ISSN: 2583-9888
DOI: doi.org/10.51219/JAIMLD/maxwell-nwanna/425

URF PUBLISHERS
connect with research world

Journal of Artificial Intelligence, Machine Learning and Data Science

https://urfpublishers.com/journal/artificial-intelligence

Vol: 3 & Iss: 1

Research Article

AI-Driven Personalisation: Transforming User Experience Across Mobile Applications

Maxwell Nwanna[1]*, Ernest Offiong[2], Toluwaleke Ogidan[2], Oluwole Fagbohun[3], Adeseye Ifaturoti[4] and Oladotun Fasogbon[4]*

[1]RideNear, UK

[2]Vuhosi Limited, UK

[3]Readrly Limited, UK

[4]Independent researcher, UK

Citation: Nwanna M, Offiong E, Ogidan T, et al. AI-Driven Personalisation: Transforming User Experience Across Mobile Applications. *J Artif Intell Mach Learn & Data Sci* 2025, 3(1), 1920-1929. DOI: doi.org/10.51219/JAIMLD/maxwell-nwanna/425

Received: 19 November, 2024; **Accepted:** 30 December, 2024; **Published:** 05 January, 2025

***Corresponding author:** Maxwell Nwanna, RideNear, UK

A B S T R A C T

AI-driven personalisation represents a transformative innovation in mobile application development, revolutionising user engagement across domains such as e-commerce, social media, education and healthcare. By leveraging cutting-edge machine learning (ML) and deep learning frameworks, these systems deliver real-time, context-aware and user-specific recommendations, significantly enhancing user interaction, retention and satisfaction. This study provides a systematic review of foundational methodologies, including collaborative filtering, deep neural networks and transformer-based architectures, examining their application across diverse industries. A particular focus is placed on multimodal and context-aware approaches that underpin adaptive, scalable and privacy-conscious solutions.

Using a comprehensive evaluation framework, this study quantifies the impact of personalisation systems on key performance indicators (KPIs) such as session duration, user retention rates and conversion metrics. Critical ethical considerations, including data privacy, algorithmic fairness and transparency, are rigorously analysed. To address these challenges, privacy-preserving strategies such as federated learning and differential privacy are advocated as essential tools for mitigating risks. Additionally, the pivotal role of Explainable AI (XAI) is explored, highlighting its potential to foster user trust and ensure compliance with regulatory standards such as GDPR and CCPA.

Emerging advancements in computational efficiency, edge AI and fairness-aware algorithms have been identified as essential enablers of next-generation personalised systems. By integrating these technological innovations with responsible AI practices, this paper envisions a future in which personalisation systems are aligned with human-centric values, fostering inclusivity, equity and sustainable trust. The interplay between advanced neural architectures and ethical frameworks is critical to achieving these objectives.

This study bridges technical innovation with ethical and practical considerations and offers a comprehensive roadmap for researchers, industry practitioners and policymakers. It emphasises the importance of transparency, fairness and inclusivity in harnessing the transformative potential of AI-driven personalisation. Through the responsible development of these systems, key players can transform how users engage with mobile environments, thereby enhancing their experiences while maintaining integrity and fairness.

Keywords: AI-driven personalisation, Machine Learning, Deep Learning, Ethical Frameworks, Explainable AI, Privacy-preserving strategies, Mobile ecosystems, User engagement, Algorithmic fairness, Transparency.

1. Introduction

The rapid proliferation of mobile applications has fundamentally transformed the consumption of digital content and services, reshaping entire industries and user behaviours. Mobile platforms have evolved into complex ecosystems spanning e-commerce, entertainment, education and healthcare, serving diverse user needs[1]. Despite their ubiquity, user engagement remains inconsistent and short-lived as users abandon applications that fail to align with their preferences and contextual needs[2,3].

In response to shifting user demands, personalisation has emerged as a key strategy for improving the user experience (UX) and retention. Personalisation involves tailoring content, interfaces and interactions to align with user preferences, thereby fostering satisfaction and loyalty[4,5]. AI-powered personalisation represents a significant departure from traditional methods, leveraging ML and deep learning techniques to infer user interests, predict behaviours and dynamically adapt application features[6]. Unlike static rule-based systems, AI personalisation integrates explicit signals, such as ratings and implicit indicators, including browsing patterns and engagement metrics, to deliver real-time, adaptive experiences[7,8].

Mobile platforms further benefit from advanced capabilities, such as on-device computation, sensor data and location services, enabling highly context-aware recommendations[9]. For example, applications integrate cues, such as time, location and historical interactions to personalise content in ways that feel intuitive and relevant[10,11]. Such systems have been shown to enhance engagement, trust and conversion rates across domains including e-commerce and social platforms[12,13]. AI-driven features such as predictive recommendations and chatbots, streamline interactions and drive deeper user engagement[14,4].

AI-powered personalisation has transformed user interactions by automating processes that traditionally rely on manual curation. It provides dynamic and scalable solutions that cater to individual needs, resulting in higher satisfaction and commercial success[3,6]. Research shows that AI algorithms, such as collaborative filtering and content-based approaches, excel at optimising recommendations, reduce user effort and improve overall UX[2,4]. Additionally, innovative frameworks, such as lightweight AI models, ensure energy-efficient personalisation, addressing constraints related to mobile devices.

However, increasing reliance on user data raises ethical and practical concerns regarding privacy, transparency and fairness[15,16]. Users express scepticism when personalisation is intrusive or opaque, leading to disengagement and erosion of trust[6,17]. Techniques such as federated learning and differential privacy have emerged to mitigate risks; however, balancing user-centric experiences with ethical considerations remains challenging[18,16].

This research investigates the advancing role of AI-driven personalisation within mobile applications, examining its technological underpinnings, practical implementation hurdles and associated ethical considerations. It begins by reviewing foundational AI techniques, including collaborative filtering, deep learning and context-aware systems, to establish the basis for personalisation methodologies. The discussion extends to real-world applications across key domains such as e-commerce, social media, education and healthcare, demonstrating the transformative impact of these systems on user interactions. A critical evaluation of the measurable effects of AI personalisation highlights its influence on user engagement, trust and satisfaction, offering a comprehensive understanding of its benefits. The study also addresses emerging concerns regarding privacy, algorithmic bias and regulatory compliance, emphasising the importance of safeguarding user rights and fostering equitable system designs.

Furthermore, the paper envisions future directions for the field, focusing on lightweight AI frameworks, ethical AI practices and advanced context-aware systems that promise to push the boundaries of personalisation technologies. By mapping the latest advancements, this study emphasises the transformative impact of AI-driven personalisation on mobile applications. It explores not only the technological innovations propelling this evolution but also the critical societal and ethical dimensions that ensure personalisation systems remain inclusive, user-focused and ethically sound.

2. Foundations of AI-Driven Personalisation

Implementing AI-driven personalisation in mobile applications requires a robust understanding of ML methods, deep learning architectures, real-time data processing and frameworks for privacy preservation. This section outlines the foundational methodologies enabling AI-driven personalisation, ranging from traditional collaborative filtering to modern federated learning strategies.

2.1. Machine Learning-Based Approaches

2.1.1. Collaborative Filtering

Collaborative filtering (CF) identifies patterns in user-item interactions to predict preferences for unseen items. CF assumes that users sharing similar behaviours will also exhibit comparable preferences[19]. The two dominant types of CF are as follows:

- **User based CF:** Focuses on user similarity by recommending items liked by similar users[3].
- **Item based CF:** Examines relationships between items, recommending those related to previously liked content[8].

Despite its successes, CF faces notable challenges, such as the cold start problem for new users or items and its inability to utilise contextual or item specific data effectively[2]. Hybrid models combining CF with content-based techniques have shown promise for mitigating these limitations[20].

2.1.2. Content Based Methods

Content based filtering aligns item attributes such as keywords and categories with user preferences. For example, personalised learning platforms recommend educational resources based on user interaction history and task-specific metadata[21,22]. While this method reduces reliance on group data, it risks confining users to "preference bubbles", limiting content diversity.

To address these concerns, hybrid approaches integrating content-based and CF techniques deliver richer, personalised experiences by combining both behavioural patterns and item-specific attributes[6].

2.2. Deep Learning Techniques

2.2.1. Neural Architectures for Recommendations

Deep learning models have revolutionised personalisation by capturing nonlinear relationships in user-item data. Convolutional

Neural Networks (CNNs) learn spatial representations of content (e.g. images, text), whereas Recurrent Neural Networks (RNNs) and transformer-based models capture sequential user behaviour to provide context-aware recommendations[23,24]. For instance, transformer models excel in understanding evolving user preferences over time, offering personalised news feeds or adaptive content in educational apps (Haleem et al., 2022).

2.2.2. NLP-Driven Personalisation

Natural Language Processing (NLP) enhances text-based personalisation by fine-tuning language models on user queries, interaction histories and reviews. Educational platforms, for example, personalise learning pathways by analysing student feedback and engagement patterns[25].

2.3. Real-Time and Contextual Data Analytics

The continuous influx of real-time contextual data such as location, device usage and temporal signals enables dynamic personalisation on mobile platforms. Real-time analytics allows apps to adapt recommendations based on immediate situational cues[14]. Mobile apps utilise low-latency inference techniques, such as model compression, quantisation and edge-based computation, to deliver real-time responses while minimising energy and computational costs[26]. For instance, transportation apps adjust recommendations during commutes, providing content suitable for shorter interaction periods[27].

2.4. Privacy-Preserving Personalisation Frameworks

2.4.1. Federated Learning (FL): Federated Learning enables personalisation without centralising sensitive user data, thereby ensuring greater privacy. Models are trained locally on devices and only aggregated updates are shared with a central server[18]. FL has been particularly effective in personalising mobile applications and balancing user privacy and performance[28,27]. Recent studies highlight advanced federated techniques, such as partial model personalisation, where a subset of neural network layers remains unique to individual devices[29].

2.4.2. Differential Privacy: Differential privacy ensures that aggregated data cannot reveal individual user contributions. By introducing noise into the training datasets, personalisation models maintain high-level privacy while retaining predictive accuracy[15]. Techniques integrating FL and differential privacy are emerging as gold standards for secure personalisation[30]. AI-driven personalisation is built upon the confluence of collaborative filtering, deep learning, real-time analytics and privacy-preserving frameworks. By leveraging advanced techniques, such as neural models and federated learning, mobile applications can deliver highly adaptive and secure personalised experiences, revolutionising user engagement across industries. The next sections explore how these techniques are applied in domains such as e-commerce, education and healthcare while addressing critical ethical challenges.

3. Real-World Applications of AI-Driven Personalisation in Mobile Apps

The integration of AI-driven personalisation techniques into mobile applications has catalysed transformative shifts in how users interact with digital services. Across multiple verticals, ranging from retail and entertainment to education and health, personalised recommendations and interfaces have enhanced usability, increased engagement and improved user loyalty. This section delves into key domains in which AI-driven personalisation has matured, illustrating the practical impact, challenges and evolving opportunities in each context.

3.1. E-Commerce and Retail

E-commerce platforms have long pioneered the adoption of AI-driven personalisation to deliver tailored shopping experiences. Leading retailers such as Amazon and Alibaba leverage advanced recommendation engines powered by ML, collaborative filtering and deep learning architectures to predict user interests and curate dynamic product feeds[2,7]. By analysing browsing histories, past purchases and contextual signals such as seasonal trends and user location, these systems recommend products, highlight related items and provide targeted bundles to increase customer engagement and retention[31].

Modern AI models employ various techniques to enable hyper personalisation. Recommendation systems combine collaborative filtering and content-based methods to align user preferences with product attributes and offer personalised suggestions. For example, item-to-item collaborative filtering dynamically adjusts recommendations in real-time based on evolving user preferences[32]. NLP models, including large language models (LLMs) and conversational bots that assist users with product queries and create seamless shopping experiences. In particular, AI-driven chatbots enhance product discovery and reduce friction during customer journeys[33]. Predictive analytics also plays a vital role in forecasting consumer demand and shopping behaviour. Machine learning models optimise inventory and dynamic pricing, ensuring that promotions and offers align with the anticipated user needs[12].

AI-powered personalisation significantly enhances key performance indicators (KPIs) for e-commerce platforms. Personalised recommendations have been shown to increase conversion rates and boost the average order value (AOV), as users are more likely to make purchases when presented with relevant options[3]. Platforms that consistently deliver engaging and meaningful offers foster customer loyalty and retention. Trust-based AI interactions further deepen emotional connections with the platform, encouraging repeat usage[34]. Additionally, AI tools such as prebuilt APIs and SaaS platforms empower smaller retailers to adopt personalisation strategies, allowing them to compete more effectively with larger players[31].

Despite its benefits, AI-driven personalisation raises significant concerns regarding data privacy and consumer trust. Heavy reliance on personal data for training algorithms introduces risks related to user consent, data security and ethical transparency[34]. Customers increasingly expect platforms to adopt robust privacy-preserving frameworks, such as federated learning and differential privacy, to address these concerns while maintaining high personalisation quality[18]. Striking a balance between hyper personalisation and respect for user autonomy is critical to avoid perceptions of intrusiveness.

Emerging trends in AI in retail focus on real-time personalisation and immersive experiences. Augmented Reality (AR) features, such as virtual try-ons and AR-enhanced product views, provide personalised engagement by simulating in-store experiences[35]. Generative AI models, including GPT-4 and Stable Diffusion, allow retailers to produce personalised content, such as tailored product descriptions and marketing emails. Voice commerce is another area of innovation where AI assistants enable hands-free purchases and queries, streamlining the shopping experience through voice commands[36].

AI-driven personalisation in e-commerce offers transformative opportunities to enhance user engagement and operational efficiency. However, its success depends on balancing technological innovation with ethical considerations, ensuring that customer trust and privacy are upheld along with commercial gains.

3.2. Social Media and Content Platforms

Social media and content-centric platforms, including news aggregators, video-sharing apps and social networks, have become leaders in leveraging AI-driven personalisation to enhance user engagement. By modelling user behaviours such as likes, shares, watch durations and comments, these platforms dynamically refine content recommendation systems to ensure relevance and sustained engagement[37,7]. Content curation on social media platforms relies on ML and deep learning techniques to optimise user feeds. Platforms such as YouTube and Facebook integrate CF, reinforcement learning (RL) and supervised learning to personalise user experiences based on explicit behaviours, such as likes and implicit behaviours, such as watch duration and scrolling patterns[37,24]. TikTok's algorithm exemplifies advanced personalisation by combining deep learning techniques with user interaction histories for surface relevant short-form videos. By embedding visual, auditory and interactive data, TikTok identifies nuanced thematic and stylistic content connections, delivers highly tailored feeds and fosters viral phenomena[12,10]. This approach has proven effective in increasing engagement as users are continuously presented with content that resonates with their preferences.

Advancements in computer vision (CV) have enabled platforms such as Instagram and TikTok to personalise rich media experiences. CNNs analyse visual features, such as objects, colours and styles in images and videos. These insights, combined with engagement metrics, refine content recommendations and targeted advertising, resulting in more tailored user experiences[33,24]. For example, Instagram uses CV to personalise feeds and advertisements by analysing their visual similarity to previously engaged content. Furthermore, CV-driven object recognition allows precise ad placement within video content, aligning brand visibility with user interests, while minimising intrusiveness[12].

While AI-driven personalisation delivers significant benefits, it also raises critical ethical concerns. Overly optimised personalised feeds risk creating "echo chambers" or "filter bubbles", where users are repeatedly exposed to content that reinforces pre-existing beliefs while limiting exposure to diverse perspectives[38,34]. Such phenomena exacerbate polarisation and hinder the balanced access to information. Algorithmic bias compounds this challenge, as biases inherent in training data can amplify unequal representation or prioritise sensationalist content to drive higher engagement[34,12].

To address these issues, platforms are adopting measures to enhance transparency and diversity. Providing users with explanations of content-ranking decisions fosters trust and awareness[24]. Incorporating diversity-aware models ensures exposure to broader perspectives, mitigating the effects of echo chambers[33]. Additionally, enabling user-controlled feeds empowers individuals to balance personalised suggestions with exploratory content, fostering a richer and more diverse experience[7].

As policymakers and developers navigate these challenges, achieving a balance between user engagement and ethical responsibility remains a pressing priority. Ensuring fair, unbiased and transparent personalisation systems is critical to fostering user trust and safeguarding against manipulative practices, ultimately enabling a more inclusive and balanced digital ecosystem.

3.3. Education and Learning Tools

AI-driven personalisation in educational technologies effectively addresses the diversity of learning styles, backgrounds and paces among learners. Educational platforms leverage ML and NLP models to dynamically adapt curricula and offer personalised lesson sequences, reading materials and practice exercises tailored to individual performance[39,40]. Language learning applications like Duolingo utilise user progression data, including time spent per exercise, error patterns and vocabulary retention, integrating these insights into RL models to predict where learners might face challenges. By proactively recommending targeted drills or contextual explanations, these systems enhance learning efficiency and user satisfaction[41,42]. Gamification features such as streak rewards and level progression further promote engagement and autonomy, although limitations, such as the "heart system," have been noted for causing user frustration[42].

Advanced intelligent tutoring systems go beyond simple feedback mechanisms by simulating one-on-one tutoring experiences. These systems employ deep learning to deliver real-time adaptive hints, adjust difficulty levels dynamically and personalise educational pathways for each learner[43,44]. For example, RL agents analyse a learner's task history and knowledge state to select the next most effective learning activity, leading to measurable improvements in educational outcomes[44]. Conversational agents like CoACH, designed for language learning, utilise RL and deep knowledge tracing to incrementally personalise exercises. This ensures concepts are introduced based on a learner's current abilities, enhancing retention and motivation[44]. Additionally, adaptive assessments supported by AI provide real-time feedback, enabling the identification of learning gaps and recommending targeted interventions[40].

The ethical considerations surrounding AI-driven education technologies remain significant. Issues such as data privacy, algorithmic bias and the potential misuse of student data necessitate robust frameworks to ensure transparency and fairness[45]. Educators and developers must also strive to balance autonomy with guidance, avoiding over-reliance on gamified features or restrictive mechanisms that might hinder the learning experience[42].

Personalised learning paths, enabled by AI-driven analytics, have demonstrated remarkable potential in bridging the gaps inherent in traditional "one-size-fits-all" curricula. Platforms like Khan Academy and Duolingo exemplify how competency-based learning experiences can be delivered by combining educational content with adaptive technologies[46]. While the challenges of implementation and ethical concerns persist, the transformative potential of adaptive learning technologies in improving retention, understanding and learner autonomy underscores their value in modern education[47]. AI-driven personalisation redefines educational practices by tailoring learning experiences to the unique needs of each individual, marking a significant advancement in the field.

3.4. Health, Fitness and Wellness Apps

The health and wellness domain exemplify how AI-driven personalisation can be both beneficial and user empowering. Fitness tracking and health apps combine user-input data (such as goals and dietary preferences) with sensor-derived data (heart rate, step counts and sleep patterns) from wearables to deliver personalised workout plans, meal suggestions and meditation sessions[14]. These apps increasingly rely on ML and advanced sensor technology to offer real-time adaptive interventions that enhance user engagement and health outcomes[48].

For example, Fitbit uses ML to interpret activity metrics and provides custom recommendations aimed at improving user health outcomes. By analysing patterns over time, for example, if a user consistently fails to meet evening workout goals, these apps might suggest morning sessions or alternative activities that are more aligned with the user's schedule and energy levels. Similarly, AI-powered health platforms, such as Shae, assess individual phenotypes to deliver hyper-personalised health recommendations, yielding measurable improvements in cardiovascular health and overall wellness[49].

Mental health applications have also begun to personalise recommendations for mindfulness practices or cognitive behavioural therapy exercises guided by user engagement and self-reported mood states. Conversational AI in healthcare, exemplified by personalised health bots, has shown promise in offering tailored exercise routines while addressing challenges, such as scalability and algorithmic biases[50]. The direct user benefit is multifaceted; personalised fitness and wellness plans can improve adherence to routines, foster a sense of achievement and ultimately contribute to better health outcomes. AI-based nudging mechanisms, integrated with fitness apps, have demonstrated sustained behavioural changes, such as increased daily steps and moderate to vigorous physical activity, underscoring the potential of personalisation in public health contexts[51]. Users feel understood and supported rather than being pressured by generic or irrelevant suggestions.

3.5. Productivity and Utility Applications

Productivity and utility apps, including task managers, note-taking tools, calendar applications and communication platforms, have introduced personalisation to streamline user workflow. By understanding usage patterns, such as when a user is most active, which types of tasks they complete first or which contacts they frequently communicate with, these apps can offer context-aware reminders, surface-relevant documents or filter notifications to prioritise essential information.

For instance, a calendar app might learn that a user prefers to tackle certain tasks early in the morning, adjusting reminders to appear before this peak productivity window. A note-taking tool could suggest templates or tags based on previously accessed content, reducing cognitive load and helping users maintain better organizational habits. By tailoring these features to individual work styles, utility apps can enhance user satisfaction, reduce frustration and save time.

Real world applications of AI-driven personalisation transcend domains and use cases. Whether it's driving sales in e-commerce, boosting engagement in social media, fostering learning in education, promoting well-being in health and fitness or enhancing efficiency in productivity tools, personalisation has demonstrated its ability to add tangible value. However, as these practices continue to evolve, understanding their impact on user experience, privacy and societal norms remains a critical endeavour. The subsequent sections explore how to evaluate these influences and address emerging ethical considerations.

4. Evaluating the Impact of AI Personalisation on User Experience

As AI-driven personalisation becomes central to mobile application design, measuring its effect on user experience (UX) emerges as a critical step in validating the efficacy and value of these systems. This section examines key performance indicators (KPIs), experimental methodologies and comparative analyses employed to quantify the influence of personalisation on user engagement, retention, trust and overall satisfaction.

4.1. Key Performance Metrics

Quantifying the benefits of AI-driven personalisation often begins with tracking fundamental user engagement metrics. Indicators such as session length, depth of content consumption, time-on-app and interaction frequencies indicate whether personalised recommendations resonate with user interests[14,7]. For example, longer session durations and increased click-through rates (CTRs) suggest that users find curated content appealing, while repeated visits and heightened activity levels indicate sustained engagement[2]. Retention rates are another critical benchmark. Personalised apps aim not only to capture users momentarily but also to foster loyalty and reduce churn. A measurable improvement in daily active users (DAU), monthly active users (MAU) or returning visitor ratios often corresponds with the relevance of personalised features[8,52].

Conversion metrics, such as increased purchases in an e-commerce app or higher subscription uptake in streaming services, quantify the impact of personalisation on commercial goals. AI-powered recommendations, by surfacing products, content or services that closely match user preferences, increase the likelihood of users taking desired actions, thereby elevating key business outcomes like revenue and long-term customer value[19,53].

4.2. Experimental Evaluation: A/B Testing and Beyond

To rigorously assess how personalisation strategies enhance UX, developers and researchers employ controlled experiments, notably A/B testing[54]. In an A/B test, one subset of users (Group A) experiences a personalised interface, while another group (Group B) interacts with a baseline or less-personalised version of the app. Comparing engagement, retention and conversion metrics across these cohorts allows stakeholders to attribute differences directly to the introduction of personalised recommendations.

Multi-armed bandit algorithms further refine A/B testing by dynamically allocating traffic between variants, favouring more successful personalisation strategies in real-time[55]. Additionally, longitudinal studies that monitor user behaviour over extended periods provide richer insights into how personalisation influences user satisfaction and trust, capturing changes that may not emerge during short-term testing windows[56].

4.3. Qualitative User Feedback and Behavioural Analysis

Quantitative KPIs are essential, but qualitative feedback is crucial in evaluating personalisation. User surveys, app store reviews and interviews shed light on subjective factors, such as perceived relevance, ease of use and fairness of recommendations[3]. Sentiment analysis of textual feedback and user-generated content offers additional insights into emotional responses to personalised features[57]. Behavioural analysis refines this understanding by examining subtle signals, such as hesitations before clicks, partial content consumption or rapid task completion. For example, a productivity app might track whether a user swiftly completes the recommended tasks or frequently dismisses them, indicating how well personalisation aligns with the user's workflow.

4.4. Benchmarking Against Non-Personalised Methods

Evaluating personalisation's effectiveness involves comparing AI-driven systems with traditional recommendation methods or fixed-rule interfaces. For instance, a mobile news aggregator may benchmark its intelligent recommendation models against chronological feeds, showing that AI-driven personalisation results in higher CTRs, longer sessions and improved user satisfaction[24,58].

Benchmarking also reveals areas for improvement. By comparing AI-driven and non-AI systems, developers can quantify incremental value, justify investments in advanced algorithms and optimise data pipelines to further enhance personalisation capabilities[53].

4.5. Holistic Appraisal: Balancing Quantitative and Qualitative Measures

A comprehensive evaluation strategy synthesises both quantitative and qualitative metrics. While improved engagement and retention provide hard evidence of the impact of personalisation, positive user sentiment, trust and perceived relevance ensure that these effects are sustainable and ethically grounded[15,16].

Balancing efficiency (e.g. rapid increases in CTRs) with ethical considerations (e.g. avoiding manipulative recommendations) ensures that personalisation strategies responsibly serve users and developers. Such holistic evaluations guide the continuous refinement of algorithms, ensuring that AI-driven personalisation fosters trust, transparency and long-term value.

5. Ethical and Privacy Considerations

As AI-driven personalisation technologies become increasingly sophisticated and pervasive, questions arise regarding their ethical implementation and the protection of user rights. While personalisation can enhance user experience and drive engagement, it also poses significant challenges related to data privacy, algorithmic fairness and transparency. Addressing these concerns is essential for ensuring responsible and sustainable deployment of personalised systems in mobile applications[15,16].

5.1. Data Privacy and User Consent

Personalisation engines heavily depend on user data, including explicit feedback (e.g. ratings, likes) and implicit signals (e.g. browsing patterns, session durations and location history). However, the collection and storage of these data raises critical risks, such as unauthorised access, data leakage and misuse of personal information[15,53]. High-profile breaches in centralised databases that store sensitive user profiles have demonstrated potential to undermine user trust and cause reputational damage to service providers. Privacy-enhancing technologies (PETs) have emerged as critical tools to mitigate these risks. Federated learning, for instance, allows models to train locally on user devices, transmitting only aggregated updates to a central server without exposing raw data[18]. Differential privacy introduces controlled noise into datasets, ensuring that individual contributions remain confidential while preserving the utility of the aggregated results[15]. These techniques enable high-quality personalisation, while safeguarding user confidentiality.

Additionally, user-centric consent mechanisms such as granular data-sharing preferences and transparent privacy settings empower users to make informed decisions about how their data are used[17]. For example, applications such as MyFitnessPal incorporate intuitive consent flows, enabling users to understand and control their data's role in personalisation processes[57].

5.2. Algorithmic Fairness and Bias

Algorithmic bias arises when personalisation models systematically favour or disadvantage specific groups of users, content creators or item categories. For example, recommendation engines trained on skewed datasets may disproportionately favour content aligned with dominant demographics, marginalising minority groups[59]. Similarly, personalised content feeds risk reinforcing stereotypes or creating "filter bubbles, which limit users' exposure to diverse perspectives[38].

Mitigating bias requires targeted interventions at multiple stages of the model's development life cycle. Pre-processing methods, such as balancing training datasets and in-processing techniques, such as fairness-aware algorithms, can reduce bias during training[60]. Post-processing adjustments to model outputs further ensure equitable treatment across user groups. Metrics like equalised odds or disparate impact measures enable developers to quantify and rectify imbalances in recommendation outcomes[61]. Fairness is a technical and social challenge. Inclusive personalisation systems not only broaden content exposure but also foster trust and inclusivity, ultimately enhancing user satisfaction and loyalty.

5.3. Transparency and Explainability

Users are more likely to trust and engage with personalised recommendations when they understand how these suggestions are generated. However, the complexity of modern machine learning models often renders the decision-making process opaque[62]. Explainable AI (XAI) techniques have been developed to address this opacity. For instance, simple explanations like "You received this recommendation because you watched similar videos" or visual insights into feature importance can demystify the logic behind recommendations. Advanced XAI methods, such as feature attribution algorithms, highlight the most influential user interactions or content attributes shaping personalised decisions[63].

Transparency also benefits developers, regulators and auditors. Detailed documentation of algorithms, data usage policies and model architectures enables stakeholders to identify compliance issues, mitigate biases and refine personalisation frameworks[17]. Platforms, such as Netflix, have successfully implemented user-facing explainability tools, increasing trust without overwhelming users with technical details[57].

5.4. Regulatory Compliance and Emerging Standards

The evolving regulatory landscape underscores the importance of ethical personalisation practices. Frameworks like the European Union's General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA) impose stringent requirements on data collection, user consent and the explainability of automated decisions[16,53]. These regulations encourage the adoption of privacy-preserving methods, user-friendly consent flows and mechanisms by which users contest or review algorithmic decisions.

Companies are now adopting privacy-first design principles to align with these framework s, ensuring compliance while maintaining innovation. Emerg ing industry standards, such as ISO/IEC guidelines for AI governance, provide additional guidance for balancing techno logical advancement with ethical considerations. Align ing personalisation systems with such principles not only ensu res legal compliance but also builds user trust and fosters sustainable growth. Ethical and privacy considerations form a critical dimension of AI-driven personalisation. Challenges s uch as data privacy, algorithmic bias and transparency must be addressed using a combination of privacy-preserving techniq ues, fairness-aware algorithms and XAI methods. Adhering to evolving regulatory standards ensures responsible deployment, while fostering user trust and satisfaction. By proactively addressing these issues, developers and organisations can ensure that personalisation enhances user experiences without comp romising fundamental rights or societal values.

6. Future Directions and Opportunities

The rapid evolution of AI-driven personalisation in mobile device applications underscores the immense potential for further innovation. As models become more adept at interpreting user intent, context and preferences, emerging techniques promise enhanced adaptivity, improved fairness and more holistic user experiences. This section explores key frontiers in personalisation research, focusing on advanced AI models, context-aware approaches, computational efficiencies and the integration of responsible AI practices.

6.1. Advanced Deep Learning Models and Multimodal Personalisation

Future personalisation frameworks integrate diverse data modalities, such as text, images, audio and video, to create richer user profiles and more nuanced prediction[7]. Transformer-based architectures, such as BERT and GPT, which are capable of capturing long-range dependencies and contextual nuances, have already demonstrated significant success in improving recommendation systems[64,24]. These models promise to enhance user engagement by offering explanations and personalised suggestions that are contextually relevant and emotionally resonant[63].

Multimodal personalisation holds transformative potential in applications such as e-commerce and entertainment. For instance, analysing a combination of user queries, product images and reviews can provide precise and tailored recommendations for online shoppers[53]. Similarly, entertainment platforms could leverage sentiment analysis and emotion recognition (within ethical and legal boundaries) to adapt content dynamically, enriching user satisfaction[65].

Static user profiles, although useful, often fail to account for the fluid nature of human preferences and environments. Dynamic contexts such as location, time of day, user mood and current activities can significantly enhance the relevance of recommendations[14]. Incorporating sensor data from GPS, accelerometers and wearable devices, along with external information such as weather forecasts or local events, enables apps to achieve situational awareness and adapt to users' needs in real-time.

For example, a fitness app might suggest exercises tailored to outdoor conditions, whereas a music streaming platform could curate playlists aligned with a user's commute duration and mood (Chiam et al., 2024)[51]. Such capabilities ensure that recommendations are not only personalised but also situationally appropriate, thereby deepening user trust and satisfaction.

As personalisation models gro w increasingly complex, ensuring computational efficiency becomes a priority, particularly for mobile applications. Techniques such as model compression, distillation and quantisation enable deep learning models to run locally on devices, reducing latency and enhancing user privacy[26]. By moving inference to the edge, these optimisations eliminate the need for constant cloud-based communication, conserving device resources and ensuring real-time responsiveness.

"Edge AI" represents a significant shift towards decentralised personalisation, aligning with privacy-conscious trends by minimising data transmission. This approach not only safeguards sensitive information, but also facilitates instantaneous feedback loops, ensuring that user experiences remain seamless and adaptive[18,48].

As personalisation technologies become more pervasive, the need for ethical AI practices has grown. Researchers and developers are exploring fairness constraints that can be integrated into training objectives, ensuring equitable treatment across diverse user groups without compromising accuracy[60,61]. This focus on fairness aligns with emerging regulatory frameworks such as the GDPR and CCPA, which advocate transparency and accountability in automated decision-making processes[16,53].

Explainable AI (XAI) techniques are also advancing, offering users clearer and more intuitive insights into the decision-making processes behind personalised recommendations. For example, feature attribution methods can highlight user interactions or contextual factors that influence specific recommendations, foster trust and reduce suspicion. These innovations not only improve user satisfaction but also enhance regulatory compliance, enabling organisations to navigate complex governance landscapes effectively.

Proactively adopting responsi ble AI practices presents organisations with opportunities to differentiate themselves. By embedding ethics into their personalisation strategies, developers can position their solutions as trustworthy and user-centric, setting benchmarks for indust ry-wide standards. AI-driven personalisation stands at the cusp of a transformative era, driven by multimodal data int egration, contextual intelligence, computational advancements an d responsible AI innovations.

As developers refine these systems, balancing technical sophistication with ethical considerations is critical for ensuring sustainable growth. Organisations can revolutionise the concept of personalisation in creating significant, just and credible interactions by capitalising on these nascent possibilities, whilst simultaneously elevating user experiences.

7. Conclusion

AI-driven personalisation represents a paradigm shift in how mobile applications interact with users, advancing from static, generic interfaces to dynamic, context-sensitive systems. This paper has examined the role of ML and deep learning techniques in enabling such transformations, highlighting their applications across diverse domains such as e-commerce, social media, education and health[2,7]. By leveraging multimodal inputs and contextual signals, AI has redefined user experience, fostering engagement, retention and satisfaction.

Through the exploration of foundational algorithms, neural architectures and advanced evaluation methodologies, this study has underscored the transformative potential of AI-driven personalisation while addressing challenges related to data privacy, algorithmic fairness and transparency[15,17]. New approaches, such as multimodal models and transformer-based architectures, have demonstrated significant success in understanding user preferences and delivering adaptive and precise recommendations[53].

The shift towards computational efficiency and on-device inference further ensures scalability and privacy-preserving practices. Techniques such as federated learning, model quantisation and edge computing allow personalisation to occur closer to the user, reducing latency and safeguarding sensitive data[18,53]. These innovations not only enhance responsiveness, but also align with ethical AI principles, fostering user trust and long-term engagement.

Explainable AI (XAI) and fairness-aware frameworks play a crucial role in addressing biases and ensuring inclusivity. By providing users with transparent insights into the logic behind recommendations, these methods help build trust and meet regulatory requirements, such as GDPR and CCPA. Moreover, these frameworks support equitable treatment across diverse user groups, ensuring that personalisation remains a tool for inclusion, rather than exclusion.

Looking ahead, AI-driven personalisation is set to evolve further, integrating ethical practices with technological advancements. Stakeholders, including researchers, practitioners and policymakers, must collaborate to ensure that innovation aligns with human-centric values. Through responsible adoption of opportunities, they can maximise the benefits of personalisation to enhance digital environments, providing not just user engagement and contentment, but also fostering confidence and diversity.

8. References

1. Smith J, Johnson L. The Rise of Mobile Applications and User Engagement Patterns. Journal of Digital Innovation, 2019;12:45-60.
2. Gómez-Uribe CA, Hunt N. The Netflix Recommender System: Algorithms, Business Value and Innovation. ACM Transactions on Management Information Systems, 2015;6:1-19.
3. Ricci F, Rokach L, Shapira B. Recommender Systems Handbook. Springer, 2015.
4. Balasubramanian G The Role of AI in Enhancing Personalization in E-commerce: A Study on Customer Engagement and Satisfaction. Asian and Pacific Economic Review, 2024;17.
5. Maduku DK, Rana NP, Mpinganjira M, Thusi P, Mkhize NH. Do AI-Powered Digital Assistants Influence Customer Emotions, Engagement and Loyalty? An Empirical Investigation. Asia Pacific Journal of Marketing and Logistics, 2024;36:2849-2868.
6. Ding L, Antonucci G, Venditti M. Unveiling User Responses to AI-Powered Personalised Recommendations: A Qualitative Study of Consumer Engagement Dynamics on Douyin. Qualitative Market Research, 2024.
7. Zhang Y, Yang Q, Yu H, Zhang J, Ma M. AI-Driven Personalization Systems: A Review of Machine Learning Applications. Journal of Artificial Intelligence Research, 2019;25:45-58.
8. Hu Y, Koren Y, Volinsky C. Collaborative Filtering for Implicit Feedback Datasets. Proceedings of the IEEE International Conference on Data Mining, 2008.
9. Nama P. AI-Powered Mobile Applications: Revolutionizing User Interaction through Intelligent Features and Context-Aware Services. Journal of Emerging Technologies and Innovative Research, 2023;10.
10. Zhang Z, Chen L. Context-Aware Personalisation in Mobile Applications: A Deep Learning Approach. IEEE Transactions on Mobile Computing, 2020;19:1320-1335.
11. Xia Y, Liu Z, Wang S, Huang C, Zhao W. Unlocking the Impact of User Experience on AI-Powered Mobile Advertising Engagement. Journal of the Knowledge Economy, 2024.
12. Raji MA, Olodo HB, Oke TT, Addy WA, Ofodile OC, Oyewole AT. E-Commerce and Consumer Behavior: A Review of AI-Powered Personalization and Market Trends. GSC Advanced Research and Reviews, 2024;18:66-77.
13. Ahmed M. Assessing AI-Powered Personalization Strategies for Mid-Sized Finnish Fashion E-commerce: Enhancing Consumer Engagement and Conversion Rates. Haaga-Helia University of Applied Sciences, 2024.
14. Huang G, Zhao Y, Xu J, Wang L. AI-Driven Context-Aware Mobile Applications: Enhancing Personalisation through Sensor Data Integration. Journal of Mobile Computing Innovations, 2020;15.
15. Dwork C, Roth A. The Algorithmic Foundations of Differential Privacy. Foundations and Trends in Theoretical Computer Science, 2014;9:211-407.
16. Veale M, Binns R. Fairer Machine Learning in the Real World: Mitigating Discrimination Without Collecting Sensitive Data. Big Data & Society, 2017;4:1-17.
17. Pasquale F. The Black Box Society: The Secret Algorithms That Control Money and Information. Harvard University Press, 2015.
18. McMahan HB, Moore E, Ramage D, Hampson S. Communication-Efficient Learning of Deep Networks from Decentralised Data. Proceedings of the 20th International Conference on Artificial Intelligence and Statistics, 2017.
19. Koren Y, Bell R, Volinsky C. Matrix Factorization Techniques for Recommender Systems. IEEE Computer, 2009;42:30-37.
20. Cheng C, Yang H, Zhang S, Zhou C, Yang Y. Hybrid Recommender System: Combining Collaborative Filtering and Content-Based Approaches. Journal of Artificial Intelligence Research, 2016;22:76-92.
21. Lops P, de Gemmis M, Semeraro G. Content-Based Recommender Systems: State of the Art and Trends. In Recommender Systems Handbook, 2011;73-105.

22. Hrytsenko V, Tkachenko A, Podolyan O, Dieiev K, Ilyn L. The Role of Artificial Intelligence in Personalising Learning. Revista, 2024;21.
23. He X, Zhang H, Kan M, Chua TS. Neural Collaborative Filtering. Proceedings of the 26th International Conference on World Wide Web, 2017.
24. Sun F, Liu J, Wu J, Pei J, Zhang S. BERT4Rec: Sequential Recommendation with Bidirectional Encoder Representations from Transformers. Proceedings of CIKM, 2019.
25. Tkachenko A, Hrytsenko V, Podolyan O, Dieiev K. AI in Education: Personalising Student Learning Using Machine Learning Techniques. Revista, 2024;21.
26. Han S, Mao H, Dally WJ. Deep Compression: Compressing Deep Neural Networks with Pruning, Trained Quantisation and Huffman Coding. Proceedings of ICLR, 2016.
27. Tan AZ, Yu H, Cui L, Yang Q. Towards Personalised Federated Learning. IEEE Transactions on Neural Networks and Learning Systems, 2023.
28. Arivazhagan M, Aggarwal V, Singh AK, Choudhary S. Federated Learning with Personalization Layers. Proceedings of AISTATS, 2019.
29. Pillutla K, Malik K, Mohamed A, Rabbat M, Sanjabi M. Federated Learning with Partial Model Personalisation. Proceedings of ICML, 2022.
30. Kulkarni V, Kulkarni M, Pant A. Survey of Personalisation Techniques for Federated Learning. IEEE, 2020.
31. Hanif M, Khan MMH, Acharjee UK, Ahamed M. Smart E-Commerce Shopping: Innovations, Challenges and Future Trends. International Journal of Business, Social and Scientific Research, 2024.
32. Rutten L. Developing AI Models for Personalized Shopping Experiences in Retail. Hong Kong Journal of AI and Medicine, 2023.
33. Ajiga DI, Ndubuisi NL, Asuzu OF, Owolabi OR, Tubokirifuruar TS. AI-Driven Predictive Analytics in Retail: A Review of Emerging Trends and Customer Engagement Strategies. International Journal of Management & Entrepreneurship Research, 2024.
34. Amil Y. The Impact of AI-Driven Personalization Tools on Privacy Concerns and Consumer Trust in E-Commerce. HEC-Ecole de Gestion de l'Université de Liège, 2024.
35. Nodirovna MS. E-Commerce Trends: Shaping the Future of Retail. Open Herald: Periodical of Methodical Research, 2024.
36. Ntumba C, Aguayo S, Maina JK. Revolutionising Retail: A Mini Review of E-Commerce Evolution. Journal of Digital Marketing and Communication, 2023;3:100-110.
37. Covington P, Adams J, Sargin E. Deep Neural Networks for YouTube Recommendations. Proceedings of the 10th ACM Conference on Recommender Systems, 2016.
38. Pariser E. The Filter Bubble: How the New Personalized Web Is Changing What We Read and How We Think. Penguin Press, 2011.
39. Knewton. Adaptive learning technologies for personalised education. Retrieved from Knewton's Website, 2018.
40. Ayeni OO, Al Hamad NM, Chisom ON, Osawaru B, Adewusi OE. AI in education: A review of personalized learning and educational technology. GSC Advanced Research and Reviews, 2024;18:261-271.
41. Settles B, Meeder B. A trainable spaced repetition model for language learning. Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (ACL), 2016.
42. Saniyah SM. Duolingo and learner autonomy: Investigating the role of personalization and gamification in promoting self-directed language learning. English Journal of Education and Literature, 2023;2:141-147.
43. Anderson JR, Koedinger KR. Cognitive tutors: Lessons learned. The Journal of the Learning Sciences, 2017.
44. Whitehall B, et al. CoACH: An Interactive Conversational Agent to Aid Human Learning. Proceedings of the 2023 Neural Information Processing Systems Conference, 2023.
45. Klimova B, Pikhart M, Kacetl J. Ethical issues of the use of AI-driven mobile apps for education. Frontiers in Public Health, 2023;10.
46. Beatrice SE. Personalized Learning Paths: Leveraging Data Analytics for Tailored Education. Journal of Educational Data Science, 2024.
47. Li Z, Bonk CJ, Zhou C. Supporting learners' self-management for self-directed language learning: A study within Duolingo. Interactive Technology and Smart Education, 2024;21:381-402.
48. Palakurti NR. AI-Driven Personal Health Monitoring Devices: Trends and Future Directions. ESP Journal of Engineering & Technology Advancements, 2023;3:41-51.
49. McNulty E, Smith JP, Lee AR. Phenotype-Based Personalised Health Management: Leveraging AI to Improve Cardiovascular Outcomes. Global Health Advances, 2024.
50. Negi ST, Sinha A, Singh MK, Bagaria MK, Shrivastava K. Optimising Wellness: A Comprehensive Examination of a Conversational AI-Driven Healthcare Bot for Personalised Fitness Guidance. Proceedings of ICAIHI, 2023.
51. Chiam M, Tan J, Lim K. AI-Driven Nudging Mechanisms for Behaviour Change in Fitness Apps. International Journal of Public Health Innovations, 2024.
52. Zhou X, Liu H, Wang Y. Adaptive User Interfaces: Enhancing UX Through AI-Driven Personalisation. Journal of Intelligent Systems Design, 2024.
53. Paripati N, Verma R, Kumar S. The Role of AI in Driving Engagement Through Personalisation Metrics. Journal of Emerging AI Technologies, 2024.
54. Kohavi R, Longbotham R. Online Controlled Experiments and A/B Testing in Personalisation Systems. Proceedings of KDD, 2017.
55. Slivkins A. Introduction to Multi-Armed Bandits. Foundations and Trends® in Machine Learning, 2019;12:286.
56. Burlacu A. Algorithmic Bias and Fairness in AI Personalisation: Strategies for Inclusive Design. Proceedings of the International Symposium on AI Ethics, 2024.
57. Bhuiyan M. AI-Driven Personalisation in Customer Service: Balancing Trust and Satisfaction. International Journal of Customer Relationship Management, 2024.
58. Stige K, et al. Streamlining User Experience Design with AI Personalisation: Challenges and Insights. Proceedings of the International UX Symposium, 2024.
59. Noble SU. Algorithms of Oppression: How Search Engines Reinforce Racism. NYU Press, 2018.
60. Mehrabi N, Morstatter F, Saxena N, Lerman K, Galstyan A. A Survey on Bias and Fairness in Machine Learning. ACM Computing Surveys, 2021.
61. Biega AJ, Gummadi KP, Weikum G. Equity of Attention: Amortizing Individual Fairness in Rankings. Proceedings of SIGIR, 2018.
62. Doshi-Velez F, Kim B. Towards a Rigorous Science of Interpretable Machine Learning. Nature Machine Intelligence, 2017.
63. Shin D. The Role of Explanations in AI-Supported Decision-Making: Transparency, Trust and User Satisfaction. Computers in Human Behavior, 2021;120.

64. Devlin J, Chang M, Lee K, Toutanova K. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. Proceedings of NAACL-HLT, 2019.

65. Vondrick C, Pirsiavash H, Torralba A. Anticipating Visual Representations from Unlabelled Video. Proceedings of CVPR, 2016.