A Comprehensive Survey of Personalization Models: Classical, Hybrid, and Emerging Sentiment-Aware Approaches Across Telecom and E-Commerce

Venkata Sai Sandeep Velaga
Senior Software Engineering AT&T
Plano, Texas, USA
sandeepnvelaga@gmail.com

Abstract

Digital platforms that aim to enhance customer retention, engagement, and monetization have made it necessary to have personalization systems. In specific cases, Telecom and e-commerce, adaptive models are critical in the process of suggesting plans, forecasting churn, price optimization, and customer experience. This paper introduces a survey of personalization models with a classification into classical models like rule-based systems, collaborative filtering and content-based filtering also known as hybrid architecture that combines several algorithms together to achieve better performance. Moreover, the paper will discuss recent developments such as sentiment-aware personalization, optimization with reinforcement learning, dynamic pricing with text analytics, and integrating large language models (LLMs) into pipeline recommendation. An ordered comparison of approaches is done on the basis of accuracy, scalability, computational performance, explainability, and business implications. Lastly, research gaps are defined and future directions suggested, which are multimodal personalization, responsible AI, regulatory compliance, and sentiment-driven price optimization frameworks.

Keywords- *telecom, e-commerce, personalization models*

1. Introduction

The accelerated digital revolution in telecommunication and e-commerce has created enormous amounts of user-generated information, such as browsing history and purchase records, call detail records (CDRs), feedback messages, social sentiment score, etc [1][2]. Personalization has been one of the strategic differences in such a competitive field, allowing organizations to personalize user experiences, decrease churn, maximize conversions, and offer real-time intelligent suggestions [3]. The earlier rule-based systems have undergone development leading to collaborative filtering, hybrid systems and recent developments of larger machine learning and deep neural networks. The introduction of LLMs and sentiment-aware analytics has also altered personalization architecture and given systems a chance to utilize context, emotion and subtle human intent [4][5].

Telecom operators use personalization to recommend data packs, predict churn, detect fraudulent patterns, and provide location-based offers [6][7]. E-commerce platforms rely on personalization for product recommendation, price optimization, bundling strategies, and customer lifecycle management. As consumer expectations shift, personalization systems increasingly require explainability, cross-channel integration, fairness, and adaptability. This article presents a structured, multi-dimensional survey that covers classical algorithms, hybrid systems, and emerging sentiment-aware approaches, with special attention to telecom and e-commerce applications.

2. Literature Review

Many researchers have worked in the telecom and e-commerce domain to boost the sentiment analysis at each hierarchy. Some of them are presented below. Figure 1 shows the summary of all the models present for telecom and E-Commerce.

2.1 Classical Personalization Models

These are some traditional models mainly based on fixed rules and filtering process.

2.1.1 Rule-Based Systems

Rule-based personalization was among the earliest techniques used in telecom and retail platforms. These systems operate on predefined conditions (IF-THEN rules) created by domain experts. For example, “IF customer has low usage AND high complaints, THEN recommend retention pack.” Although interpretable and easy to implement, they suffer from limited adaptability, inability to learn from user behavior, and poor scalability in dynamic environments.

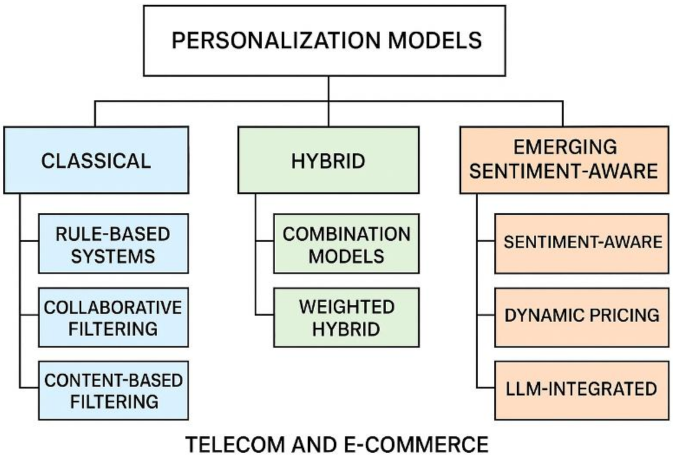

Figure 1: Summary of Personalization Models

2.1.2 Content-Based Filtering

Content-based systems examine the attributes of the items and compare them to profiles of the users. In e-commerce, the model absorbs such characteristics as brand, category, price range, and textual product descriptions. Equivalent reasoning is used in the case of telecom with attributes on plans like data limits, or data validity period or voice minutes. These systems are very strong when it comes to relevance, which is personalized but they have the tendency to form filter bubbles, suggesting only what is related to how a user has behaved before.

2.1.3 Collaborative Filtering

One of the most significant approaches to the personalization literature is collaborative filtering (CF). It extracts recommendations on the basis of similarities in users (user-user CF) or on the basis of similarities among items (item-item CF). The CF was enhanced with matrix factorization, which is a dimensionality reduction method and the latent user-item representations. The problem with CF is, however, cold start, sparse data, and sensitivity to abrupt changes of behavior - typical in seasonal of telecom or promotional events of e-commerce.

2.2 Hybrid Personalization Models

Hybrid models combine two or more classical methods to ensure a high accuracy and coverage. Examples include:

1. Content–Collaborative Hybrid: Widely used in platforms like Amazon and Netflix, this approach enriches collaborative filtering with item features to address sparsity and cold start problems [8].
2. Rule-Based + ML Hybrid: Telecom companies combine business rules (e.g., regulatory restrictions, geographical limitations) with machine learning models to deliver business-compliant recommendations.
3. Weighted Hybrid Systems: Multiple algorithms contribute scores that are weighted and aggregated. Useful for applications requiring balanced explainability and accuracy.

The hybrid models have been widely used in practical systems due to the fact that they are balanced in terms of interpretability, scalability and performance.

2.3 Deep Learning Approaches

Deep learning revolutionized personalization by modeling complex, non-linear interactions. Key architectures include:

1. Neural Collaborative Filtering (NCF): Learns latent representations via multi-layer neural networks [9][10].
2. Recurrent Neural Networks (RNNs) and Transformers: Capture sequential patterns, crucial for modeling browsing sessions, plan usage cycles, or clickstream data [11].
3. Autoencoders: Used for recommendations in sparse environments by reconstructing user–item matrices [12].

Telecom applications frequently adopt sequence-learning models to predict user behaviour over time (e.g., recharge cycles, data usage patterns).

2.4 Sentiment-Aware Personalization

New studies point to the importance of textual data, the reviews, chat records, tweets, in which sentiments are part of the purchasing or usage decision. Sentiment-sensitive personalization combines:

1. **Sentiment analysis from customer feedback**
2. **Emotion classification from social media**
3. **Aspect-based opinion mining for product features**

In telecom, sentiment-aware systems help identify dissatisfaction triggers (network issues, billing errors) and recommend corrective offers. Emotions can enhance the product recommendation in e-commerce, particularly in lifestyle, fashion and entertainment products.

General-purpose LLMs such as GPT, BERT, and domain-conditioned versions improve contextually sensitive sentiment reading, which can be used to model preferences more subtly.

2.5 Reinforcement Learning-Based Personalization

The reinforcement learning (RL) models personalization as the sequential decision-making process. Commonly used applications are: Dynamic pricing, Real-time offer adaptation, Click-through rate (CTR) optimization and Churn prevention strategies.

The aim of RL agents is to maximize cumulative reward which may be long-term customer engagement. It has been argued to be especially useful in telecom to optimize plan suggestions, or e-commerce to optimize session-level conversions.

2.6 LLM-Integrated Recommendation Systems

LLMs have of late taken the center stage in personalization studies. Their capabilities include:

1. Understanding natural-language queries
2. Generating personalized descriptions
3. Integrating multi-modal data
4. Enhancing cold-start recommendations
5. Blending structured and unstructured user signals

LLM has conversational shopping assistants in e-commerce. They enhance customer support, provide generation and intent prediction in telecom.

3. Research Gap

Although the studies on personalization were quite numerous, there are still some gaps related to personalization research in case of telecom and e-commerce:

3.1 Lack of Cross-Domain Adaptability

In the majority of models, isolated datasets are used. There is little study on the models that generalize between telecom and e-commerce or transfer knowledge effectively.

3.2 Insufficient Use of Sentiment for Pricing

Sentiment analysis is a popular topic but its application in dynamic pricing or determination of personalized offer value is not well researched.

3.3 Explainability Challenges

Deep models are highly accurate and not interpretable. The telecom regulators require clear decisions on pricing, plan recommendations and fraud prediction.

Figure 2 represents the research gap in the domain of e-commerce and telecom.

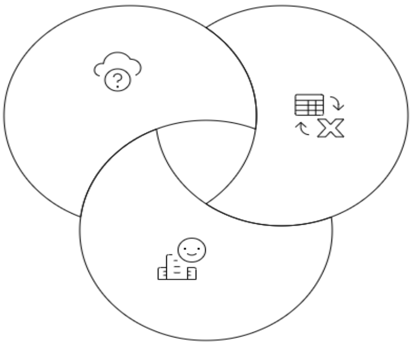

Figure 2: Research Gap

3.4 Limited Real-Time Personalization

There are many systems that are offline, real-time personalization and latency constraints is a research problem, especially in high-volume telecom scenarios.

3.5 Sparse Research on Ethical and Regulatory Compliance

Personalization entails sensitive user information. Not many researches deal with fairness, mitigation of bias, compliance with GDPR, and responsible AI frameworks.

3.6 Underutilized Behavioral Signals

Examples of unique data generated through telecom include: CDRs, mobility pattern, call duration, frequency of recharging mobile phone and network quality of service records. These indicators are not well represented in scholarly literature.

4. Discussion

4.1 Comparative Assessment of Personalization Techniques

4.1.1 Accuracy vs. Interpretability

Such classical models as rule-based systems and content-based filtering are highly transparent and less accurate. Deep learning and hybrid models offer better performance, but are not interpretable making their use in telecom a regulatory challenge.

4.1.2 Computational Efficiency

1. **Collaborative filtering:** relatively lightweight.
2. **Hybrid models:** moderate computational load.
3. **Deep models & LLM-based systems:** require significant computing resources for training and inference.

This is because telecom operators have millions of transactions every day, and they want models that strike a balance between speed and accuracy.

4.2 Sector-Specific Personalization Insights

4.2.1 Telecom

These behavioral and experiential factors have a very strong impact on telecom personalization and the combination of the two helps operators to know the needs of customers more accurately. Recharge history indicates the spending behavior and type of preferred plans whereas the usage patterns indicate the level of data consumed, calling habits and preferences of service. The network quality perception of complaints and QoS metrics would help to determine in areas where users might be feeling dissatisfied. Churn likelihood scores also allow firms to identify risky customers and use specific retention tactics. The customer support interaction provides an extra dimension of context in that it is able to record the user concern, feedback and sentiment, enabling the telecom providers to design a more relevant, proactive and personalized service experience.

Sentiment-aware models integrate is essential because of the common dissatisfaction manifested in the social media or helpline contacts.

4.2.2 E-Commerce

Key drivers include:

- Browsing patterns
- Product reviews
- Cart abandonment signals
- Purchase frequency

The set of these behavioral cues contributes to the heart of e-commerce personalization strategies and assists platforms in knowing their intentions, preferences, and areas of hesitation more accurately. Browsing habits show what the users are reading, whereas product reviews give the sentiment signals that narrow down relevancy [13]. Cart discarding underlines the situations of doubt, allows prompt intervention, and frequency of purchases allow identifying loyalty and forecasting a future purchasing cycle. As conversational artificial intelligence gets enhanced with LLM, recommendation processes are getting sophisticated, providing contextualized replies, understanding subtle queries, and providing more elaborate and adaptable personalization to all customer journey phases.

4.3 The Role of Sentiment in Future Personalization

Sentiment-aware models will likely influence:

1. **Dynamic pricing:** adjusting price sensitivity based on user emotions.
2. **Customer retention strategies:** tailoring offers for unhappy customers.
3. **Contextual recommendations:** understanding user mood shifts.

Sentiment is particularly important in telecom, where customer frustration quickly leads to churn.

4.4 Future Integration of LLMs

LLMs can also dramatically transform personalization pipelines, adding more underlying contextual reasoning to them, allowing the systems to determine the intent behind the user in a more subtle and accurate way. Multi-modal learning, i.e. combining the image, text, and behavioral patterns cues can enable more comprehensive and holistic user profiles resulting in recommendations reflecting the preferences more closely in the real world. Another way that LLMs are used to overcome the cold-start problem is through general world knowledge and semantic understanding to produce meaningful suggestions in scenarios where user information is sparse. They also support customized conversational interfaces that adjust to tone, objectives, and previous interactions of a user, and make a more natural and intuitive interaction. Though these benefits exist, scalability with large scale implementations in businesses is difficult because of the computational power needed, low-latency answers needed in real-time applications, and the growing privacy, data protection and regulatory issues.

4.5 Towards Ethical and Explainable Personalization

Explainable AI approaches including feature attribution and interpretable embeddings should be incorporated into the personalization systems in the future because recommendations and pricing decisions made by these methods need to be transparent and comprehensible to users and regulators alike. Simultaneously, fairness audits are needed to avoid discriminatory pricing or biased content recommendation to make sure that personalization is fair among the various demographic and behavioral clusters. These systems should also comply with the international regulations frameworks including GDPR and industry level policies like TRAI regulations, which control the use of data, consent management and price disclosure. Telecom companies, in particular, are subject to high-risk regulatory control, and it is extremely important that their personalization models ensure the high level of accountability, effective data management, and compliance at all the implementation levels.

5. Conclusion

This survey delivered an embodiment of personalization strategies, including classical rule-based and collaborative filtering models; hybrid, deep learning, sentiment-conscious, reinforcement learning, and LLM-based systems. Telecom and e-commerce markets were identified as fruitful in terms of behavioral data and the requirement to have personalization that is dynamic and scalable. Although the situation has greatly improved, the gaps in research concerning explainability, cross-domain generalization, sentiment-based pricing models, and regulation-acceptable personalization frameworks are still present. Future research should center its attention on multimodal personalization, real-time inference, optimization with fairness consideration, and integration of LLMs into production-level pipelines. The rapid derivatives of customer engagements necessitate the next level of personalization, which is intelligent, ethical, context-aware, and sentiments-sensitive, which will ultimately become the future of digital experience engineering.

REFERENCE

[1] Gajula, Y. (2025). Sentiment-Aware Recommendation Systems in E-Commerce: A Review from a Natural Language Processing Perspective. *arXiv preprint arXiv:2505.03828*.

[2] Daniel, S., Olaoye, G., & Ejaz, U. (2025). Deep Learning Models for Sentiment Analysis in E-Commerce.

[3] Dritsas, E., & Trigka, M. (2025). Machine Learning in e-Commerce: Trends, Applications, and Future Challenges. *IEEE Access*.

[4] Kumar, M., Khan, L., & Chang, H. T. (2025). Evolving techniques in sentiment analysis: a comprehensive review. *PeerJ Computer Science*, *11*, e2592.

[5] Ramdoss, V. S., & Rajan, P. D. M. (2025). Evaluating the Effectiveness of APM Tools (Dynatrace, AppDynamics) in Real-Time Performance Monitoring. *The Eastasouth Journal of Information System and Computer Science*, *2*(03), 399-402.

[6] Ramdoss, V. S. (2025). AI-ENHANCED GRPC LOAD TESTING AND BENCHMARKING. *International journal of data science and machine learning*, *5*(01), 7-10.

[7] Chen, H., Sirikham, A., & Konpang, J. (2025). Recommendation of A-Share Stocks based Graph Dual-Attention Self-Learning. *IEEE Access*.

[8] Chaturvedi, R. P., Mishra, A., Asthana, S., Parashar, M., & Nayyar, P. (2025). 11 Embroilment of Deep Learning in Business Analytics for Sustainable Growth. *Intelligent Business Analytics: Harnessing the Power of Soft Computing for Data-Driven Insights*.

[9] Mishra, A., Gupta, P., & Tewari, P. (2022). Global U-net with amalgamation of inception model and improved kernel variation for MRI brain image segmentation. *Multimedia Tools and Applications*, *81*(16), 23339-23354.

[10] Mishra, A., Chaturvedi, R. P., Sharma, H., Kumar, P., Asthana, S., & Parashar, M. (2024, August). Brain Tumor Detection using Optimized Stochastic Gradient Descent Function. In *2024 International Conference on Electrical Electronics and Computing Technologies (ICEECT)* (Vol. 1, pp. 1-6). IEEE.

[11] Chaturvedi, R. P., Mishra, A., Ansari, M. D., Kushwaha, A. S., Mittal, P., & Singh, R. K. (2025). A new local tetra pattern in composite planes (LTcP) technique for classifying brain tumors using partial least squares and super-pixel segmentation. *International Journal on Smart Sensing and Intelligent Systems*, *18*(1).

[12] Vashishth, T. K., Sharma, K. K., Kumar, B., Chaudhary, S., & Panwar, R. (2024). Enhancing customer experience through AI-enabled content personalization in e-commerce marketing. *Advances in digital marketing in the era of artificial intelligence*, 7-32.

[13] Mittal, P. (2025). Digital Transformation in Project Management Revolutionizing Practices for Modern Execution. In *Project Management Information Systems: Empowering Decision Making and Execution* (pp. 205-232). IGI Global Scientific Publishing.