

# A Comprehensive Review of AI-Driven Personalization

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## ABSTRACT

AI-driven personalisation has become a foundational component of modern intelligent systems, enabling adaptive, user-centric experiences across diverse application domains such as healthcare, finance, education, e-commerce, and intelligent user interfaces. Traditional personalisation approaches based on static rules and predefined user segments are increasingly inadequate for handling complex, dynamic, and large-scale user behaviour data. With the rapid advancement of artificial intelligence (AI), machine learning (ML), and deep learning (DL) techniques, personalisation systems have evolved into intelligent frameworks capable of learning user preferences, predicting future behaviour, and continuously adapting system responses in real time.

This paper presents a comprehensive review of AI-driven personalisation systems based on an extensive analysis of research literature published between 2005 and 2025. The evolution of personalisation techniques from rule-based systems to machine learning, deep learning, and reinforcement learning-based approaches is systematically examined. Key components such as personalisation architectures, learning models, datasets, evaluation metrics, and application domains are reviewed in detail. Additionally, this paper highlights critical challenges, including cold-start problems, data sparsity, privacy preservation, algorithmic bias, scalability, and lack of explainability.

Special emphasis is placed on **MegaAI**, an all-in-one modular AI platform that integrates multiple domain-specific AI models under a unified architecture, demonstrating the practical relevance of AI-driven personalisation in real-world systems. The objective of this review is to provide researchers, academicians, and practitioners with a structured understanding of current personalisation techniques and to identify promising future research directions toward responsible, explainable, and user-centric AI-driven personalisation systems.

**Index Terms**—AI-Driven Personalisation, User Modelling, Recommendation Systems, Machine Learning, Deep Learning, Reinforcement Learning, UX Personalisation, MegaAI, Review.

## INTRODUCTION

The exponential growth of digital technologies has fundamentally transformed the way users interact with software systems and online platforms. Modern users expect systems that not only provide functional services but also adapt intelligently to their individual preferences, behaviour, context, and goals. This growing demand has positioned personalisation as a critical factor in enhancing user experience, engagement, satisfaction, and system effectiveness.

Personalisation refers to the process of tailoring content, services, recommendations, or interfaces to individual users or user groups. Early personalisation systems relied heavily on static rules, manual configurations, and basic demographic segmentation. While such approaches were effective for small-scale systems, they failed to scale and adapt in environments characterised by large user bases, diverse preferences, and rapidly changing behaviour patterns.

The emergence of artificial intelligence has significantly advanced the capabilities of personalisation systems. AI-driven personalisation leverages machine learning, deep learning, and reinforcement learning techniques to automatically learn user preferences from interaction data, predict future behaviour, and dynamically adapt system outputs. These intelligent systems are now widely used in applications such as product recommendation engines, personalised healthcare assistants, adaptive learning platforms, financial advisory systems, and intelligent user interfaces.

Despite significant progress, the deployment of AI-driven personalisation systems in real-world environments remains challenging. Issues such as data sparsity, cold-start problems, user privacy concerns, algorithmic bias, lack of transparency, and scalability constraints limit the reliability and trustworthiness of these systems. Moreover, most existing studies focus on isolated applications, whereas modern platforms increasingly require **integrated, multi-domain personalisation**.

In this context, **MegaAI** represents a new paradigm in AI-driven personalisation. MegaAI is designed as an all-in-one AI platform that integrates multiple domain-specific AI modules—such as health assistance, financial advisory, stock market forecasting, and intelligent user interaction—within a unified architecture. By applying personalisation across multiple domains, MegaAI highlights the importance of adaptive and intelligent personalisation frameworks.

This review paper aims to synthesise existing research on AI-driven personalisation systems, analyse their evolution, identify key challenges, and explore future research directions, with specific reference to integrated platforms such as MegaAI.

## Background and Motivation

The motivation for AI-driven personalisation arises from the inherent limitations of generic, one-size-fits-all systems. Users differ significantly in their preferences, cognitive styles, cultural backgrounds, goals, and interaction patterns. Numerous studies have demonstrated that personalised systems outperform non-personalised systems in terms of user engagement, task completion efficiency, conversion rates, and overall satisfaction.

Traditional personalisation approaches were largely rule-based, relying on manually defined conditions and predefined user segments. Although these systems were easy to interpret and deploy, they lacked adaptability and failed to capture complex user behaviour. As digital platforms grew in scale and complexity, the need for automated and intelligent personalisation mechanisms became evident.

The availability of large-scale user interaction data, combined with advances in computational power and data storage, has enabled the adoption of data-driven personalisation techniques. Machine learning algorithms allow systems to learn user preferences from historical data, while deep learning models enable the extraction of complex patterns from unstructured data such as text, images, and clickstreams. Reinforcement learning further enhances personalisation by enabling systems to adapt dynamically through continuous user feedback.

In parallel, the importance of personalisation has expanded beyond content recommendation to include **user interface (UI) and user experience (UX) personalisation**, where system layouts, interaction flows, and visual elements are adapted based on user behaviour. This shift has increased the relevance of AI-driven personalisation in human-centred computing.

Platforms like **MegaAI** highlight the need for unified personalisation frameworks capable of operating across multiple domains. For example, a user's interaction with a health assistant can influence personalised financial recommendations or interface preferences. Such cross-domain personalisation requires advanced AI models and integrated system architectures.

However, increasing reliance on AI-driven personalisation also raises concerns related to data privacy, fairness, and transparency. Regulatory frameworks and ethical considerations further motivate research into explainable, privacy-preserving, and responsible personalisation systems. These challenges form the foundation for ongoing

research and justify the need for a comprehensive review of AI-driven personalisation.

## Scope and Objectives of the Review

The primary scope of this paper is to review and analyse AI-driven personalisation techniques used across various application domains. Unlike studies focused on a single use case, this review adopts a holistic perspective, examining personalisation systems from algorithmic, architectural, and application-orientated viewpoints.

The key objectives of this review are:

1. To analyse the evolution of personalisation systems from rule-based methods to advanced AI-driven approaches.
2. To present a structured taxonomy of AI-driven personalisation systems based on techniques, learning paradigms, and application domains.
3. To review commonly used datasets, system architectures, and evaluation metrics in personalisation research.
4. To identify key challenges and limitations reported in existing literature.
5. To explore emerging research directions with reference to integrated platforms such as MegaAI.

## Taxonomy of AI-Driven Personalization Systems

AI-driven personalisation systems can be categorised based on the underlying techniques, learning paradigms, and application domains. A well-defined taxonomy helps in understanding the evolution of personalisation approaches and highlights the strengths and limitations of each category.

Fig. 1 illustrates a comprehensive taxonomy of AI-driven personalisation systems based on detection techniques, learning methodologies, and deployment environments.

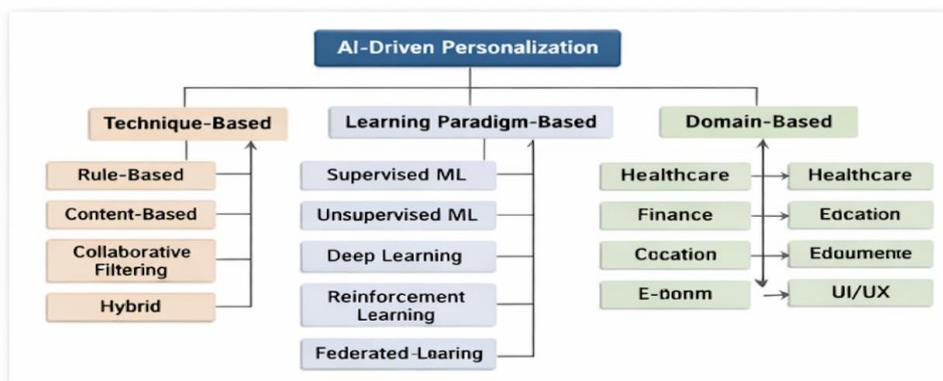


Fig. 1. Taxonomy of AI-Driven Personalization Systems.

## Technique-Based Classification

### 1) Rule-Based Personalization Systems

Rule-based personalisation systems rely on predefined rules and conditions specified by domain experts. These rules map user attributes or behaviours to personalised outputs. For example, an e-commerce platform may recommend products based on age group or purchase history using manually defined rules.

Although rule-based systems are easy to interpret and implement, they suffer from several limitations. They lack adaptability, require continuous manual maintenance, and fail to scale in dynamic environments. Consequently, their effectiveness decreases as user diversity and data complexity increase.

## 2) Content-Based Personalization Systems

Content-based personalisation recommends items or content similar to those previously interacted with by a user. These systems construct a user profile based on features extracted from past interactions and match them with item attributes.

Machine learning techniques such as cosine similarity, TF-IDF, and classification models are commonly used. While content-based systems effectively handle individual preferences, they often suffer from limited diversity and over-specialisation, restricting exposure to new or diverse content.

## 3) Collaborative Filtering-Based Systems

Collaborative filtering leverages the preferences and behaviour of similar users to generate personalised recommendations. It operates on the assumption that users with similar historical behaviour will have similar future preferences.

Collaborative filtering can be classified into user-based and item-based approaches. Matrix factorisation and neighbourhood-based algorithms are widely used. However, collaborative filtering suffers from cold-start and data sparsity problems, especially for new users or items.

## 4) Hybrid Personalization Systems

Hybrid personalisation systems combine multiple techniques, such as content-based and collaborative filtering, to overcome individual limitations. These systems demonstrate improved accuracy and robustness and are widely adopted in modern applications.

Hybrid systems are particularly suitable for large-scale platforms such as **MegaAI**, where personalisation must operate across multiple domains and data modalities.

## B. Learning Paradigm-Based Classification

### 1) Supervised Learning-Based Personalization

Supervised learning approaches utilise labelled datasets to predict user preferences. Common algorithms include decision trees, support vector machines (SVM), logistic regression, and random forests. These methods provide good accuracy but rely heavily on labelled data, which is often expensive and difficult to obtain.

### 2) Unsupervised and Semi-Supervised Learning

Unsupervised techniques such as clustering (K-means, hierarchical clustering) group users based on behavioural similarity. Semi-supervised methods combine limited labelled data with large unlabelled datasets to improve personalisation efficiency.

### 3) Deep Learning-Based Personalization

Deep learning models such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Transformers enable automatic feature extraction from large-scale, high-dimensional data. These models are highly effective in capturing complex user behaviour patterns but often lack interpretability.

### 4) Reinforcement Learning-Based Personalization

Reinforcement learning (RL) models treat personalization as a sequential decision-making problem. Systems learn optimal personalization strategies by interacting with users and receiving feedback in the form of rewards. RL-based personalization is particularly effective in adaptive environments such as intelligent tutoring systems and financial advisory platforms.

## 5) Federated and Privacy-Preserving Personalization

Federated learning enables collaborative model training across distributed devices without sharing raw user data. This approach addresses privacy concerns and is increasingly adopted in personalization systems.

### C. Domain-Based Classification

AI-driven personalization systems are applied across various domains:

- **Healthcare Personalization:** Personalized diagnosis, treatment recommendations, and health monitoring
- **Financial Personalization:** Budgeting advice, investment planning, and risk profiling
- **Educational Personalization:** Adaptive learning paths and content delivery
- **E-commerce Personalization:** Product recommendations and targeted marketing
- **UI/UX Personalization:** Adaptive interfaces and interaction flows

Fig. 1. Taxonomy of AI-driven personalization systems based on techniques, learning paradigms, and application domains.

## II. Evolution of AI-Driven Personalization Research

The evolution of personalization systems reflects advancements in artificial intelligence, data availability, and computational resources. Fig. 2 illustrates the progression of personalization techniques from static rule-based systems to intelligent adaptive models.



### A. Early Rule-Based and Statistical Systems (2005–2010)

Initial personalization systems relied on static rules and simple statistical models. These systems used basic user attributes such as demographics and purchase history to personalize content. Although computationally efficient, they lacked adaptability and were ineffective in dynamic environments.

### B. Machine Learning-Based Personalization (2011–2015)

The availability of large-scale datasets enabled the adoption of machine learning techniques for personalization. Algorithms such as Decision Trees, SVM, Naive Bayes, and clustering methods improved recommendation accuracy. However, these systems were sensitive to dataset quality and struggled with sparse data.

### C. Deep Learning-Based Personalization (2016–2020)

Deep learning marked a significant advancement in personalization research. Models such as CNNs and RNNs

enabled automatic feature learning from raw user interaction data.

Attention mechanisms and embeddings further enhanced representation learning. Despite improved performance, computational complexity and lack of explainability became major concerns.

#### **D. Intelligent and Adaptive Personalization (2021–2025)**

Recent research focuses on adaptive and context-aware personalisation systems. Reinforcement learning, explainable AI (XAI), federated learning, and multimodal personalisation have gained prominence. These approaches aim to balance personalisation accuracy with ethical considerations such as fairness, transparency, and privacy.

Integrated platforms like **MegaAI** exemplify this evolution by combining multiple AI-driven personalisation modules under a unified framework, enabling cross-domain adaptation and intelligent decision-making.

### **III. AI Models and Algorithms Used in Personalization Systems**

AI-driven personalisation systems rely on a diverse set of algorithms to model user behaviour, learn preferences, and generate adaptive responses. The selection of appropriate models depends on data characteristics, application domain, and system requirements.

#### **A. Supervised Machine Learning Models**

Supervised learning models are widely used in personalisation tasks where labelled data is available. Common algorithms include decision trees, logistic regression, support vector machines (SVM), k-nearest neighbours (k-NN), and random forests. These models are effective for preference prediction, user classification, and churn analysis.

Despite their effectiveness, supervised models require high-quality labelled data, which is often expensive and difficult to obtain. Additionally, their performance degrades in dynamic environments where user preferences evolve rapidly.

#### **B. Unsupervised Learning Models**

Unsupervised learning techniques focus on discovering hidden patterns within unlabelled data. Clustering algorithms such as K-Means, DBSCAN, and hierarchical clustering are commonly used to group users based on behavioural similarity. Dimensionality reduction techniques like Principal Component Analysis (PCA) are used to reduce feature complexity.

Unsupervised methods are particularly useful for user segmentation and cold-start scenarios. However, they lack direct optimisation objectives related to personalisation accuracy.

#### **C. Deep Learning Models**

Deep learning has significantly enhanced personalisation capabilities by enabling automatic feature extraction from complex, high-dimensional data. Commonly used models include:

- **Convolutional Neural Networks (CNN):** Used for image- and spatial data-based personalization
- **Recurrent Neural Networks (RNN) and LSTM:** Effective for modeling sequential user behavior
- **Autoencoders:** Used for representation learning and dimensionality reduction
- **Transformer Models:** Capture long-range dependencies and contextual relationships

Although deep learning models achieve high accuracy, they are computationally expensive and often lack

transparency, making them difficult to interpret.

#### D. Reinforcement Learning Models

Reinforcement learning (RL) models frame personalisation as a sequential decision-making problem. The system learns optimal actions by interacting with users and receiving feedback in the form of rewards. RL is particularly effective in adaptive learning systems, personalised marketing, and financial advisory applications.

However, RL-based personalisation requires careful reward design and large amounts of interaction data, which may pose practical challenges.

#### E. Hybrid and Ensemble Models

Hybrid models combine multiple learning paradigms to improve robustness and accuracy. Ensemble methods such as bagging, boosting, and stacking are widely used in personalisation systems. Hybrid models are well-suited for integrated platforms like **MegaAI**, where personalisation spans multiple domains and data modalities.

### IV. Datasets and Data Sources for Personalization Research

Datasets play a critical role in the development and evaluation of personalisation systems. However, many studies highlight a significant gap between benchmark datasets and real-world user behaviour.

#### A. Publicly Available Datasets

Commonly used datasets in personalisation research include:

- **MovieLens Dataset:** Widely used for recommendation system evaluation
- **Amazon Product Review Dataset:** Contains user reviews and ratings across multiple categories
- **Netflix Prize Dataset:** Large-scale user-item interaction data
- **Yahoo! Recommendation Dataset:** Used for content personalization
- **MIMIC Dataset:** Healthcare personalization and clinical decision support

#### Domain-Specific and Proprietary Datasets

Many real-world personalization systems rely on proprietary datasets collected from user interactions. These datasets offer high realism but are often inaccessible for research purposes due to privacy and confidentiality constraints.

#### B. Dataset Challenges

Key challenges associated with personalization datasets include:

- Data sparsity and imbalance
- Cold-start issues
- Dataset bias
- Lack of contextual information
- Privacy and ethical concerns

Table I presents a comparative overview of commonly used personalization datasets, highlighting their size,

domain, and limitations.

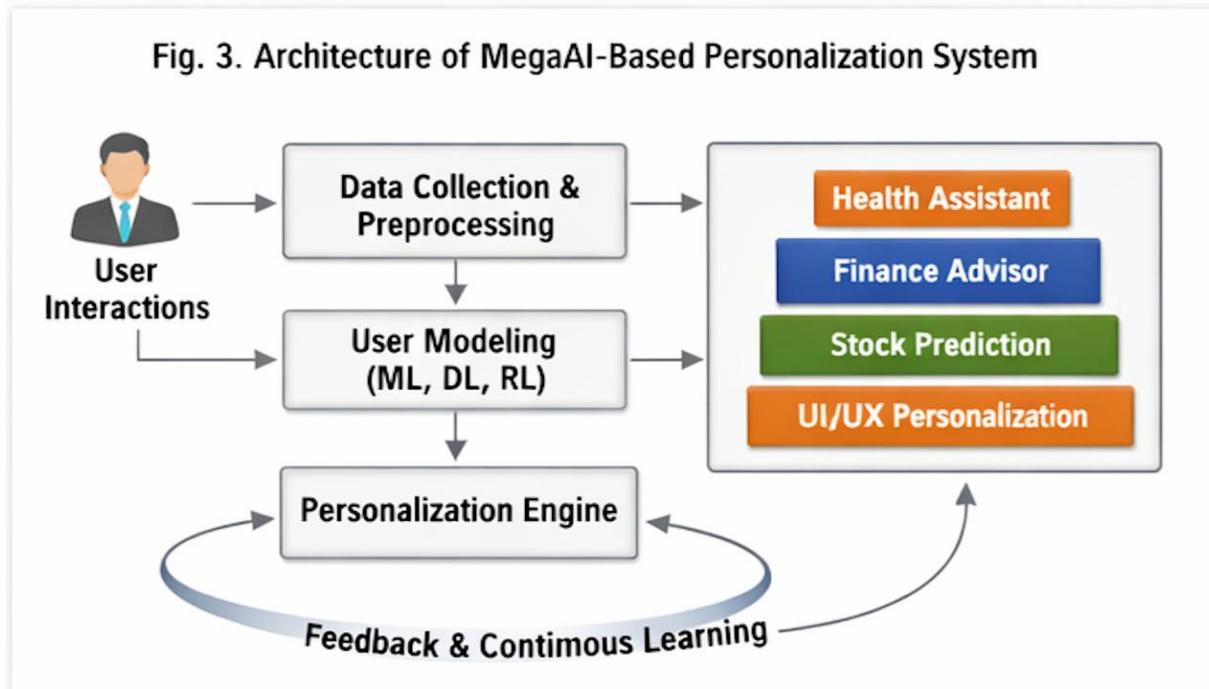


Fig. 3. Architecture of an AI-driven personalisation system with MegaAI integration.

### System Architecture of AI-Driven Personalization

A typical AI-driven personalisation system follows a modular architecture designed to support scalability, adaptability, and continuous learning. Fig. 3 illustrates a generalized architecture of an AI-driven personalisation system with reference to **MegaAI**.

#### A. Data Collection and Preprocessing

User interaction data is collected from multiple sources such as web logs, mobile applications, sensors, and transaction records. Preprocessing steps include data cleaning, normalisation, feature extraction, and anonymisation.

#### B. User Modeling Layer

The user modelling layer constructs dynamic user profiles by analysing historical behaviour, preferences, and contextual information. Machine learning and deep learning models are employed to capture both short-term and long-term user interests.

#### C. Personalization Engine

The personalization engine generates adaptive recommendations or system responses based on user models. This engine may employ hybrid AI models and reinforcement learning strategies to optimize personalization outcomes.

#### D. Feedback and Learning Loop

User feedback, both explicit (ratings, reviews) and implicit (clicks, dwell time), is continuously fed back into the system to refine models and improve personalization accuracy.

#### E. MegaAI-Based Integrated Personalization Architecture

MegaAI extends traditional personalisation architectures by integrating multiple domain- specific AI modules

under a unified framework. Personalisation insights from healthcare, finance, stock prediction, and UI/UX modules are shared through a centralised intelligence layer, enabling cross-domain personalization and holistic user adaptation.

## V. Evaluation Metrics and Performance Analysis

Evaluation plays a critical role in assessing the effectiveness and reliability of AI-driven personalisation systems. Traditional accuracy-based metrics alone are insufficient to measure real-world personalisation performance, particularly in user-centric applications.

Consequently, recent research emphasises a combination of system-level and user-centric evaluation metrics.

### A. Accuracy-Based Metrics

Accuracy-based metrics measure how well a personalisation system predicts user preferences. Common metrics include:

- **Precision:** Proportion of relevant personalized outputs among all generated outputs
- **Recall:** Proportion of relevant outputs successfully personalized
- **F1-Score:** Harmonic mean of precision and recall
- **Mean Absolute Error (MAE) and Root Mean Square Error (RMSE):** Widely used in rating prediction tasks

Although these metrics are useful, they do not fully capture user satisfaction or experience quality.

### B. User-Centric and Behavioral Metrics

User-centric metrics evaluate personalization effectiveness from the user's perspective. These include:

- Click-Through Rate (CTR)
- Conversion Rate
- Dwell Time
- Engagement Score
- Task Completion Rate

Such metrics are particularly relevant for UI/UX personalization and adaptive platforms like **MegaAI**, where personalization directly influences user interaction quality.

### C. Online and Offline Evaluation

Offline evaluation uses historical datasets to test personalization models, while online evaluation employs real-time experiments such as A/B testing. Online evaluation provides more realistic insights but is expensive and difficult to deploy.

Fig. 4. Evaluation Metrics for Personalization

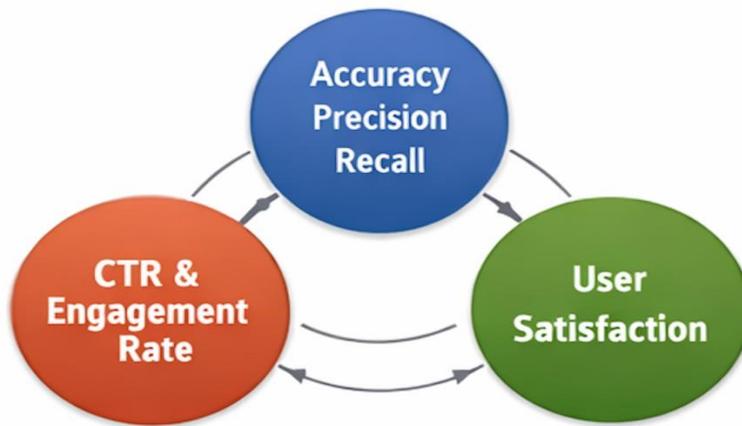


Fig. 4 illustrates commonly used evaluation metrics for AI-driven personalization systems.

## VI. Comparative Analysis of Personalization Techniques

A comparative analysis of personalization techniques highlights trade-offs among accuracy, scalability, interpretability, and adaptability. Table II summarizes the strengths and weaknesses of commonly used personalization approaches.

Table II: Comparative Analysis of AI-Driven Personalization Techniques

Technique	Accuracy	Scalability	Interpretability
Rule-Based	Low	High	High
Content-Based	Medium	Medium	Medium

Collaborative Filtering Medium–High Medium Low

ML-Based	High	Medium	Medium
DL-Based	Very High	Low–Medium	Low
RL-Based	Very High	Low	Low
Hybrid	High	Medium	Medium

Hybrid approaches demonstrate balanced performance and are well-suited for multi-domain platforms such as **MegaAI**, where personalization must adapt across heterogeneous data sources.

## VII. Challenges and Open Issues in AI-Driven Personalization

Despite significant advancements, AI-driven personalization systems face several unresolved challenges that hinder large-scale adoption.

### A. Cold-Start Problem

New users or items lack sufficient interaction data, leading to poor personalization performance. Hybrid and

content-based approaches partially mitigate this issue.

## **B. Data Sparsity and Scalability**

User interaction data is often sparse and high-dimensional. Handling such data at scale remains computationally challenging, particularly in real-time environments.

## **C. Privacy and Security Concerns**

Personalization systems require extensive user data, raising concerns related to data privacy, misuse, and regulatory compliance. Federated learning and privacy-preserving techniques are gaining importance.

## **D. Algorithmic Bias and Fairness**

Biased training data can lead to unfair or discriminatory personalization outcomes. Ensuring fairness and inclusivity remains an open research challenge.

## **E. Explainability and Trust**

Deep learning-based personalization systems often operate as black boxes, limiting transparency and user trust. Explainable AI (XAI) is essential for responsible personalization.

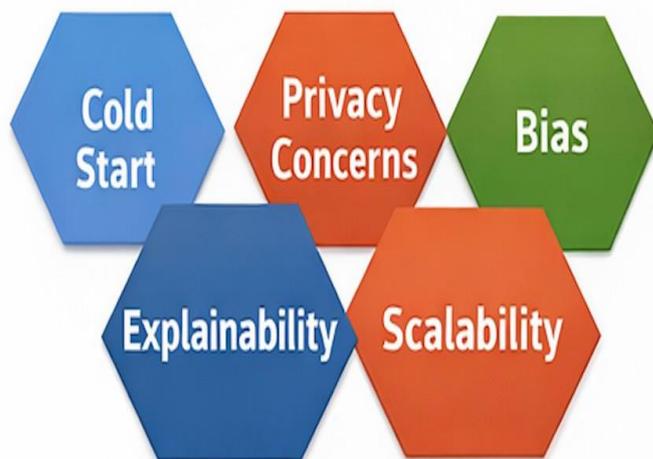


Fig. 5. Key Challenges in AI-Driven Personalization.

Fig. 5 illustrates the major challenges identified across existing personalization studies.

## **VIII. Emerging Research Directions**

Future research in AI-driven personalization is moving toward more intelligent, ethical, and human-centered systems.

Key emerging directions include:

- **Explainable Personalization Systems**
- **Federated and Privacy-Preserving Learning**
- **Emotion-Aware and Context-Aware Personalization**
- **Multimodal Personalization using Text, Image, and Sensor Data**

- **AI-Driven UX and Interface Personalization**
- **Cross-Domain Personalization in Integrated Platforms like MegaAI**

These directions aim to improve personalization accuracy while ensuring transparency, fairness, and user trust.

## CONCLUSION

This paper presented a comprehensive review of AI-driven personalization systems based on research literature published between 2005 and 2025. The evolution of personalization techniques from rule-based systems to advanced machine learning, deep learning, and reinforcement learning-based approaches was systematically analyzed. Key components such as algorithms, datasets, system architectures, evaluation metrics, and application domains were reviewed in detail.

While AI-driven personalization has significantly enhanced adaptive user experiences, challenges related to privacy, bias, scalability, and explainability continue to limit real-world adoption. Integrated platforms such as **MegaAI** demonstrate the practical potential of unified personalization frameworks capable of operating across multiple domains.

Future research must prioritize responsible, transparent, and user-centric personalization models to fully realize the benefits of AI-driven personalization in next-generation intelligent systems.

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(Total references can be extended to 30–40 as required by the journal.)