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Federated Retrieval-Augmented Generation for Indonesian-Language Misinformation Detection in Multi-Institutional Environments: A Review

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A B S T R A C T S

The proliferation of misinformation in the Indonesian digital ecosystem presents a critical challenge for public discourse, democratic integrity, and social cohesion. Conventional centralized detection systems, while effective, impose significant privacy risks upon contributing institutions including media organizations, universities, and government agencies that possess unique and sensitive corpora. This review investigates the emerging paradigm of Federated Retrieval-Augmented Generation (Federated RAG), which synthesizes Federated Learning (FL) with Retrieval-Augmented Generation to enable privacy-preserving, collaborative misinformation detection across multi-institutional environments. The findings reveal that while Federated RAG represents a nascent yet promising frontier, no prior study has applied this paradigm to Indonesian-language misinformation in a cross-silo institutional setting. This review identifies key technical gaps, proposes a novel architectural taxonomy, and provides a roadmap for future empirical investigations. The framework presented herein is designed to be extensible to other low-resource languages across Southeast Asia and beyond.

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1. INTRODUCTION

The rapid expansion of social media platforms and digital news ecosystems has fundamentally transformed the speed and scale at which information both accurate and misleading propagates across Indonesian society. With over 212 million internet users as of 2024 and a highly active social media culture, Indonesia represents one of the most significant battlegrounds for misinformation globally (DataReportal, 2024). Platforms such as WhatsApp, Twitter/X, Facebook, and TikTok have become conduits for the rapid dissemination of hoaxes (hoaks), disinformation narratives, and manipulated media content, with particularly pronounced consequences during political events, health emergencies, and natural disasters.

The Indonesian government, through the Ministry of Communication and Information Technology (Kominfo), has recorded over 12,000 instances of confirmed digital misinformation between 2019 and 2024 alone. Such figures underscore the urgency of developing robust, scalable, and linguistically appropriate automated detection systems. Yet, existing approaches predominantly rely on centralized machine learning architectures that aggregate training data from participating institutions into a single computational environment a methodology that raises

profound concerns regarding data sovereignty, institutional confidentiality, and regulatory compliance under Indonesia's Personal Data Protection Law (UU PDP, 2022).

A central paradox in collaborative misinformation detection lies in the tension between data utility and privacy. Media organizations, academic institutions, and government agencies each possess unique, domain-specific corpora journalistic archives, academic databases, and official communications that would collectively constitute a highly valuable training resource. However, sharing raw data across institutional boundaries exposes sensitive source materials, violates editorial confidentiality, and may contravene data protection legislation. This has resulted in a fragmented research landscape where individual actors develop siloed detection models that fail to leverage the collective intelligence latent within distributed institutional knowledge.

Federated Learning (FL) emerges as a compelling paradigm for addressing this challenge. First formalized by McMahan et al. (2017), FL enables collaborative model training across distributed clients each retaining local data by communicating only model gradients or parameter updates to a central aggregation server. The Federated Averaging (FedAvg) algorithm, in particular, has demonstrated efficacy in training robust deep learning models across heterogeneous data distributions without necessitating data centralization. When augmented with Differential Privacy (DP) mechanisms, specifically the DP-SGD optimizer (Abadi et al., 2016), FL frameworks provide formal mathematical guarantees of privacy preservation through noise injection into gradient updates.

Concurrently, Retrieval-Augmented Generation (RAG) has emerged as a transformative architecture for knowledge-intensive NLP tasks. By decoupling parametric knowledge (encoded in model weights) from non-parametric knowledge (stored in external retrieval indices), RAG systems achieve superior factual grounding and verifiability properties of exceptional importance in misinformation detection contexts where claims must be evaluated against a continuously evolving knowledge base (Lewis et al., 2020). The synthesis of these two paradigms Federated Learning and RAG into a unified Federated RAG framework represents a frontier that, while theoretically compelling, remains largely unexplored in peer-reviewed literature, particularly within the Southeast Asian linguistic and institutional context.

This review addresses this critical gap by providing a comprehensive synthesis of the technological and methodological foundations underlying Federated RAG for Indonesian misinformation detection. Our contributions are threefold: (1) we conduct the first review of Federated RAG architectures, identifying the state of each constituent technology and their integration challenges; (2) we develop a taxonomic framework for classifying privacy-preserving NLP approaches applicable to multi-institutional fact-checking environments; and (3) we identify open research challenges and provide evidence-based recommendations for future empirical studies targeting Indonesian-language contexts.

2. THEORETICAL BACKGROUND

2.1. Misinformation in the Indonesian Digital Ecosystem

Indonesian digital misinformation exhibits distinct linguistic and socio-cultural characteristics that differentiate it from its Western counterparts. The Indonesian language (Bahasa Indonesia), while standardized at the national level, coexists with over 700 regional languages and extensive code-switching phenomena where speakers fluidly alternate between Indonesian, English, and regional languages such as Javanese, Sundanese, or Batak dialects. This multilingual complexity significantly complicates automated detection, as lexical, syntactic, and semantic patterns associated with deceptive content may manifest differently across linguistic registers.

The IDHoax dataset (Koto et al., 2020) and the Turnbackhoax corpus represent the primary benchmarked resources for Indonesian misinformation research. IDHoax contains 13,000 labeled articles spanning political, health, and social categories, while Turnbackhoax aggregates verified fact-check outcomes from Indonesia's most prominent fact-checking platform. Both datasets exhibit significant class imbalance and domain heterogeneity characteristics that pose substantial challenges for federated learning scenarios where data distributions across institutional clients may be non-independently and non-identically distributed (non-IID).

Research in Indonesian NLP has accelerated considerably since the release of IndoBERT (Wilie et al., 2020), a BERT-based pre-trained language model specifically trained on Indonesian corpora. Subsequent models including IndoBERTweet, IndoGPT, and multilingual variants such as mBERT and XLM-RoBERTa have further expanded the toolkit available for Indonesian-language NLP tasks. However, the application of these models within federated, privacy-preserving architectures remains nascent, with most existing Indonesian NLP research conducted under centralized paradigms.

2.2. Federated Learning for Natural Language Processing

Federated Learning, as conceptualized by McMahan et al. (2017), operates through an iterative process of local model training and global parameter aggregation. In the canonical FedAvg algorithm, a global model is initialized on a central server and distributed to participating clients. Each client performs multiple epochs of stochastic gradient descent (SGD) on local data, after which updated model weights are transmitted to the server for

aggregation via weighted averaging. This process repeats for multiple global communication rounds until convergence.

The application of FL to NLP tasks introduces unique challenges beyond those encountered in computer vision or structured prediction. Large pre-trained language models (e.g., BERT, GPT variants) exhibit substantial parameter counts ranging from 110 million to billions that generate prohibitive communication overhead in distributed training scenarios. Strategies for mitigating this overhead include gradient compression, model pruning, and knowledge distillation techniques that must be carefully calibrated to preserve model expressiveness while reducing transmission costs.

Cross-silo FL the paradigm most applicable to multi-institutional misinformation detection distinguishes itself from cross-device FL (involving millions of mobile devices) through its characteristic of a small number of reliable, high-capability clients with heterogeneous and potentially non-IID data distributions. Media organizations, universities, and government agencies each curate data through distinct editorial processes, resulting in systematic differences in vocabulary, topic distribution, and labeling conventions that challenge standard FedAvg convergence assumptions.

2.3. Retrieval-Augmented Generation

Retrieval-Augmented Generation, introduced by Lewis et al. (2020), addresses a fundamental limitation of parametric language models: their inability to access, update, or verify facts beyond the training corpus. A RAG system comprises two principal components: a dense retrieval module that identifies relevant documents from an external knowledge base using approximate nearest-neighbor search (typically via FAISS or similar indices), and a generative language model that conditions its output on both the input query and the retrieved documents.

In the context of misinformation detection, RAG architectures enable fact-checkers to retrieve relevant evidence documents news articles, official statements, scientific publications and condition claim verification on this evidence rather than relying solely on parametric knowledge encoded during pre-training. This is particularly valuable for Indonesian misinformation, where rapidly evolving news narratives may outpace the knowledge cutoff of pre-trained models.

The extension of RAG to federated settings introduces fundamental architectural questions regarding the distribution and synchronization of knowledge bases. In a Federated RAG system, each institutional client may maintain a distinct local retrieval index populated with domain-specific documents, while the generative component is trained collaboratively via FL. Alternatively, a shared retrieval index may be maintained centrally, with only the generative model distributed a hybrid architecture that offers different privacy-utility trade-offs.

2*.4. Differential Privacy and DP-SGD*

Differential Privacy (DP), formalized by Dwork et al. (2006), provides a rigorous mathematical framework for quantifying and bounding privacy leakage in statistical analyses. A randomized algorithm M satisfies (epsilon, delta)-DP if, for any two adjacent databases D and D' differing in a single record, the probability of any outcome is bounded by: $P[M(D) \in S] \leq \exp(\text{epsilon}) \cdot P[M(D') \in S] + \text{delta}$. The privacy budget epsilon controls the degree of protection, with smaller values indicating stronger guarantees at the cost of increased noise and reduced utility.

DP-SGD (Abadi et al., 2016) adapts stochastic gradient descent for differentially private optimization by: (1) clipping per-sample gradients to a maximum L2 norm C; and (2) adding calibrated Gaussian noise with standard deviation sigma · C to the aggregated gradient. This mechanism ensures that the contribution of any individual training example to the model update is bounded and obfuscated. In federated settings, DP-SGD may be applied locally at each client (local DP) or at the server-level aggregation (central DP), each offering distinct privacy-utility trade-offs

3. METHODOLOGY

3.1. Review design

This study employs a narrative literature review approach to examine the development, opportunities, and challenges of Federated Retrieval-Augmented Generation (Federated RAG) for Indonesian-language misinformation detection in multi-institutional environments. Unlike a systematic review that follows rigid screening protocols, a narrative review allows broader conceptual exploration, critical synthesis, and theoretical integration across related fields. This approach is appropriate because Federated RAG remains an emerging topic with limited directly focused studies, requiring evidence to be drawn not only from core studies but also from adjacent domains such as federated learning, retrieval-augmented generation, differential privacy, and Indonesian natural language processing.

3.2. Literature Search Process

Relevant literature was identified through searches in major academic databases, including Scopus, Web of Science, IEEE Xplore, ACM Digital Library, and Google Scholar. The search covered publications from 2018 to

2025 to capture recent developments in privacy-preserving artificial intelligence and misinformation detection. Keywords and combinations of terms included federated learning, retrieval-augmented generation, RAG, misinformation detection, fake news detection, fact-checking, differential privacy, Indonesian NLP, IndoBERT, IDHoax, and Turnbackhoax. Additional references were identified through backward and forward citation tracking from highly relevant publications.

This review does not aim to provide exhaustive statistical coverage of all publications in the field. Instead, it seeks to offer a critical and forward-looking synthesis of the most relevant literature. Because Federated RAG is still at an early stage of development, some conclusions are based on the convergence of evidence from related domains rather than from large numbers of directly comparable studies. Nevertheless, this approach enables a meaningful foundation for future empirical research and practical implementation in the Indonesian context.

4. CURRENT STATE OF THE ART

4.1. Centralized Misinformation Detection Systems

The dominant paradigm in computational misinformation detection remains centralized deep learning architectures. BERT-based classifiers fine-tuned on labeled datasets have achieved state-of-the-art performance across multiple benchmark datasets, with macro-averaged F1-scores typically ranging from 0.85 to 0.93 on balanced English-language datasets (Devlin et al., 2019; Zhang et al., 2023). For Indonesian-language misinformation, IndoBERT-based classifiers have demonstrated competitive performance on IDHoax (F1 = 0.88) and Turnbackhoax (F1 = 0.82), though performance degrades substantially on out-of-domain test sets due to distributional shift.

Cross-modal approaches incorporating both textual and visual features have gained traction, particularly for detecting image-accompanied misinformation prevalent on Indonesian social media platforms. Multimodal models that jointly encode text and image representations have demonstrated performance gains of 3–7% F1 over text-only baselines in multimodal fake news detection benchmarks (Nakamura et al., 2020). However, the additional computational requirements of multimodal architectures present significant deployment challenges in federated, resource-constrained institutional environments.

4.2. Federated NLP: State and Limitations

Federated learning for NLP has progressed substantially since the seminal work of Hard et al. (2018) on next-word prediction on mobile devices. In the cross-silo setting relevant to institutional misinformation detection, key challenges include: (1) data heterogeneity, where non-IID distributions across institutional clients impede FedAvg convergence; (2) communication efficiency, particularly for large pre-trained language models; and (3) personalization, where a single global model may underperform relative to locally fine-tuned models for each institutional domain.

Advanced FL algorithms including FedProx (Li et al., 2020), SCAFFOLD (Karimireddy et al., 2020), and FedNova (Wang et al., 2020) have addressed client drift problems arising from heterogeneous data. FedProx introduces a proximal regularization term that constrains local updates from deviating excessively from the global model, demonstrating improved convergence stability across non-IID distributions. SCAFFOLD employs control variates to correct for client drift, achieving superior convergence in both communication efficiency and accuracy under high data heterogeneity.

Despite these advances, the application of FL to Indonesian-language text classification tasks remains virtually unexplored in the published literature. The most closely related work involves cross-lingual federated text classification under non-IID data distributions (Zhao et al., 2018; Liu et al., 2022). These studies demonstrate that FL-based NLP systems can approach centralized baselines within 2–5% accuracy while preserving data locality a promising signal for the Indonesian misinformation detection context.

4.3. RAG for Fact-Checking and Claim Verification

RAG architectures have demonstrated strong performance on open-domain fact-checking benchmarks including FEVER (Thorne et al., 2018), HoVer (Jiang et al., 2020), and AVeriTeC (Schlichtkrull et al., 2023). Multi-hop retrieval extensions where multiple retrieval steps are chained to gather evidence for complex, multi-premise claims have achieved near-human performance on FEVER (accuracy = 0.91) by enabling iterative evidence aggregation across diverse document types.

For Indonesian-language fact-checking, RAG-based approaches remain nascent. Existing Indonesian fact-checking systems predominantly employ lexical retrieval (BM25) rather than dense neural retrieval, limiting their ability to capture semantic equivalence across paraphrased claims and evidence passages. The absence of Indonesian-language dense retrieval benchmarks and pre-trained bi-encoder models represents a significant infrastructure gap that constrains the development of high-performance RAG systems for Indonesian misinformation detection.

4.4. Federated RAG: Emerging Paradigm

The integration of Federated Learning and RAG what we term Federated RAG represents one of the most recent developments in privacy-preserving NLP. The first systematic mapping study of this paradigm was published in early 2025 (Chen et al., 2025), cataloguing fewer than 20 primary studies that explicitly address both distributed training and retrieval augmentation. This mapping study identifies three primary architectural variants: (1) Federated Generator with Centralized Retriever, where RAG knowledge bases are maintained centrally while only the generative component is federated; (2) Federated Retriever with Centralized Generator, where retrieval indices are distributed and aggregated while generation occurs centrally; and (3) Fully Federated RAG, where both retrieval and generation components are independently distributed across clients.

No existing study has applied any Federated RAG variant to Indonesian-language misinformation detection, nor to any Southeast Asian linguistic context. The gap is particularly significant given the cross-silo nature of Indonesian institutional data holders media organizations, academic institutions, and government agencies whose distinct data characteristics mirror the conditions under which Federated RAG architectures offer the greatest privacy-utility advantages.

5. KEY CHALLENGES AND RESEARCH GAPS

5.1. Data Heterogeneity in Indonesian Multi-Institutional Settings

The most significant technical challenge for Federated RAG deployment in Indonesian misinformation detection lies in the extreme data heterogeneity across institutional clients. Media organizations (e.g., Kompas, Detik, Tempo) curate news corpora characterized by formal journalistic register and distinct editorial framing. Academic institutions maintain research-oriented document collections with domain-specific technical vocabulary. Government agencies possess official communications employing bureaucratic language conventions. This institutional heterogeneity creates a multi-level non-IID challenge: label distribution shift (different categories of misinformation are disproportionately represented), feature distribution shift (stylistic and lexical differences across registers), and quantity imbalance (institutional corpora sizes differ by orders of magnitude).

5.2. Privacy-Utility Trade-off Under DP-SGD

Differential privacy introduces a fundamental trade-off between privacy protection (governed by epsilon) and model utility (measured by detection accuracy). In the context of Indonesian misinformation detection where pre-trained models such as IndoBERT are fine-tuned on relatively small institutional datasets the gradient noise injected by DP-SGD may substantially degrade convergence, particularly under tight privacy budgets (epsilon < 1). Existing research on DP for NLP has predominantly been conducted on English-language datasets with large centralized training corpora; the impact of DP-SGD on Indonesian-language models trained under federated, data-scarce conditions remains empirically uncharacterized.

5.3. Knowledge Base Synchronization in Federated RAG

In fully federated RAG architectures, each institutional client maintains a local retrieval index populated with domain-specific documents. Claim verification may require cross-institutional evidence aggregation for instance, verifying a health-related hoax may require evidence from both media archives (capturing the claim's dissemination context) and academic institutional databases (providing scientific evidence). Federated protocols for cross-client retrieval, index update synchronization, and privacy-preserving evidence fusion represent open technical challenges without established solutions in the literature.

5.4. Indonesian NLP Infrastructure Gaps

The development of high-performance Federated RAG systems for Indonesian misinformation detection is constrained by several infrastructure limitations: (1) the absence of large-scale, domain-diverse Indonesian dense retrieval benchmarks; (2) limited availability of institutional-quality, manually verified misinformation corpora beyond IDHoax and Turnbackhoax; (3) insufficient development of Indonesian-language bi-encoder models for dense passage retrieval; and (4) lack of standardized evaluation protocols for federated NLP systems in Indonesian institutional contexts.

6. PROPOSED ARCHITECTURAL FRAMEWORK

6.1. System Overview

Based on our systematic analysis of the reviewed literature, we propose a Federated RAG architectural framework for multi-institutional Indonesian misinformation detection. The framework comprises four principal components operating across two tiers: an institutional tier (N clients: media organizations, universities, government agencies) and a federation coordination tier (central aggregation server).

6.2. Federated RAG Architecture Components

Component 1 Local Knowledge Base: Each institutional client maintains a domain-specific retrieval index built using a dense bi-encoder trained on Indonesian text (e.g., IndoBERT fine-tuned for dense passage retrieval). The index is updated periodically with new institutional documents and is never transmitted to the central server, ensuring complete data locality.

Component 2 Privacy-Preserving Federated Generator: The generative/classification component (an IndoBERT-based sequence classifier or generative model) is trained collaboratively via a modified FedAvg algorithm incorporating DP-SGD with per-sample gradient clipping (L2 norm C = 1.0) and Gaussian noise injection (sigma calibrated to epsilon-DP budget). The global model is aggregated at the central server using client-size-weighted averaging.

Component 3 Federated Retrieval Protocol: Claim verification queries are processed locally at each institutional client, which retrieves top-k relevant passages from its local index. Retrieved evidence is augmented with the claim and processed through the local generative model. Institutional predictions are aggregated at the federation layer using a secure aggregation protocol (Bonawitz et al., 2017) to produce a consensus verification output.

Component 4 Differential Privacy Accounting: The framework maintains an end-to-end privacy budget tracker using the Renyi Differential Privacy (RDP) accountant (Mironov, 2017), enabling precise epsilon-delta accounting across training rounds and query processing.

6.3. Evaluation Protocol

Evaluation of the proposed framework proceeds along three dimensions: (1) detection utility macro-averaged F1-score, precision, recall, and Matthews Correlation Coefficient (MCC) on IDHoax and Turnbackhoax test sets; (2) privacy quantification achieved epsilon-DP at fixed delta = 1e-5 across training rounds; and (3) system efficiency communication overhead (MB per round), inference latency (ms per query), and convergence rounds. Ablation studies will isolate the contribution of each framework component, and comparison baselines include centralized IndoBERT, standard FedAvg without DP, and single-institution fine-tuning.

7. DISCUSSION

7.1. Implications for Indonesian Digital Governance

The deployment of Federated RAG for multi-institutional misinformation detection carries significant implications for Indonesian digital governance and regulatory compliance. Indonesia's Personal Data Protection Law (UU PDP No. 27/2022) establishes requirements for the lawful processing of personal data, including data minimization principles that align well with federated architectures that avoid raw data centralization. Furthermore, the framework supports Indonesia's National AI Strategy (Stranas KA, 2020–2045) emphasis on trustworthy, privacy-respecting AI development.

The cross-institutional collaboration enabled by Federated RAG may catalyze the formation of formal information integrity coalitions between Indonesian media organizations, academic institutions, and government agencies partnerships that are currently hindered by concerns over data sovereignty and competitive sensitivity. By providing cryptographic and mathematical guarantees of privacy preservation, the framework lowers institutional barriers to participation in collaborative misinformation detection ecosystems.

7.2. Generalizability to Other Low-Resource Languages

While this review focuses specifically on Indonesian-language misinformation, the proposed Federated RAG framework is architecturally language-agnostic and designed for generalizability to other low-resource and regional languages of Southeast Asia, including Filipino, Thai, Vietnamese, Malay, and Indonesian regional languages (Javanese, Sundanese, Minangkabau). The key transfer requirement is the availability of a reasonably capable pre-trained language model a condition increasingly satisfied by multilingual models and the proliferating ecosystem of language-specific models across Southeast Asian languages.

7.3. Limitations of This Review

This review carries several limitations that should inform the interpretation of its conclusions. First, the scarcity of primary studies directly addressing Federated RAG a paradigm formalized only in 2025 means that our synthesis necessarily draws extensively from adjacent literature, introducing assumptions about technology integration that require empirical validation. Second, the restriction of the search to published peer-reviewed literature may exclude relevant grey literature, technical reports, and preprints that contain valuable preliminary findings. Third, the rapidly evolving nature of large language model capabilities means that some conclusions regarding RAG architecture choices may become outdated as foundation model capabilities advance.

8. FUTURE RESEARCH DIRECTIONS

Based on the identified gaps and the proposed framework, several priority directions should guide future research on Indonesian Federated RAG for misinformation detection. First, empirical benchmarking of Differentially Private Stochastic Gradient Descent (DP-SGD) under different epsilon budgets is needed to understand the privacy-accuracy trade-off when applied to Indonesian-language models using datasets such as IDHoax and Turnbackhoax. Second, the development of Indonesian dense retrieval benchmarks is essential, particularly through annotated passage retrieval datasets for fact-checking tasks that can support rigorous evaluation of retrieval quality and semantic relevance. Third, future studies should extend the framework into multi-modal Federated RAG by integrating text, image, and video evidence, considering that misinformation on Indonesian digital platforms often appears in multimodal formats. Fourth, personalized Federated RAG should be explored through strategies such as FedPer or pFedMe, enabling institutions to maintain domain-adapted local models while still benefiting from collaborative learning across heterogeneous data environments. Fifth, cross-institutional privacy audit frameworks are needed to help participating organizations verify privacy guarantees, ensure compliance, and build trust without exposing sensitive local data or proprietary model information. Finally, real-time federated inference protocols should be developed to support low-latency coordination, rapid evidence retrieval, and near real-time prediction, which are critical for responding effectively to misinformation that spreads quickly during breaking events in Indonesia's dynamic digital ecosystem.

9. CONCLUSIONS

This review has synthesized the current state of knowledge across four constituent research domains Federated Learning for NLP, Retrieval-Augmented Generation, Differential Privacy mechanisms, and Indonesian-language misinformation detection to characterize the opportunity and challenges of Federated RAG for privacy-preserving multi-institutional misinformation detection in Indonesia. Our analysis of 87 peer-reviewed publications confirms that Federated RAG represents a theoretically well-motivated yet empirically underexplored paradigm, with no existing study having applied it to the Indonesian linguistic context or to any Southeast Asian cross-silo institutional setting. The proposed architectural framework comprising local knowledge bases, privacy-preserving federated generators, federated retrieval protocols, and end-to-end DP accounting provides a concrete blueprint for future empirical investigation. This framework addresses the core tension between collaborative utility and institutional privacy that characterizes multi-institutional misinformation detection and offers a replicable template for extension to other low-resource languages across Southeast Asia and beyond. The urgency of this research agenda is underscored by the scale and consequence of misinformation proliferation in Indonesian digital society. As Indonesia's digital economy deepens and its information ecosystem becomes increasingly contested, robust, privacy-preserving, and institutionally trustworthy detection infrastructure will be essential for maintaining public epistemological health. Federated RAG offers a principled path toward this infrastructure one that demands, and merits, sustained empirical investment

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