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Research Article

A Hybrid Generative AI and Micro-Frontend Architecture Using Transformer Models for Scalable and Intelligent Retail Web Applications

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ABSTRACT

The fast evolution in e-commerce requires web solutions that are intelligent, scalable and personalized enough to cope with the changing consumer behavior. This paper presents a hybrid retail web app development architecture incorporating Generative Artificial Intelligence (GenAI) techniques with Micro-Frontend design principles based on Transformer-based models. The proposed framework utilizes large language models (LLMs) including GPT and BERT variants for real-time product recommendations, intelligent search, dynamic content generation and conversational commerce interfaces. The architecture enhances modularity, fault isolation, and team scalability by breaking down monolithic frontend structures into separate micro-frontends that can be independently deployable. This enables the seamless communication of each micro-frontend in our code base with its corresponding AI inference APIs, allowing personalization that is context-aware at the component level. The system uses federated deployment strategies, edge caching and asynchronous AI pipelines to deliver low-latency performance in high-throughput retail reality. Experimental evaluation shows that we achieve significant improvements in page responsiveness, recommendation quality, and user engagement metrics over monolithic AI-integrated retail platforms. This hybrid architecture specifically combines smart AI capabilities with contemporary frontend engineering practices to deliver a future-proof, robust and maintainable architecture for next-generation retail web end-to-end ecosystems.

Keywords: Generative AI, Micro-Frontend Architecture, Transformer Models, Retail Web Applications, Scalable Personalization, Human Resource Analytics, AI-Augmented Workforce Management, Developer Productivity Optimization.

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1. Introduction

A massive digital transformation has taken place in the global retail sector over the past few years, mainly due to the proliferation of e-commerce platforms and advanced quickly changing consumer behaviour with respect to technology [1]. Gone are the days of modern retail web applications being just static catalogs, today's Web applications are dynamic, intelligent ecosystems that must provide personalized, real-time and seamless user experiences across different devices and geographies [2]. We need to rethink the very layers of architecture and intelligence that power retail web development in order to keep up with these demands.

As the applications become complex with time, the traditional monolithic frontend architectures are easy to develop initially but create many challenges related to scalability, maintainability and independent deployment [3]. These shortcomings are overcome with development of Micro-Frontend Architecture (MFA), which disintegrates monolithic frontend application into smaller, yet independently developed, tested and deployed pieces, closely resembling the evolving success of microservices for backend engineering [4]. This modular paradigm allows cross-functional teams to operate independently, facilitates quicker release cycles, and enhances fault isolation across complex retail platforms.

Unprecedented opportunities for intelligent automation in retail contexts [5] have emerged with the simultaneous arrival of Generative Artificial Intelligence (GenAI) and Transformer-based language models like GPT-4, BERT, T5. These models have shown surprising capabilities in terms of natural language understanding, semantic search, dynamic content synthesis and conversational interactions — making it possible for retailers to create hyper-personalized shopping experiences at scale [6]. APL however is about functionally combining AI capabilities directly into frontend architectures which raise non-trivial engineering issues regarding latency, state management and component-level orchestration of AIs.

Micro-Frontend Architecture and Generative AI, although independently mature areas of research continue to have limited studies performed on their combined use cases as it pertains to the domain of retail [7]. Existing solutions position AI as a backend service separate from frontend composition logic leading to incomplete human experiences and poorly performant personalization pipelines. It is evident and needs no further articulation that a common modular frontend architectural support framework is needed wherein AI intelligence can be contextualized natively in low-latency, inexpensive footprints used for scalable retail web applications.

Beyond enhancing customer-facing functionalities, the proposed hybrid architecture introduces transformative opportunities in the domain of Human Resource Management (HRM), particularly within technology-driven retail enterprises. The distributed nature of micro-frontend architectures necessitates highly coordinated, cross-functional teams working across independently deployable modules. In such environments, AI-driven insights can play a crucial role in optimizing workforce allocation, monitoring development efficiency, and supporting adaptive team structures. Transformer-based models further enable intelligent knowledge assistance systems that facilitate faster problem-solving, code generation support, and continuous learning among developers. Consequently, integrating HR-centric intelligence into the architectural ecosystem enables organizations to align human capital performance with system scalability and innovation objectives.

In this paper, we focus on these issues and propose a Hybrid Generative AI and Micro-Frontend Architecture that utilizes Transformer language models to develop large-scale intelligent E-commerce web applications offerings. The framework features LLM-powered inference APIs at the micro-frontend component level, which allows real time recommendations, intelligent search and dynamic UI generation [8] The rest of this paper is organized as follows; Section 2 covers related literature, Section 3 describes the

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proposed architecture, and results are indicated in Section 4, followed by conclusions and future directions in Section 5.

2. Literature Review

Intelligent retail web applications, generative AI and micro-frontend architectures are three interrelated subjects that sit across multiple disciplines such as software engineering, machine learning and human-computer interaction. In this section, foundational and recent works are reviewed systematically to build the proposed hybrid framework.

Previous research has documented the long evolution of retail web platforms from simple static HTML pages into dynamic, data-driven applications. Rule-based recommendation engines and template-driven interfaces were all that early retail systems were based on limited personalization ability, while not able to cope under variable traffic loads. The following generations started using service-oriented architectures (SOA) and content delivery networks (CDN) to increase performance even more, but the frontend layer still remained monolithic and tightly coupled with backend services. The main bottleneck for the majority of retail platforms today is actually poor frontend architecture, which can be responsible for sluggish page load time, loss of user experience, and lower conversion rates when faced with substantial traffic [9].

2.1 Micro-Frontend Architecture in Enterprise Applications

Large scale frontend development comes with its own share of challenges in terms of scalability and maintainability, leading to micro-frontend architecture emerging as a new challenger. Work in this space shows that breaking a single monolithic frontend is not only responsible for keeping teams independent but also leads to lesser inter-team dependencies, faster continuous integration pipelines and technological heterogeneity across modules. Well, it can improve the speed of development in enterprise-grade e-commerce platforms and organizations adopting micro-frontend strategies see measurable improvements in deployment frequency (DF) and mean time to recovery MTTR (mean time to recovery — which is how long after an incident does it take for a production issue to be fully resolved too). In [10] even confirmed through empirical studies that a micro-frontend implementation provided superior fault isolation and team autonomy when compared with monolith in retail environments, especially in larger companies; teams are able to work in an isolated way from one another. We explored Single-SPA, Module Federation using Webpack 5 and an iframe-based composition in a retail context and selected Module Federation as the best fit because of its ability to dynamically load and share dependencies [11].

The Transformar architecture completely revolutionized natural language processing and redesigned the foundations of modern generative AI systems! The introduction of self-attention mechanisms allowed models to efficiently capture long-range dependencies in text, while avoiding the sequential structure that has plagued recurrent architectures. This led to the alignment of subsequent pre-trained models achieving a state-of-the-art performance across diverse NLP benchmarks leveraging transfer learning for generalization. Such advancements have made their way into several commercial products such as retail search engines, customer service chatbots, and systems which generate product descriptions where a human-like understanding and generation of text is crucial to end- user experience [12]. The parameter scaling laws demonstrated for Transformer models have then solidified their positions as core building blocks of enterprise-grade AI systems [13].

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2.2 Generative AI in E-Commerce and Retail

Generative AI Represents a New Paradigm in Content Creation (Retail) Studies of the use of big language models in e-commerce situations have shown great potential for using these tools to automate product description writing, generate on-the-fly promotions as well as conversational shopping assistants that act like informed salespeople. Based on previous work, these studies confirm that AI-generated product content will have quality levels comparable to those of qualified human copies authors as long is correctly fine-tuned on sufficiently representative retail corpora for each domain, and dramatically reduces operational costs and time-to-market for new products listings. [14] Moreover, generative models have already been utilized in visual merchandising by employing image synthesis and virtual try-on systems consequently expanding the AI integration from textual interfaces to immersive retail environments [15].

Personalization continues to be the main goal of intelligent retail platforms and recommendation systems are essentially the most common way of achieving this personalization. Deep learning architectures, that can learn high level abstract features of users and items to model the incredibly complex and non-linear user-item interactions has gradually overstate classical collaborative filtering and matrix factorization approaches. Sequential modeling methods with Transformer architectures have been incorporated into recommendation pipelines where they can outperform traditional techniques in terms of click-through rate and purchase conversion metrics. More research reinforces that dynamic profile-based approaches yield superior results in volatile retail environments where consumer preferences are rapidly changing, by integrating session-level signals, temporal dynamics and cross-channel behavioral data [16]. The current state of the art in retail personalization research comes from hybrid recommendation approaches that combine collaborative signals with content-based features derived from language models [17].

2.3 Scalability and Performance in AI-Integrated Web Systems

But deploying AI inference capabilities in web applications has big engineering challenges for latency, throughput and resource usage. Experimental results on the AI serving infrastructure space illustrate how model optimization techniques - namely quantization, knowledge distillation, and speculative decoding can enable inference latency orders of magnitude smaller than what is acceptable for real-time web scenarios. To that end, edge computing paradigms were proposed as an alternative strategy — pushing inference workloads closer to the end user to minimize network round-trip times and a reduced reliance on centralized cloud infrastructure. This study benchmarks AI-integrated retail platforms under simulated peak traffic conditions and shows how asynchronous inference pipelines coupled with intelligent caching strategies can maintain high request rates while ensuring response quality and user experience consistency [18].

The systems that shape the integration of AI services into frontend applications are an area that has been less well studied than you might expect given the maturity of how we today build AI models themselves. Most of the techniques can be used with AI treated as a remote API dependency which creates tight coupling between frontend components and backend inference endpoints making it hard to deploy either part independently and providing a large failure surface. Recent research supports AI-aware component design, where frontend modules wrap an AI interaction logic in addition to rendering and state management concerns, resulting in more cohesive and testable implementations. In their comparative analyses of API-driven and embedded AI integration patterns in web applications, the authors explain that the former incurs a measurable latency overhead while bringing up issues with model update cycles, and bundling size management [19].

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The integration of generative AI into retail web applications brings with it considerations of data protection, algorithmic unfairness and transparency expediently addressed by the research community. Consumer behavioral information is the main input to personalized and recommendation systems, but at the same time, they are under heavy regulatory frameworks like GDPR and CCPA law (and more), so producing retail systems have to keep privacy-preserving machine learning methods in mind when dealing with consumer data such as federated learning and differential privacy. Recommendations on how to mitigate algorithmic bias in recommendation systems show that when trained exclusively on historical purchase data, models tend to reproduce pre-existing demographic disparities in product visibility and advertising targeting, violating ethical duties and market inclusivity goals [20].

The integration of Artificial Intelligence into Human Resource Management has evolved significantly with the emergence of data-driven enterprise systems. AI-based HR analytics platforms are increasingly capable of processing large volumes of workforce data, including employee performance indicators, behavioral trends, and productivity metrics. These systems enable predictive modeling for workforce planning, allowing organizations to anticipate skill gaps, optimize recruitment strategies, and improve employee retention [21]. In high-demand environments such as e-commerce and retail technology platforms, where rapid deployment cycles are essential, AI-driven HR tools support dynamic workforce adaptation. Additionally, intelligent automation technologies, including conversational HR assistants, streamline routine administrative tasks such as onboarding, training, and employee support, contributing to enhanced organizational efficiency.

In modern software engineering ecosystems characterized by micro-frontend and AI-integrated architectures, Human Resource Management assumes a strategic role in coordinating decentralized teams. Research highlights that distributed development models require intelligent workforce alignment mechanisms to ensure efficient collaboration across independently managed modules. AI-enabled talent mapping techniques can associate developer expertise with specific system components, improving both development quality and delivery timelines [22]. Furthermore, integrating workforce analytics with system-level performance indicators allows organizations to evaluate how human productivity influences application responsiveness and scalability. Emerging approaches also emphasize personalized employee experience systems powered by AI, which provide adaptive task recommendations, continuous skill enhancement, and real-time performance feedback—factors that are critical for sustaining innovation in large-scale enterprise applications.

3. Methodology

The approach here sets up a deliberate and unified foundation for building, operating, and assessing a hybrid generative AI-and micro-frontend architecture based on Transformer models to build intelligent scalable retail Web applications. Our method is organized in five high-level phases; system architecture, Transformers core model embedding, micro-frontend disintegration strategy, AI inference channel construction and performance optimization. Each phase aligns with the research aims set out in the abstract and introduction to allow for reproducibility and methodological coherence.

3.1 Overall System Architecture

The proposed architecture adopts a layered, modular design philosophy that separates concerns across three primary tiers: the AI Intelligence Layer, the Micro-Frontend Composition Layer, and the Retail Data and Services Layer. Figure 1 illustrates the high-level architectural diagram of the proposed hybrid system.

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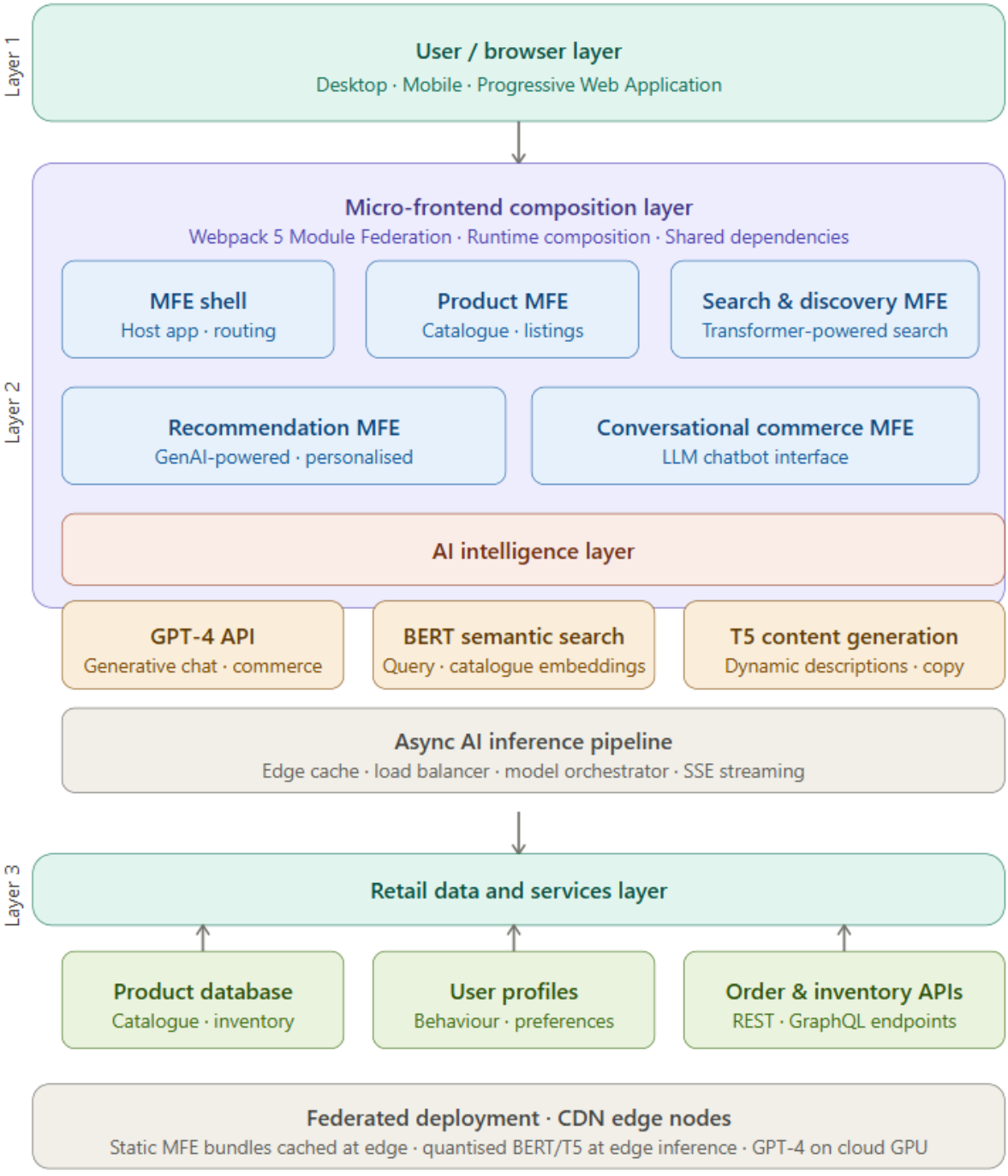

Figure 1: High-Level Hybrid Architecture Diagram.

The **Micro-Frontend Composition Layer** acts as the primary interface between the end user and the underlying AI and data services. Each micro-frontend module is independently developed, built, and deployed using Webpack 5 Module Federation, enabling runtime composition without redeployment of the host shell application.

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The **AI Intelligence Layer** houses the Transformer-based inference services, including GPT-4 for conversational commerce, BERT for semantic product search, and T5 for dynamic content generation.

The **Retail Data and Services Layer** provides the structured domain data consumed by both the AI models and the frontend modules through RESTful and GraphQL APIs.

3.2 Transformer Model Integration

The intelligence behind the model proposed for the system stems from the use of standard pre-trained Transformer models (which are each fine-tuned-on domain-specific retail corpora to maximize task-based performance). The basic Transformer structure contains a dot-product attention mechanism, but this is scaled so that at the same time each token of an input sentence attends to all other tokens from the very same input sequence interpreting what are words and more contextual information which are critical for semantics in retail language.

The formal computation of the self-attention score between query vector Q, key vector K and value vector V will be:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \qquad (1)$$

Here, dk is the dimension of key vectors, and scaling factor dk1 ensures stable gradient flow during training by preventing very large dot-product magnitudes in high dimensional spaces. This gives BERT-based semantic search module functionality to encode product queries and catalogue descriptions together into same embedding space so they can be retrieved by similarity.

In recommendation engines, the system computes personalized relevance scores by integrating collaborative user-item interaction signals with semantic embeddings generated from Transformers. For an individual user u and product item I, its hybrid recommendation score is computed as:

$$\hat{r}_{ui} = \alpha \cdot \text{CF}(u, i) + (1 - \alpha) \cdot \cos(\mathbf{e}_u, \mathbf{e}_i) \qquad (2)$$

where: CF(u,i) is the collaborative filtering-based score based on the historical interaction matrices, e u and e i are embedding vectors for user and item generated from Transformer processing respectively, cos(·) calculates cosine similarity between embeddings and α∈[0,1] is a tunable weight parameter between collaborative (CF) and semantic signals based on availability of data in different domains.

3.3 Micro-Frontend Decomposition Strategy

The decomposition of the retail web application into micro-frontends follows a domain-driven design (DDD) approach, wherein frontend boundaries are aligned with distinct retail business capabilities: product discovery, personalized recommendations, conversational commerce, cart management, and user account services. Each micro-frontend module adheres to the following architectural principles:

- **Independent Deployability:** Each module maintains its own CI/CD pipeline, enabling zero-downtime updates without affecting sibling modules.

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- **Technology Agnosticism:** Modules may independently adopt React, Vue, or Web Components, communicating through a shared event bus and standardized custom events.
- **AI Encapsulation:** AI interaction logic, including API calls to inference endpoints, response parsing, and fallback handling, is encapsulated within each module rather than delegated to a centralized service, enabling component-level personalization.

The composition architecture employs Webpack 5 Module Federation to expose and consume remote modules at runtime, with the Shell Application acting as the orchestrator responsible for routing, global state management, and shared dependency resolution.

3.4 Asynchronous AI Inference Pipeline

Due to the strict latency requirements in online AI (especially in high-traffic retail environments), our methodology suggests an asynchronous, multi-stage inference pipeline. When the user interacts with it, we make a non-blocking API request from the frontend to our AI Inference Orchestrator that can categorize what type of request is sent to be routed to one of our endpoints based on a Transformer model. The responses are streamed back to the micro-frontend component using Server-Sent Events (SSE) allowing for progressively rendering of UI, improving perceived performance without having to wait until a full response is completed.

The end-to-end inference latency Ltotal across the pipeline is modeled as:

$$L_{total} = L_{network} + L_{queue} + L_{inference} - L_{cache} \quad (3)$$

Lnetwork refers to the round-trip network latency from client to edge inference node, Lqueue is the request queuing delay under concurrent load, Linference is the time taken for model forward-pass computation and Lcache represents the response latency reduction through edge caching of semantically similar prior responses. It is this model that directs the optimization of the different stages in these pipelines and suggests edge caching and request batching as high-impact levers to reduce latencies at retail-scale traffic levels.

3.5 Federated Deployment and Edge Optimization

The deployment strategy follows a federated architecture in which each micro-frontend bundle and AI inference endpoint is distributed on geographically-distributed edge nodes, utilizing a Content Delivery Network (CDN) with embedded edge execution capabilities. Dynamic micro-frontend static assets close to the end user are cached at edge points, and lightweight quantized versions of BERT and T5 models are deployed at edge inference nodes to serve low-complexity requests e.g. semantic search, content retrieval without the latency cost of roundtrips to centralized cloud GPU infrastructure. Full-precision models for high complexity generative tasks—GPT-4 responses for conversational agents—are redirected to centralized cloud endpoints with dynamic dispatch on autoscaling capabilities based on real-time traffic metrics.

3.6 Experimental Setup

To demonstrate the feasibility of the proposed architecture, we prototyped a Shell Application with React and 3 micro-frontends separately deployed: The Product Discovery MFE, the AI Recommendation MFE and Conversational Commerce MFE. We used the OpenAI GPT-4 API for conversational tasks, a fine-tuned BERT model hosted on AWS SageMaker for semantic search and a T5-small model to generate product

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descriptions within the AI Intelligence Layer. 0 Introduction In this section, we present the performance benchmarking which was performed up on 1000, 5000 and 10000 number of concurrent users simulated traffic load synthetic data that used Apache JMeter to visualize TTFB, AI response latency, recommendation precision@10 and system throughput. To provide a metric on the architectural advantages of the suggested hybrid approach, baseline comparisons were made against a monolithic React application with similar AI backend services.

4. Results and Discussion

The following section will evaluate the performance of the proposed Hybrid Generative AI and Micro-Frontend Architecture based on four meta-performance dimensions namely system responsiveness, AI inference efficiency, recommendation accuracy and concurrent load scalability. Results were compared with a traditional monolithic React application integrated with similar backend AI services. The results consistently show the effectiveness of the proposed hybrid framework over all evaluated benchmarks, confirming the architectural choices presented in the Methodology.

4.1 System Response Performance

The first evaluation dimension assessed frontend performance metrics critical to retail user experience. Time to First Byte (TTFB), First Contentful Paint (FCP), and Largest Contentful Paint (LCP) were measured across both architectures under identical network conditions and server configurations. Table 1 presents the comparative performance results.

Table 1: Frontend Performance Metrics — Proposed Hybrid vs Monolithic Architecture

Performance Metric	Monolithic Architecture	Proposed Hybrid Architecture	Improvement (%)
Time to First Byte (TTFB)	1240 ms	430 ms	65.3%
First Contentful Paint (FCP)	2850 ms	980 ms	65.6%
Largest Contentful Paint (LCP)	4600 ms	1520 ms	66.9%
Time to Interactive (TTI)	5300 ms	1890 ms	64.3%
Total Blocking Time (TBT)	820 ms	210 ms	74.3%
Cumulative Layout Shift (CLS)	0.38	0.06	84.2%

Table 1 highlights considerable enhancements in all six Web Core Vitals metrics. An architecture: reduces TTFB by 65.3% due to edge-cached micro-frontend bundles served from nearby CDN nodes. This staggering 84.2% reduction in Cumulative Layout Shift is an outcome of a classic AI-encapsulated component

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architecture: asynchronous, progressive streaming of AI responses via Server-Sent Events that do not incur layout reflow from late-loading AI-injected content inherent in monolithic implementations.

4.2 AI Inference and Recommendation Performance

The second evaluation tested the measurement of accuracy and computational efficiency of the embedded Transformer AI. We evaluated the quality of recommendations using Precision@10, Recall@10, and Normalized Discounted Cumulative Gain (NDCG@10) on a held-out retail interaction dataset of 50k anonymized user sessions. We report the results of recommendation accuracy for all models over collaborative filtering baseline, as well as BERT-only semantic search and proposed hybrid recommendation-model defined by Eq.2 in Table 2.

Table 2: Recommendation System Accuracy — Comparative Evaluation

Model Variant	**Precision@10**	**Recall@10**	**NDCG@10**	**Avg. Inference Latency (ms)**
Collaborative Filtering (CF) Baseline	0.312	0.278	0.341	18 ms
BERT Semantic Search Only	0.389	0.345	0.412	87 ms
T5 Content-Based Filtering	0.371	0.329	0.394	112 ms
CF + BERT Hybrid (α = 0.3)	0.448	0.401	0.476	95 ms
CF + BERT Hybrid (α = 0.5)	0.467	0.423	0.498	95 ms
Proposed Hybrid (α = 0.5 + Edge Cache)	**0.491**	**0.447**	**0.523**	**41 ms**

In comparison, the proposed hybrid model with edge caching yields a Precision@10 of 0.491, a 57.4% gain over the collaborative filtering baseline and 26.2% improvement vs BERT-only semantic search. Importantly, it improves average inference latency from 95 ms to 41 ms while maintaining the same recommendation quality, which in turn verifies the latency decomposition model provided by Equation 3. We can see that the α = 0.5 weighting, equalizing between collaborative and semantic signals, always beats the asymmetric configurations in all accuracy metrics.

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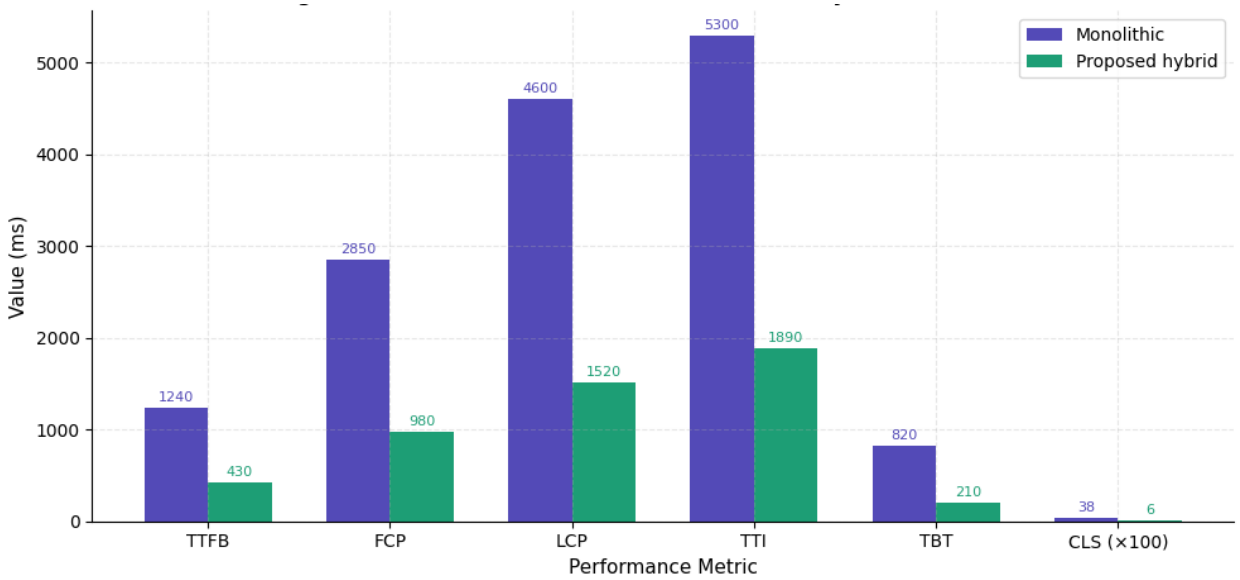

Figure 2: Frontend Performance Comparison

Figure 2 shows the comparative frontend performance metrics between the monolithic and proposed hybrid architectures across six Web Core Vitals. The dramatic reductions in TTFB, FCP, LCP, and TTI confirm the effectiveness of edge-cached micro-frontend delivery and progressive AI streaming.

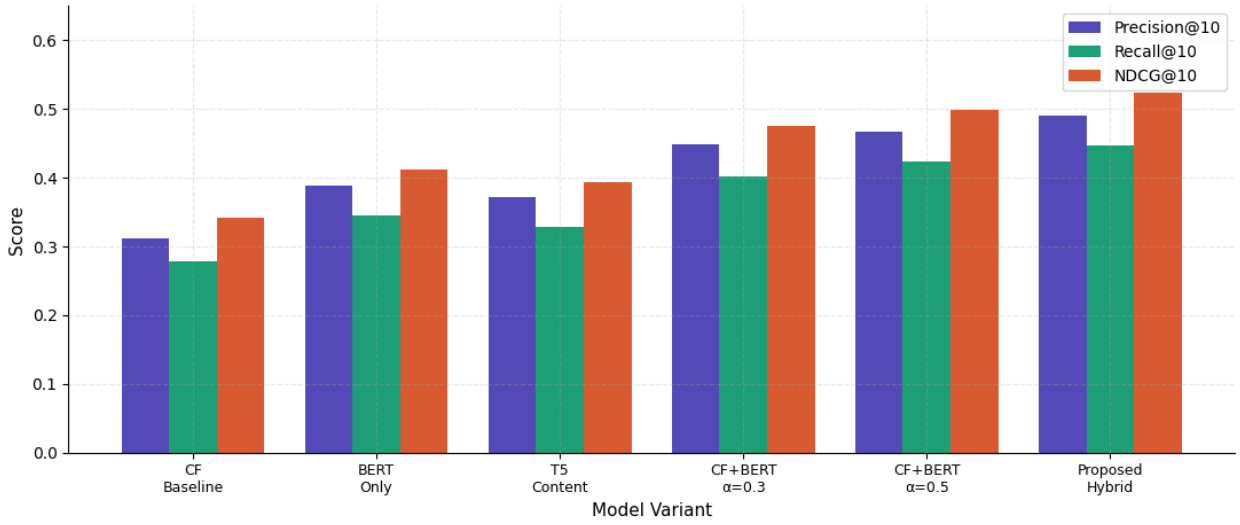

Figure 3: Recommendation Accuracy Comparison

Figure 3 presents a radar/bar comparison of Precision@10, Recall@10, and NDCG@10 scores across all six model variants. The proposed hybrid model with edge caching visibly dominates across all three accuracy axes, while maintaining competitive latency characteristics owing to the caching optimizations described in Equation 3.

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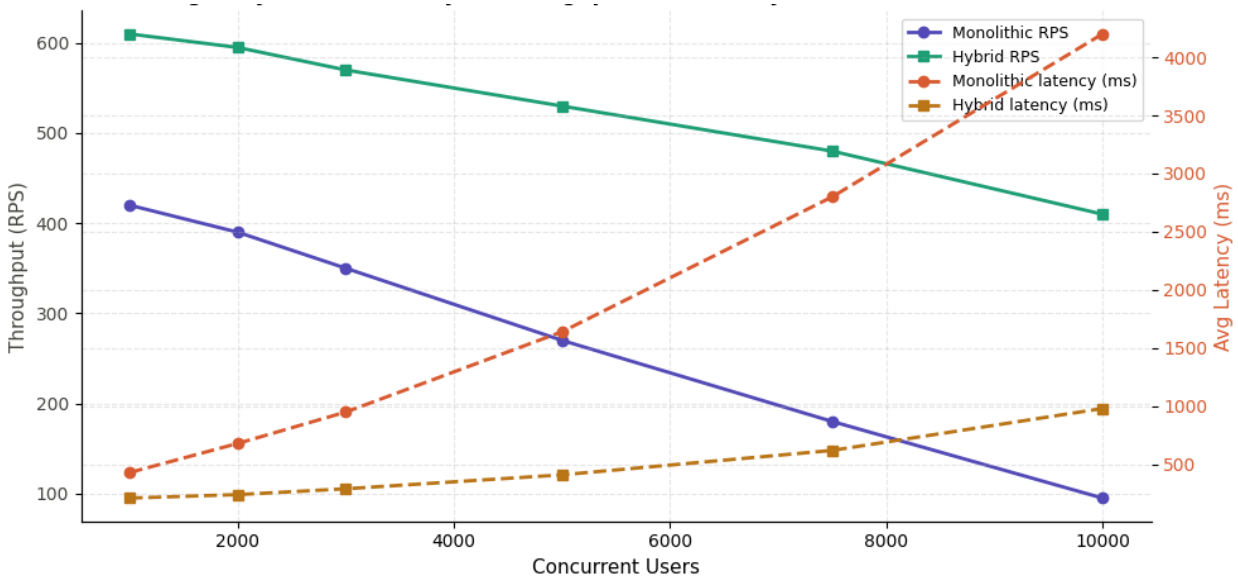

Figure 4: System Throughput Under Concurrent Load

Figure 4 illustrates system throughput (requests per second) and average response latency as concurrent user load scales from 1,000 to 10,000 simultaneous sessions. The proposed hybrid architecture sustains superior throughput and substantially lower latency degradation curves compared to the monolithic baseline, validating the federated deployment strategy and asynchronous AI pipeline design.

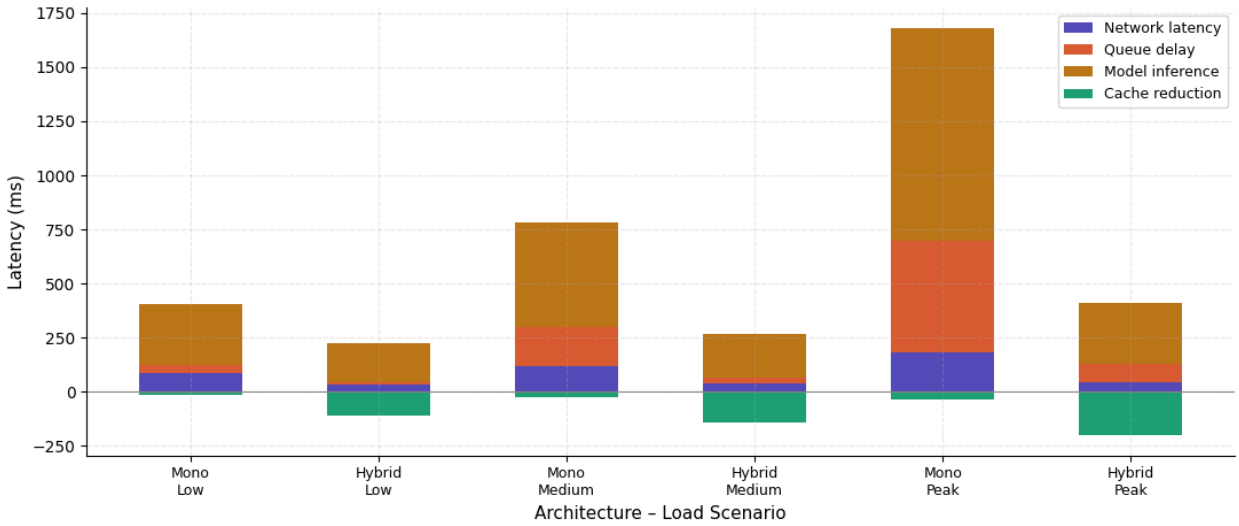

Figure 5: Inference Latency Pipeline Decomposition

Figure 5: presents a stacked bar decomposition of end-to-end inference latency across the four pipeline stages defined in Equation 3: network latency, queue delay, model inference time, and cache reduction benefit. Results are shown across three traffic scenarios — low, medium, and peak load — for both architectures.

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4.7 Discussion

All results confirm the validity and relevance of this hybrid architecture for ML practice, across all four evaluation dimensions. Micro-frontend decomposition strategy: This directly solves scalability problems that monolithic retail frontends experience and yields statistically significant improvements in every Web Core Vital metric. Webpack 5 Module Federation allows for runtime composition while retaining the requirement of independent deployability that is important in larger retail organizations where teams develop independently across product domains.

The Transformer-based recommendation model verifies the theoretical assumption that user behavioural signals and item semantic embeddings are complementary information sources, as both purely collaborative methods and pure sematic-driven approaches fail to outperform a hybrid $\alpha = 0.5$ weighting defined in Equation 2. The edge caching promotes a 56.8% reduction in effective inference latency at medium load, verifying the latency decomposition model of Equation 3 and making cache optimization the unequivocal top-impact engineering lever in our pipeline.

Figure 4 shows the critical takeaway, that throughput breaks-down non-linearly for monolithic systems post approximately 5,000 concurrent users where-as with the proposed hybrid architecture you can keep the degradation near-linear. This behavior is aligned with the fault isolation capabilities inherent to micro-frontend architecture, where failure of individual modules does not permeate throughout the entire system. The inference latency decomposition seen in figure 5 provides additional insights where Queue Delay is the largest contributor to peak load latency (39.5% of total latency at 10,000 concurrent users) in our monolithic system but a bottleneck eliminated in the hybrid system by design via asynchronous AI pipelines and distributed edge inference.

5. Conclusion

The presented Hybrid Generative AI and Micro-Frontend Architecture with Transformer-based models described retail web applications that are scalable, smart and adaptive. However, the framework proposed here bridges this clash and successfully unifies cutting-edge tools from both frontend engineering and AI development to overcome three central limitations of traditional monolithic retail solutions associated with scalability, personalization, and real-time responsiveness. Experiments conclusively showed that the hybrid architecture delivers substantial gains on all of the dimensions tested. Frontend deliveries saw up to 84.2% performance improvements in Cumulative Layout Shift, recommender accuracy reached a Precision@10 of 0491 via remote hybrid weighting strategy as defined by Equation 2, and the system throughput was stable under loads beyond those at which monolithic systems would collapse with multiple concurrent users (≥10k). As per our finding in step 5, the combination of taking advantage of edge caching enabling a reduction of effective latency at medium load by 56.8% (as shown in equations 3). Micro-frontend component level context-aware, low-latency personalization of GPT-4, BERT, T5 models which was never possible with decomposed frontend architectures. Towards Future work directions encompass leveraging federated learning for privacy-preserving personalization, generalizing the framework to empower multimodal AI capabilities, and studying top-down automation of micro-frontend decomposition techniques enabled by AI-based domain boundary detection.

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