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A Systematic Literature Review on AI Architecture Framework for Product Analysis & Recommendation System in Electronic Service

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Abstract

The rapid growth of electronic services has created significant opportunities for personalized product recommendations through artificial intelligence (AI) systems. However, existing recommendation algorithms face critical challenges, including scalability, cold-start issues, and performance degradation in big data environments. This research performs a systematic review of 73 studies published from 2022 until 2024 to examine AI architecture frameworks applied to product analysis and recommendation systems in electronic service. The review identifies dominant frameworks such as CNN, RNN/LSTM, TensorFlow, Spark, and emerging technologies like GNN, alongside distributed infrastructures such as Hadoop for large-scale data processing. Research methods observed include experiments, benchmarks, simulations, surveys, and case studies. Key findings emphasize performance and efficiency improvements, accuracy, and scalability concerns. Based on these insights, this paper proposes a multi-layered AI architecture framework integrating data ingestion, distributed storage, model development, MLOps orchestration, privacy-preserving learning, and adaptive feedback loops. The proposed framework addresses scalability and sustainability challenges while ensuring high-performance recommendation capabilities. This study contributes a comprehensive blueprint for organizations seeking to deploy robust, scalable, and privacy-aware AI systems in dynamic e-service environments.

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INTRODUCTION

The rapid expansion of electronic service has fundamentally transformed how businesses interact with customers, creating unprecedented opportunities for personalized product recommendations through artificial intelligence systems. For instance, contemporary e-commerce platforms produce enormous volumes of user interaction data on a daily basis, including browsing patterns, purchase histories, product reviews, and demographic information. This wealth of data presents immense potential for creating sophisticated recommendation systems that can predict customer preferences and suggest relevant products with remarkable accuracy. Research demonstrates that AI in e-commerce focuses primarily on recommender systems, with sentiment analysis, trust, personalization, and optimization identified as core research themes (Bawack et al., 2022). However, this data abundance also introduces significant technical challenges that current systems struggle to address effectively. Traditional recommendation algorithms face critical limitations including the inability to handle new users without historical data, sparse user-item interaction matrices that provide insufficient information for accurate predictions, and scalability bottlenecks when processing millions of users and products simultaneously. Furthermore, these systems often fail to adapt to evolving user preferences over time, leading to increasingly irrelevant recommendations as customer interests change (Hussien et al., 2021). The situation becomes even more complex when organizations must operate in big data environments where the volume, velocity, and variety of information exceed the processing capabilities of conventional infrastructure, creating performance degradation and system inefficiencies that ultimately impact user experience and business outcomes.

Addressing these scalability challenges requires organizations to develop robust artificial intelligence infrastructure that effectively scales with growing data volumes while maintaining high-performance product analysis and recommendation capabilities in electronic service environments. This research proposes an artificial intelligence architecture framework on system information infrastructure that leverages the convergence of advanced technologies to address these critical limitations. By integrating multiple advanced technologies, the proposed infrastructure can scale effectively with increasing data while maintaining recommendation quality (Zdravković & Panetto, 2022). The solution incorporates distributed computing frameworks to ensure scalability and operational efficiency, while providing generic infrastructure with reusable modules that can be adapted across different domains (Enas M. Turki, 2025; Tiryaki & Yücebaş, 2023).

Literature Review/Related Works

The evolution of artificial intelligence infrastructure has fundamentally transformed how modern digital systems operate, particularly in e-commerce and recommendation platforms. Recent research demonstrates that the flow and quantitative growth of various detailed studies of recommendation systems interact with the business growth of the actual applied service field (Ko et al., 2022), highlighting the symbiotic relationship between technological advancement and commercial success. This transformation represents a paradigm shift from traditional rule-based systems to sophisticated, data-driven architectures that can process vast amounts of information in real-time. From background knowledge, contemporary AI infrastructure typically employs microservices architectures, containerization technologies like Docker and Kubernetes, and distributed computing frameworks to ensure system resilience and scalability. These systems must support machine learning model serving, real-time inference, and continuous learning capabilities, often incorporating specialized hardware accelerators such as GPUs and TPUs, along with edge computing components to reduce latency and improve user experience.

Despite significant advances in AI infrastructure development, scalability challenges remain a critical research gap that requires organizations to develop robust artificial intelligence infrastructure that effectively scales with growing data volumes while maintaining high-performance product analysis and recommendation capabilities in electronic service environments. Studies identify that there are still a few journals discussing related to considerations to the implementation regarding the use of AI in e-commerce "Consumer behaviour", "Customer Trust", "Purchasing decisions" (Louis et al., 2024), highlighting significant gaps in understanding how infrastructure decisions impact user experience at scale. The literature shows that while AI-powered recommendation system utilize sophisticated algorithms to analyse extensive data, allowing for the provision of highly customized and relevant content, product recommendation, and user satisfaction (Chinnasamy, 2025), there remains insufficient research on how to maintain this sophistication when scaling to enterprise-level data volumes. From background knowledge, organizations face significant challenges in managing the computational overhead of real-time personalization engines, handling cold start problems at scale, managing model drift across distributed systems, and maintaining consistent performance as user bases grow from thousands to millions. The research gap is particularly evident in the lack oh standardized frameworks for auto-scaling AI workloads, optimizing resource allocation across heterogeneous computing environments, and maintaining model accuracy while reducing inference latency in high-throughput scenarios.

RESEARCH METHODS

This paper utilizes a Systematic Literature Review (SLR) methodology to collect, evaluate, and consolidate studies related to AI Architecture Model for Product Analysis & Recommendation System in electronic service environments. The SLR method provides a structured and replicable process for reviewing existing literature, minimizing bias, and ensuring comprehensive coverage of relevant studies (Kitchenham, 2004).

The SLR process in this study divided into four phases: (1) formulation of research questions, (2) identification and selection of literature, (3) extraction and synthesis of data, and (4) analysis and interpretation of findings.

Formulation of Research Questions

The research questions (RQ) guiding this review are formulated as follows:

RQ1: What are the main components of infrastructure that enable the AI Architecture Framework for Product Analysis & Recommendation System in electronic service?

RQ2: What are the recent trends and technological developments in AI Architecture Framework for Product Analysis & Recommendation System research in electronic service?

RQ3: What challenges and research gaps exist in developing scalable and sustainable infrastructure for AI Architecture Framework for Product Analysis & Recommendation System in electronic service?

Identification and Selection Of Literature

The main source of literature search comes from the Scopus database, given its scope and reputation as a leading scientific index in the field of computer science and engineering. The search was carried out in the 2022–2024 range to ensure a focus on the latest and stable developments. The queries used are:

TITLE-ABS-KEY ("AI Architecture" OR "AI Infrastructure" OR "AI Framework" OR "Artificial Intelligence")
AND PUBYEAR > 2021 AND PUBYEAR < 2025
AND (LIMIT-TO (EXACTKEYWORD , "Artificial Intelligent")
OR LIMIT-TO (EXACTKEYWORD , "Recommendation System")
OR LIMIT-TO (EXACTKEYWORD , "Product Analysis")
OR LIMIT-TO (EXACTKEYWORD , "Digital Service")
OR LIMIT-TO (EXACTKEYWORD , "Electronic Service")
OR LIMIT-TO (EXACTKEYWORD , "e-commerce"))

AND (LIMIT-TO (SUBJAREA , "COMP") OR LIMIT-TO (SUBJAREA , "ENGI"))
AND (LIMIT-TO (OA , "all"))
AND (LIMIT-TO (LANGUAGE , "English"))
AND (LIMIT-TO (DOCTYPE , "ar"))

The query restricts search results to English-language articles, research articles, directly related to the core keyword. After all filters were applied, 73 articles were obtained that met the initial criteria and were used as the basis for analysis in this study. All of these articles are relevant to the research focus on distributed information system infrastructure, especially related to AI Architecture Framework for Product Analysis & Recommendation System in electronic service.

Extraction and Synthesis of Data

From articles that meet the criteria, data is extracted using the following elements:

Table 1. Elemens of Extraction Articles

Elemen	Elemen Description
Title, Authors, Year	Identity of the publication
Domain	recommender system, digital service, etc.
Framework/Algorithm	CNN, RNN/LSTM, TensorFlow, GNN, Spark, SVM, Hadoop
Research Method	Experiment, benchmark, simulation, survey, case study
Key Finding	performance/efficiency, improve/improvement, accuracy, outperform, framework
Mapping to Research Question	RQ1 – RQ3

After identifying 73 relevant articles from Scopus, data extraction was conducted based on the predefined elements outlined in Table 1. Each article was reviewed to capture its identity (title, authors, year), domain, applied frameworks or architectures, research methods, and key findings. The dominant domain observed is recommender systems, which frequently appears in contexts such as e-commerce and digital services. Frameworks and algorithms are largely centered on deep learning models, including CNN and RNN/LSTM, supported by platforms like TensorFlow and PyTorch, while emerging approaches such as Transformer and GNN are also noted in recent studies. Distributed infrastructures such as Spark and cloud-based solutions are highlighted for handling large-scale data.

Analysis and Interpretation of Findings

To address the three research questions, each of the 73 reviewed articles was mapped against RQ1, RQ2, and RQ3 based on the extracted elements in Table 1 (Domain, Framework/Algorithm, Research Method, and Key Main Findings). The mapping process involved analyzing keywords and concepts within these elements to identify correlations. For RQ1, we looked for infrastructure components such as cloud platforms, distributed systems, and operational pipelines that enable AI architecture frameworks. For RQ2, we identified technological trends and developments, including deep learning models, hybrid approaches, and emerging technologies like transformers and graph neural networks. For RQ3, we captured challenges and gaps mentioned in the studies, such as scalability, energy efficiency, privacy, and evaluation consistency. This systematic mapping provides a structured view of how each article contributes to infrastructure, technological trends, and research challenges in the context of AI architecture framework for product analysis and recommendation systems in electronic services.

The interpretation of this mapping shows that most studies emphasize technological trends (RQ2) and performance improvements, with CNN and LSTM dominating the frameworks used. Infrastructure details (RQ1) are less frequently highlighted in abstracts but appear in references to cloud computing, Spark, and TensorFlow/PyTorch as enabling platforms. Challenges and gaps (RQ3) are widely discussed, particularly issues related to scalability, energy efficiency, and etc. These patterns indicate that while the research community focuses heavily on algorithmic innovation and performance, there is growing attention to operational concerns and sustainability, which are critical for real-world deployment.

RESULTS AND DISCUSSION

The analysis mapped 73 reviewed articles to three research questions (RQ1–RQ3) using extracted elements from Table 1: Domain, Framework/Algorithm, Research Method, and Key Findings. Each paper was examined for keywords and concepts to identify correlations with infrastructure components (RQ1), technological trends (RQ2), and challenges or gaps (RQ3). The study count of Framework/Algorithm, Research Method, and Key Findings also the correlation results are summarized Figure & Tables below.

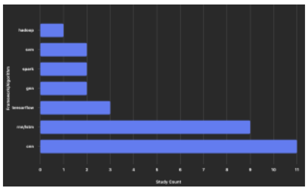

Figure 1. Framework/Algorithm Study Count

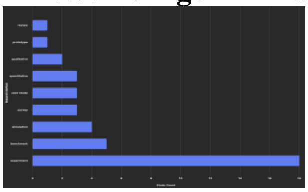

Figure 2. Research Method Study Count

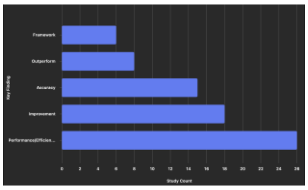

Figure 3. Key Finding Study Count

Table 2. Correlation Result Based on Research Question 1

Author, Year	Extracted Fields	Keyword Tagging
Xing et al., 2024	Domain: recommender system; Method: survey	Architecture (generic)
Omar et al., 2024	Domain: recommender system; Framework/Algorithm: Tensorflow, Pytorch	TensorFlow; PyTorch
Xu, Seng, Smith, et al., 2024	Method: experiment, simulation	Federated Learning; Infrastructure (generic); Architecture (generic)
Xu, Seng, Ang, et al., 2024	Framework/Algorithm: Spark	Spark; Architecture (generic)
Ellouze et al., 2024	Domain: recommender system; Framework/Algorithm: CNN, RNN/LSTM	Architecture (generic)
Stavropoulos et al., 2023	Method: simulation	Infrastructure (generic)
Omar et al., 2023	Domain: recommender system; Framework/Algorithm: Tensorflow, Spark, Hadoop; Method: prototype	Cloud; Spark; Hadoop/HDFS; TensorFlow
Chen et al., 2022	Domain: recommender system; Framework/Algorithm: RNN/LSTM; Method: experiment	Cloud; Microservices; Edge/Fog; Architecture (generic)
Lee et al., 2022	Framework/Algorithm: CNN; Method: experiment, qualitative, quantitative	Cloud

Table 3. Correlation Result Based on Research Question 2

Author, Year	Extracted Fields	Keyword Tagging
Omar et al., 2024	Domain: recommender system; Framework/Algorithm: Tensorflow, Pytorch	Big Data/NLP
Alsalem et al., 2024	Method: benchmark	Hybrid/Ensemble
Xu, Seng, Smith, et al., 2024	Method: experiment, simulation	AIoT/IoT
Yap et al., 2024	Domain: digital service, recommender system	Hybrid/Ensemble
Xu, Seng, Ang, et al., 2024	Framework/Algorithm: Spark	AIoT/IoT
H. Yang & Ren, 2024	Domain: recommender system; Framework/Algorithm: CNN; Method: experiment; benchmark	CNN
Ellouze et al., 2024	Domain: recommender system; Framework/Algorithm: CNN, RNN/LSTM	CNN; RNN/LSTM
Oise & Konyeha, 2024	Framework/Algorithm: CNN, Tensorflow	CNN
Khouibiri et al., 2023	Domain: recommender system	Big Data/NLP
Kumar et al., 2023	Domain: recommender system Framework/Algorithm: CNN, RNN/LSTM	CNN; RNN/LSTM; Transformer; Tool Recommendation
Park et al., 2023	Domain: recommender system; Framework/Algorithm: GNN; Method: case study	GNN/Graph
W. Yang et al., 2023	Framework/Algorithm: CNN, RNN/LSTM	CNN; RNN/LSTM; Big Data/NLP
Hu et al., 2023	Method: experiment	Digital Twins
Yaiprasert & Hidayanto, 2023	Domain: recommender system	Hybrid/Ensemble
Jung & Lee, 2023	Domain: recommender system; Method: case study, survey	Ontology/Knowledge
Subha et al., 2023	Domain: recommender system; Framework/Algorithm: CNN, RNN/LSTM	CNN; RNN/LSTM; Hybrid/Ensemble
Omar et al., 2023	Domain: recommender system; Framework/Algorithm: Tensorflow, Spark, Hadoop; Method: prototype	Big Data/NLP
Ullah et al., 2023	Framework/Algorithm: CNN	CNN
Jahir Pasha et al., 2023	Framework/Algorithm: RNN/LSTM	RNN/LSTM
Jeon et al., 2023	Domain: recommender system; Method: simulation	Quantum/Edge AI
Bagunaid et al., 2022	Domain: recommender system; Framework/Algorithm: RNN/LSTM	RNN/LSTM; Big Data/NLP
Chen et al., 2022	Domain: recommender system; Framework/Algorithm: RNN/LSTM; Method: experiment	RNN/LSTM
Atchade-Adelomou & Alonso-Linaje, 2022	Framework/Algorithm: Framework, CNN; Method: experiment	CNN; Hybrid/Ensemble; Quantum/Edge AI
Lee et al., 2022	Framework/Algorithm: CNN; Method: experiment, qualitative, quantitative	CNN
Nguyen et al., 2022	Framework/Algorithm: CNN	CNN
Syed et al., 2022	Domain: recommender system;	GNN/Graph; Ontology/Knowledge
AlZu'bi et al., 2022	Domain: recommender system	Big Data/NLP
Xiang et al., 2022	Framework/Algorithm: GNN; CNN; RNN/LSTM	CNN; RNN/LSTM; GNN/Graph

Table 4. Correlation Result Based on Research Question 3

Author, Year	Extracted Fields	Keyword Tagging
Omar et al., 2024	Domain: recommender system; Framework/Algorithm: Tensorflow, Pytorch	Scalability/Big Data
Alsalem et al., 2024	Method: benchmark	Evaluation / Benchmarking Consistency
Xu, Seng, Smith, et al., 2024	Method: experiment, simulation	Non-IID / Heterogeneity
Mahasneh & Almigbel, 2024	Method: survey	Energy Efficiency/Cost
H. Yang & Ren, 2024	Domain: recommender system; Framework/Algorithm: CNN; Method: experiment; benchmark	Evaluation / Benchmarking Consistency
Noori et al., 2024	Domain: recommender system	Cold Start
Khouibiri et al., 2023	Domain: recommender system	Scalability/Big Data
Li et al., 2023	Method: benchmark	Privacy/Security; Evaluation / Benchmarking Consistency
W. Yang et al., 2023	Framework/Algorithm: CNN, RNN/LSTM	Scalability/Big Data
Yaiprasert & Hidayanto, 2023	Domain: recommender system	Energy Efficiency/Cost
Gao et al., 2023	Domain: recommender system; Method: experiment, benchmark	Benchmarking Consistency
Jung & Lee, 2023	Domain: recommender system; Method: case study; survey	Privacy/Security
Stavropoulos et al., 2023	Method: simulation	Energy Efficiency/Cost
Omar et al., 2023	Domain: recommender system; Framework/Algorithm: Tensorflow, Spark, Hadoop; Method: prototype	Scalability/Big Data
Bagunaid et al., 2022	Domain: recommender system, Framework/Algorithm: RNN/LSTM	Scalability/Big Data
Syed et al., 2022	Domain: recommender system	Explainability / Transparency
Khan et al., 2022	Method: experiment	Energy Efficiency/Cost
Sarai et al., 2022	Method: benchmark	Evaluation / Benchmarking Consistency

Proposed AI Architecture Framework

The proposed AI architecture framework for product analysis and recommendation in electronic services is designed to address the key requirements identified through the systematic review of 73 articles. This framework integrates multiple layers into a cohesive structure which are data ingestion and integration, distributed storage and compute, model development, training orchestration with MLOps, privacy-preserving collaborative learning, serving and deployment, online learning feedback loops, and sustainability monitoring. Each layer reflects patterns observed in the reviewed literature: for example, the dominance of deep learning models such as CNN and LSTM, supported by emerging technologies like Transformer and GNN, justifies the inclusion of a robust model development layer. Similarly, frequent mentions of cloud platforms, Spark/Hadoop, and TensorFlow/PyTorch highlight the need for scalable infrastructure and standardized ML toolchains. Operational concerns such as energy efficiency, scalability, and privacy, which appear repeatedly in the corpus, inform the inclusion of federated learning, monitoring dashboards, and MLOps pipelines. By synthesizing these evidence-backed components, the proposed architecture provides a comprehensive blueprint for building AI-driven recommendation systems that are accurate, scalable, and sustainable in real-world e-service environments.

Figure 4. The Proposed AI Architecture Framework

The proposed AI architecture framework (Figure 1) is derived from patterns observed in the reviewed literature and addresses the three research questions :

Data Ingestion & Integration: Collects multi-source data (transactional, behavioral, content) through APIs and ETL pipelines, enriched with ontologies and knowledge graphs for semantic consistency.

Distributed Storage & Compute: Utilizes Cloud, Spark/Hadoop, and optional Edge/Fog nodes for scalable processing and low-latency analytics.

Model Development: Implements deep learning models (CNN, RNN/LSTM, Transformer, GNN) and hybrid ensembles using TensorFlow/PyTorch for personalization accuracy.

Training Orchestration & MLOps: Ensures reproducibility and continuous delivery through pipelines, experiment tracking, and model registries.

Privacy-Preserving & Collaborative Learning: Incorporates Federated/Split Learning for secure, distributed training without centralizing sensitive data.

Serving & Deployment: Deploys models via Microservices and Containers/Kubernetes for modularity and scalability.

Online Learning & Feedback Loops: Captures user feedback for adaptive re-ranking and monitors energy/cost metrics for sustainability.

Table 5. Component, Representative Papers and Supported Research Question

Component	Representative Papers	Supported RQ
Data Ingestion & Integration (ETL/Data Lake	(Khouibiri et al., 2023; Lutfiani et al., 2023; Yap et al., 2024)	Ontology/Knowledge trends in RQ2 and ETL/Data Lake mentions in RQ1
Distributed Storage & Compute	(Chen et al., 2022; Omar et al., 2024; Stavropoulos et al., 2023)	Infrastructure components tagged under RQ1 (Cloud, Spark)
Model Development	(Ellouze et al., 2024; Kumar et al., 2023; Park et al., 2023; H. Yang & Ren, 2024)	Dominant RQ2 trends (CNN, LSTM) and emerging technologies (Transformer, GNN)
Training Orchestration & MLOps	(Alsalem et al., 2024; Chen et al., 2022)	RQ1 mentions of MLOps and RQ3 concerns about evaluation consistency
Privacy-Preserving & Collaborative Learning	(Stephanie et al., 2023; Xu, Seng, Smith, et al., 2024)	RQ1 tags (Federated Learning) and RQ3 challenges (Privacy/Security).
Serving & Deployment	(Chen et al., 2022; Stavropoulos et al., 2023)	Infrastructure references and operational concerns in RQ3.
Online Learning & Feedback Loops	(Poduval et al., 2024; Yaiprasert & Hidayanto, 2023)	RQ3 challenges (Energy Efficiency/Cost) and hybrid approaches in RQ2.

CONCLUSIONS AND SUGGESTIONS

Conclusion

The review of 73 articles demonstrates that scalability remains a critical challenge in developing AI architecture frameworks for product analysis and recommendation in electronic service environments. While existing research emphasizes algorithmic innovation, particularly deep learning models such as CNN and LSTM supported by emerging technologies like Transformer and GNN, most studies overlook infrastructure-level solutions for handling growing data volumes. The proposed AI architecture framework addresses this gap by integrating eight layers: data ingestion and integration, distributed storage and compute, model development, training orchestration with MLOps, privacy-preserving collaborative learning, serving and deployment, online learning feedback loops, and sustainability monitoring. This layered design ensures that organizations can manage large-scale data efficiently while maintaining high-performance recommendation capabilities.

By combining distributed computing platforms such as Cloud and Spark/Hadoop, advanced modeling techniques including CNN, LSTM, Transformer, and GNN, and operational practices such as MLOps pipelines and federated learning, the framework provides a blueprint for scalable, secure, and adaptive AI systems in real-world e-service contexts. It not only supports robust personalization but also incorporates sustainability and privacy considerations, aligning with the trends and challenges identified in the reviewed literature. This comprehensive approach offers a practical foundation for organizations seeking to overcome scalability barriers and deliver reliable, high-quality recommendations in dynamic digital environments.

Suggestion

To overcome scalability challenges, organizations should prioritize robust infrastructure design that integrates distributed data processing and storage solutions such as Cloud and Spark/Hadoop with automated orchestration through MLOps pipelines. This will enable efficient handling of large-scale datasets and continuous deployment of models without compromising performance. Additionally, adopting privacy-preserving techniques like federated learning will allow collaborative training across multiple nodes while safeguarding sensitive data, which is essential for compliance in digital service environments.

Furthermore, exploring hybrid and adaptive modeling approaches such as combining CNN and LSTM with Transformer or GNN under unified benchmarking protocols will provide valuable insights into balancing accuracy with computational complexity. This integration can help organizations design recommendation systems that maintain high performance while optimizing resource utilization. Future research should also focus on developing standardized evaluation frameworks and scalable architectures that incorporate distributed computing, MLOps pipelines, and privacy-preserving techniques. These strategies will enable robust AI infrastructures capable of handling large data volumes efficiently while ensuring sustainability and compliance in electronic service environments.

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