emails into

knowledge graphs for smart response generation. Their approach leverages RAG with smaller models to provide factually correct responses using dynamically updated KGs, addressing privacy concerns by keeping sensitive data locally rather than sending it to cloud-based LLM providers. The system focuses on using KG-based retrieval to enhance LLM responses for personal queries and smart reply generation. However, this work focuses on retrieval-based personalization rather than updating LLM knowledge as personal information changes.