



(RESEARCH ARTICLE)



# AI-powered personalization: How machine learning is shaping the future of user experience

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## Abstract

AI is changing the face of user interaction in almost every niche, including e-Commerce, social networks, and SaaS. With the help of incredible computing techniques, AI is making it possible to deliver the right content, recommendations and interacting results in front of users according to their preferences. This work discusses how personalization has developed in virtual space, from simple recommendations to subsequent and sophisticated prediction patterns. It often focuses on e-commerce sites, social networks, and SaaS applications in which user targeting, product recommendations, variable pricing, content management, and advertising contribute to customer interest. AI makes a customer's experience smoother and more efficient by presenting products and services in a way that seamlessly meets and, in many cases, exceeds their expectations as well as the needs of the business. Nevertheless, this article also discusses issues such as data protection, the problem of algorithm inclination, and the rapidly evolving question of values inherent within deep data mining.

**Keywords:** Artificial Intelligence; Social Network; Machine Learning; User Interaction; GDPR

## 1. Introduction

AI and machine learning are considered indispensable in today's digital age, and they allow firms to devise structures that can learn independently. The key difference, compared to conventional applications, where a process needs to be taught how to execute a process, is that AI and ML processes enable systems to learn a lot of data and come up with conclusions independently. It has led to the creation of super systems that can perform arduous activities that earlier required human intellect and hard work, such as natural language understanding, image identification or even facial and autonomous driving. (Russell & Norvig, 2010). AI is considered a machine's ability to mimic human intelligence in various activities, including learning. At the same time, ML is a form of AI that produces algorithms that could enable a machine to make decisions with the assistance of data provided (Goodfellow, Bengio, & Courville, 2016).

By combining AI and ML into the technologies within modern society, several improvements in the functionalities of various applications have occurred. For example, in the healthcare sector, these technologies are used to accurately detect and diagnose diseases, develop patient-specific treatment strategies, and manage workflow and operations (Esteva et al., 2019). In the financial industry, AI algorithms are applied for fraud detection, credit risk evaluation and algorithmic trading, changing industry dynamics (Heaton, Polson & Witte, 2017). Moreover, ML models are essential in the cybersecurity industry to address complex cyber threats by analyzing patterns in traffic datasets that might indicate an attack (Buczak & Guven, 2016).

AI and ML have also exercised the potential for self-enhancement, another reason for developing auto systems. As another example, self-driving cars require biochemical neural networks to decipher the images and infer in a few

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microseconds about the vehicle's decisions and actions about its environment (Levinson et al., 2011). Likewise, in robotics, AI and ML help robots to perform tasks like object recognition, manipulation, and interaction in environment structures, which enhances its usage in manufacturing, logistics, and even in home automation (Kragic et al., 2018).

However, there are various limitations to AI & ML usage in today's developed technology. All the privacy, transparency, and ethical implications still make headlines. The cases when trained algorithms turn into bigotry due to bias in the data or model construction became worrisome as it deepens the problem rather than solves it in certain spheres, for example, crime prediction or employment choices (Angwin et al., 2016). However, the so-called "black box" problem related to some AI algorithms hampers attempts to explain the mechanisms behind these systems and build trust in their functioning, thereby aiding their broader implementation (Doshi-Velez & Kim, 2017).

### **1.1. The Rising Importance of User Experience (UX) Enabled by AI**

Artificial Intelligence (AI) is now widely accepted to improve UX, making interactions with systems more friendly, effective, and natural. UX is a broader concept than usability, covering the totality of the customer's experience, which includes emotional and physical aspects of use and the service delivery process. AI plays a significant role in enhancing those aspects by using real-time data analysis techniques, machine learning algorithms and NLP techniques to predict the behaviour and interest of users (Hassenzahl & Tractinsky, 2006). Switching user's experience, AI helps increase involvement, satisfaction, and user loyalty, which helps optimize the general user experience.

The first way that AI impacts UX is the most important: personalization. Due to user data like browsing history, purchase history and engagement, AI systems can suggest relevant products to users and content to share. This personalization level is prevalent in developing e-commerce platforms where recommendation systems recommend products according to user interactions, increasing the likelihood of buying options and ensuring the consumer is delighted (Ricci, Rokach & Shapira, 2015). Similarly, in social media communities, AI patterns feed streams to provide relevant content that is despotic to meet the intended users' objective and keep them immersed for as long as possible (Kaplan & Haenlein, 2010).

Another area where AI has significantly impacted UX is using virtual assistants and chatbots to improve system-user relations. These tools issue on-the-fly responses tuned to specific contexts, which can effectively provide related and fast responses to user queries and requests. For example, Siri, Alexa, and Google Assistant are virtual assistants that use natural language processing and machine learning algorithms, which allow the device to interpret the user commands and execute them like setting reminders, playing music, answering asked questions or making technology readily available and interactive (Hoy, 2018). In this respect, the intuitive interaction decreases user complexity as every user operation can be completed smoothly without any hindrances.

Accessibility is another crucial use of AI that enhances the inclusivity of online platforms. AI can support disabled people in using websites and applications with the help of specific technologies like image recognition, speech-to-text, and many more. For example, an integration of a screen reader helps visually impaired persons to translate texts displayed on the screen into speech, while automatic caption and translation allow users to get content in the desired language (Moran, 2016). These capabilities ensure a broad and diverse community can access and benefit from various digital arenas. This underscores the promise that AI will make online spaces more accommodating to everyone by visualizing an empathetic environment.

AI often increases the level of UX, but its integration has a hitch. The big data brings a significant problem: the user identity and the information used to train AI models. However, one must realize that the same algorithm may harbour some bias that could ultimately affect the target user detrimentally when she is from a minority. For example, learning with data containing prejudice could result in the recommendation system recommending prejudice despite having no logical foundation or not recommending some users despite specific recommendation criteria (Noble, 2018). However, with these challenges, AI also presents solutions. Incorporation of ethical practices includes the use of diverse datasets, incorporation of ethical practices when developing the organization's AI models, transparency of all decisions made by AI models, and the promoters of the use of AI must ensure that the adverse impacts that may occur will be disadvantageous to the user. This gives us the confidence that AI can create positive change with UX in the future.

### **1.2. Problem Statement**

There are three different typical ways to achieve a personalized user experience. However, the problem with these three types of methods is that they have two significant drawbacks: scalability and flexibility compared to AI and ML. Often, such fundamental approaches employ a prescriptive model or rudimentary segmenting that categorizes users into a broad bin of age or behaviour track history. As such, these methods are helpful for customization to a

lesser degree because they have a different level of detail and are more dynamic than individual users (Adomavicius & Tuzhilin, 2005). Thus, users get main content and recommendations that do not personally interact with their interests and activities, and they get bored and unsatisfied. The first shortcoming of the previously used personalization strategies is that extensive data collection, analysis, and use occurs in real-time. Solving most problems accompanying typical systems is almost impossible since most systems use models that cannot be changed during runtime to accommodate new user behaviours and preferences.

For instance, a rule-based recommendation system in an e-commerce platform to assist the user with an item recommendation based on their previous purchases can only do this but lacks the knowledge of new interests or context awareness such as seasonality or events (Ricci, Rokach, & Shapira, 2015). This rigidity leads to the provision of wrong or irrelevant recommendations to the users, a loss of confidence, and incapacities in the service being utilized.

Traditional personalization techniques need to scale better in terms of the rich contexts and varied digital spaces that are the hallmarks of the current digital ecosystem. The fact that users engage with multiple devices and interfaces creates a unique challenge in providing a combined and integrated personalized experience. Traditionally, conventional systems do not capture the interactions that have happened in different touch points in an integrated manner and provide inconsistent experiences across various touchpoints, including social media interactions, mobile app usage, and website browsing history (Bodapati, 2008). This lack of cohesion can be especially critical within the omnichannel context, as a consistent user experience across available channels is necessary for high user engagement and loyalty.

It's also the colossal disadvantage that traditional approaches to personalization consume resources in greater quantity. Rule-based/mechanical systems or manually segmented ones could take significant time and resources from marketers and developers to maintain or adjust frequently due to user data changes. This manual approach is time-consuming, error-prone, and driven by the human expert's rules of thumb, hunches, and experience (Jannach et al., 2011). However, often, such systems fail to support themselves for many users, so they do not find their applications in many user-based digital platforms and services.

The absence of methods to apply personalization to business production activities eliminates, in fact, negative impacts on business outcomes. Generic user experiences lead to lower user engagement, higher bounce rates, and lower conversion rates since the content, products, and services offered are not relevant to consumers' needs and wants. On the other hand, the use of customization through artificial intelligence can significantly improve user perception and loyalty to a site or service. Such a discernible divergence underlines the urgent need to harness AI and ML to satisfy emerging consumer expectations of highly elastic and configurable mass customization.

### **1.3. Objectives**

To establish the practical implications of this work, the following research objectives would be achieved:

1. Understand how Machine Learning concepts are applied in the context of personalisation across multiple interfaces.
2. See how the different personalization resulting from ML affects the User Experience commonly referred to as UX.
3. Analyse the advantages and disadvantages of using ML for personalisation: separate technical and ethical issues.
4. forecast for this approach in the future of using ML to create the personalization factor for UX can be made as the way forward.

### **1.4. Scope and Significance**

This article is dedicated to personalisation, which is based on the reinvention of artificial intelligence to improve the customer experience in different business sectors, including electronic business, social media, and software as a service. This paper discusses the application of machine learning to personalize the interaction, content, and services to the user to enhance the user's interaction, satisfaction, and loyalty.

This study is significant because it evaluates the pros and cons of using AI for personalization. The article outlines the crucial importance of AI in satisfying today's users' expectations by focusing on transforming user interactions with the help of AI, such as recommendations, content filtering, and interfaces. It also considers data protection, various ethical

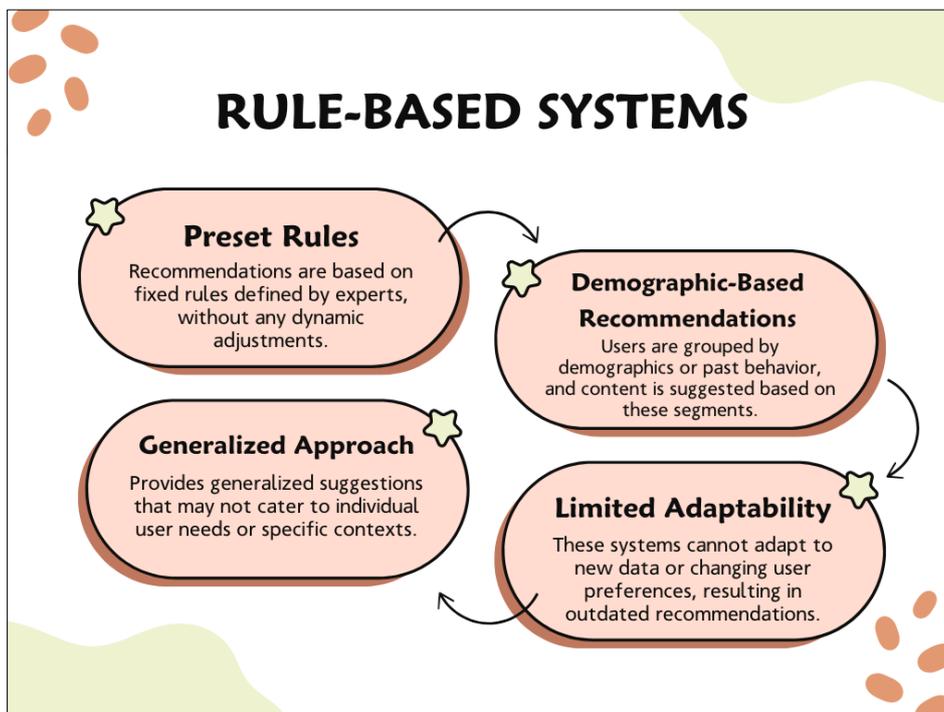
issues, and the need for regulated AI practices, which could serve as an informative resource for businesses seeking to use AI to enhance user experience.

## 2. Literature review

### 2.1. Evolution of Personalization Techniques

The development and enhancement of personalization methods have also progressed from the dependence on rule single methodology to a more advanced and integrated artificial intelligence. Rule-based systems, which were amongst the first to be employed for personalization, are developed by domain specialists with preset rules. Of them, the mechanisms discussed in the first type of systems split up consumers and provide them content/recommendations to purchase based on demographic or prior related characteristics. Being solely based on rules, these systems quickly get bored, so to speak, failing to adapt to the further shift of user preferences or to switch to a different context in which a recommender is used, providing a more general, less personalized approach toward the users (Ricci et al., 2015).

As the morphology of digital environments became more sophisticated and the users' demand for relevant content diversified, the shortcomings of relying solely on rules became apparent. They failed to cope with real time user generated data or be able to adapt their recommendations based on new data as it was uploaded into the system. This created the need for incremental advancement of personalization methodologies that would improve on the ability to monitor and feedback user behaviour at a finer level. Overall AI concepts along with ML helped improve the advancements of personalisation technology.. These systems use algorithms that can develop an understanding of user information by looking for the patterns and trends not found in conventional if-then decision-making trees (Adomavicius & Tuzhilin, 2005).

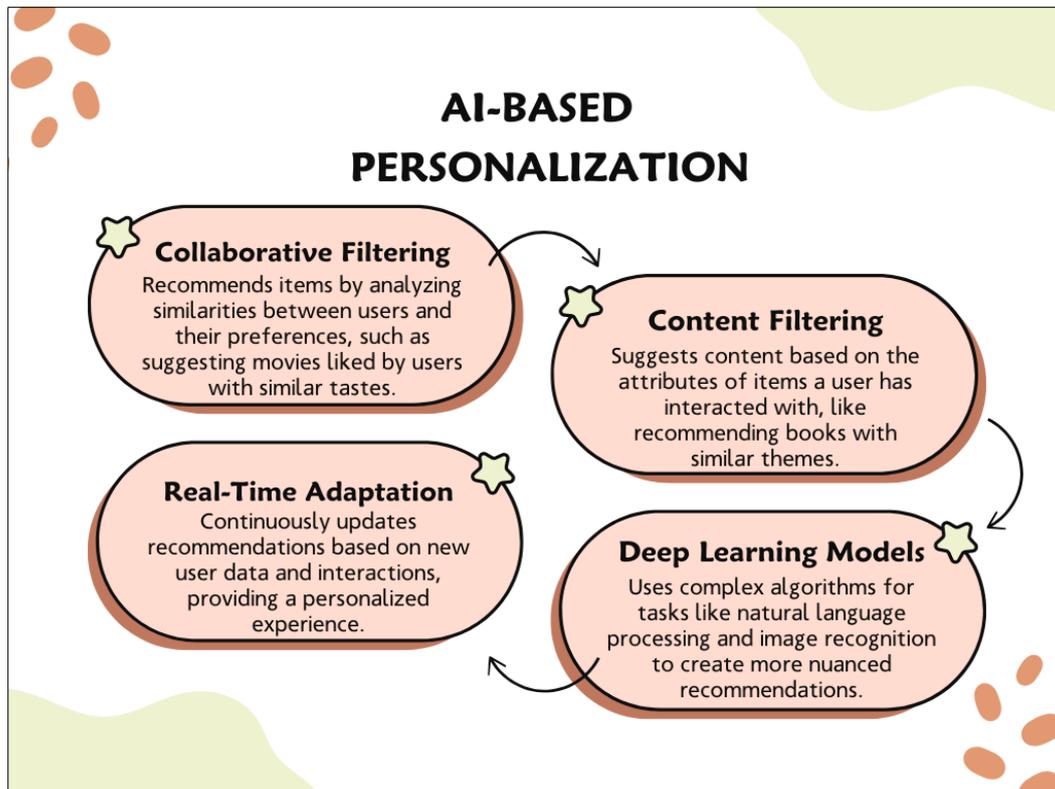


**Figure 1** Diagram of Rule-Based Personalization Techniques

AI personalization uses concepts under the ML algorithm, including collaborative and deep learning, to provide individual user experiences. For example, collaborative filtering evaluates the similarities of users and items to recommend items preferred by similar users, or content filtering compares the features of the items on which the user interacts to suggest related content. These models can update their recommendations every time new data is received; thus, they can update user preferences in real time (Koren, Bell, & Volinsky, 2009). Deep learning models, in contrast, are well suited to answering questions about user interactions and situations and are commonly applied in NLP and image identification for personalized content curation (Zhang, Y., & Yang, Q., 2017).

What used to be a rigid and systematically determined rule of recommendation has been improved dramatically as platforms implement more adaptive AI opinions. For instance, in an e-commerce context, an AI model can use customer browsing behaviour, previous purchasing trends, and even current trends to predict products that customers need. Likewise, in social networks, AI algorithms could suggest more relevant content feeds to users, which will lead to a better and more engaging user experience (Ricci et al., 2015).

However, there are the following challenges of applying personalization based on AI: Topics like privacy, fairness, and explanation have not become any less important, even if their implementation has improved. AI models rely on the quality and richness of data taken as a basis for the model, and thus, data prejudice will lead to prejudiced recommendations which neglect or stereotype certain users (Noble, 2018). Furthermore, since these models are often complex, it becomes hard to have flexibility in how they are built, and even more importantly, it raises legitimacy questions on how specific recommendations are generated (Doshi-Velez & Kim, 2017).



**Figure 2** Diagram of AI-Based Personalization Techniques

## 2.2. Machine Learning Algorithms in Personalization

Recommendations based on users' information are the cornerstone of customer experience customization. These recommendations, powered by machine learning algorithms that process vast amounts of user data, are instrumental in enhancing user satisfaction. Among the most popular methods are collaborative filtering, content-based filtering, and hybrid filtering.

Collaborative filtering has been frequently applied to personalized recommendations and is still one of the most common algorithms. It attempts to find user likenesses or in the items/records the user is interested in. Collaborative filtering primarily comprises two categories: user-based and item-based. User-based CF has a nearer resemblance with other users who have similar behaviour in their transactions and recommends items that similar users prefer. Collaborative filtering based on items suggests similar items a user has used and compares them with comparable items that other users prefer. This approach allows for making recommendations without understanding the items to be recommended. However, the above method leans exclusively on users' users' interactions (Ricci et al., 2015). However, we must recognize that collaborative filtering has disadvantages, such as cold start problems while working with new users or items with low rates to create profiles.

Comparing to Collaborative Filtering Content-based filtering is valuable method but also have some disadvantages. Interestingly, in so doing, it does not take into consideration other users behaviour but rather the characteristics of items. This approach suggests items that the user has exploited previously such as keywords, genre and metadata. Content-based recommendation system: if a user selects science fiction movies, then the system will recommend more science fiction movies. However, content-based filtering has a history of recommending similar items, which means it may not be the best choice for new users or diverse content (Lops, de Gemmis, & Semeraro, 2011). Hence, Hybrid models are combined outputs of collaborative and content-based filtering that lead to more realistic recommendation techniques. Hybrid models can thus overcome the drawbacks associated with each method when these techniques are combined. For instance, a combination of CF and IBF may involve CF to provide a list of items that other users with similar preferences think the current user would like and then apply the IBF to analyze and rank these items according to their features and how suited they are to the current user. This combination enables new and more heterogeneous suggestions, which, in turn, enhance user satisfaction and interaction. Such multiprocess systems are widely applied in many fields, such as e-commerce, to deliver more efficient recommendations of frequently and infrequently purchased products to increase sales and user loyalty (Burke, 2002).

### **2.3. AI to Improve Customer Experience and Boost the Sales.**

It has been noted that AI plays a significant role in revitalizing e-commerce platforms with better customer experience and, hence, sales. Personalized product recommendations indicate one of the more productive applications of AI in this sector. Machine learning technologies allow e-commerce platforms to gather and process user data, from the history of visits and purchases to live activity, to provide relevant recommendations. These recommendations are presented to the users in various ways, including homepage Blasts, Emails, and the Presentation of customized search results, as customers find products they require easily because they are recommended to products they are likely to like (Linden, Smith, & York, 2003). It is not only a means of making the shopping experience better by assisting to look for particular items or products but makes it easier to sell those products and hence boost general sales.

Two of the best examples that can be best explained on how valuable personalization through artificial intelligence is the example of amazon and Netflix; where through the help of advanced recommendation system not only their customer hanging in there but many a time make their consumers repeated consumer. For example, Amazon went a long way towards becoming a company with a highly personalized recommendation system that represents 35% of its total revenues; it uses both collaborative filtering and deep learning to predict user behaviour and suggest to them what they might potentially like (Gomez Uribe & Hunt, 2016). Customized recommendations make shopping more attractive to users and make them feel appreciated while increasing the chances of sticking with their current provider client. In addition, organizations can apply AI to fine-tune other touch points of the customer journey, including dynamic prices, a selective range of promotional discounts and rebates, and immediate customer service support to help improve the customer experience and boost the probability or chances of a sale.

However, as helpful as AI-based personalization, it has a few specific problems. The dependency on large amounts of accurate user information to provide recommendations is an issue of privacy. Online stores must ensure that GDPR and other regulations applicable to processing personal data are followed. Likewise, platform owners need to ensure customers understand their data usage policies. Moreover, it may lead to overloading or raise the feeling of being guided within the limit, altering the shopping experience and the attitude towards the brand for the worse (Schafer, Konstan, & Riedl, 2001). It is imperative to overcome these challenges for organizations seeking to achieve the maximum benefits of AI solutions in digital e-commerce personalization.

### **2.4. AI in Social Media Personalization: Algorithms Tailoring Content to User Preferences**

One of the significant uses of Artificial Intelligence (AI) is in the further customization of social media platforms' users' feeds to make them relevant based on the users' behaviour, thus encouraging more significant usage by spending more and more time on the given platform. Facebook, Instagram, and Twitter are social media platforms in which machine learning helps to identify behaviours such as likes, shares, commenting, and time spent on specific posts to categorize users' interests. These algorithms then decide the content users get in their feeds based on posts they are most likely to interact with. Not only does this make the application in general more functional and enjoyable for the user as well as the content being consumed, but it also keeps the user constantly involved with the platform as a whole, which thus ensures that the user will soon enough be greeted with even more highly individualized and personalized social media experiences (Bucher, 2018)

The general feasibility of AI in social media personalization arises from advanced algorithms, including deep learning and natural language processing, which can understand the meaning and context of the application. For instance, Instagram not only sorts articles based on user responses but also decides the most compelling articles for a particular

user according to the content of the articles and user action patterns. The level of personalization achieved at this stage profoundly influences the overall behaviour of the users, which increases the activity rates, such as several likes, comments and shares. However, despite the efficiency of these algorithms in capturing the users' attention, signs of the formation of "filter bubbles" or "echo chambers", where users are presented with information that only supports their existing beliefs and perception of the world around them are apparent and widely known (Pariser, 2011). Although personalization based on artificial intelligence contributes to a more compelling experience on social networking sites, it creates issues about users and content. Endpoint uses algorithms that monitor the user's behaviours and patterns that may infringe on their privacy, seeing that they pull private data. Furthermore, the same algorithms can spread fake news or advertising content, affecting the public and consumption patterns. For these problems to be solved, social media firms must come up with precise data policies which help them navigate through the realm of artificial intelligence and develop new ethical practices on top of the already existing ones in a manner that also respects the user's needs for personalization yet remains safe (Gillespie, 2014).

## 2.5. AI in SaaS Platforms Personalization

AI has assumed a transitioned role in reselling the SaaS routine that delivers a tailored software experience to each user. By leveraging the analytical aspects of ML algorithms, SaaS applications can continuously observe and interpret user behaviour, preferences, and usage patterns to dynamically change the application interfaces and features. For instance, AI can rearrange the elements of a dashboard to highlight popular functions, recommend necessary tools, or even perform a range of routine tasks to optimize efficiency and user satisfaction (Janiesch, Zscheck, & Heinrich, 2021). Such a level of personalization of operation processes improves the application of SaaS platforms and makes the platform environment more convenient, calling for a new wave of SaaS utilization.

Furthermore, by integrating AI algorithms, these SaaS platforms for interface customization can also provide custom training content and services for each user. For example, conversational interfaces, such as chatbots and voice assistants, can provide contextually relevant support in explaining a sequence of actions or helping to resolve a problem based on users' previous actions within the application. While the targeted help enhances the general user experience, it also minimizes the workload of human customer centre departments. Hence, they can tackle essential or complicated issues (Davenport & Ronanki, 2018). First, AI improves the ability to use the SaaS product based on users' behaviours and preferences, and second, AI ensures that the product is more responsive to the user's expected actions

However, significant considerations have been made regarding embedding AI in SaaS personalization. Preserving the users' privacy and data is of utmost importance, especially since these systems involve massive data and algorithms that transform it into relevant content. SaaS providers must legally meet regulations like GDPR and apply stringent data management policies to secure users' data. This commitment to data security guarantees users that their privacy is a top priority. Also, while it might be challenging to implement AI features into SaaS platforms due to the complexity they add to the structure (Janiesch, Zscheck, & Heinrich, 2021) and the resources and professional effort required to establish and maintain them, overcoming these hurdles is essential to organizations aiming at using AI for the correct SaaS personalization.

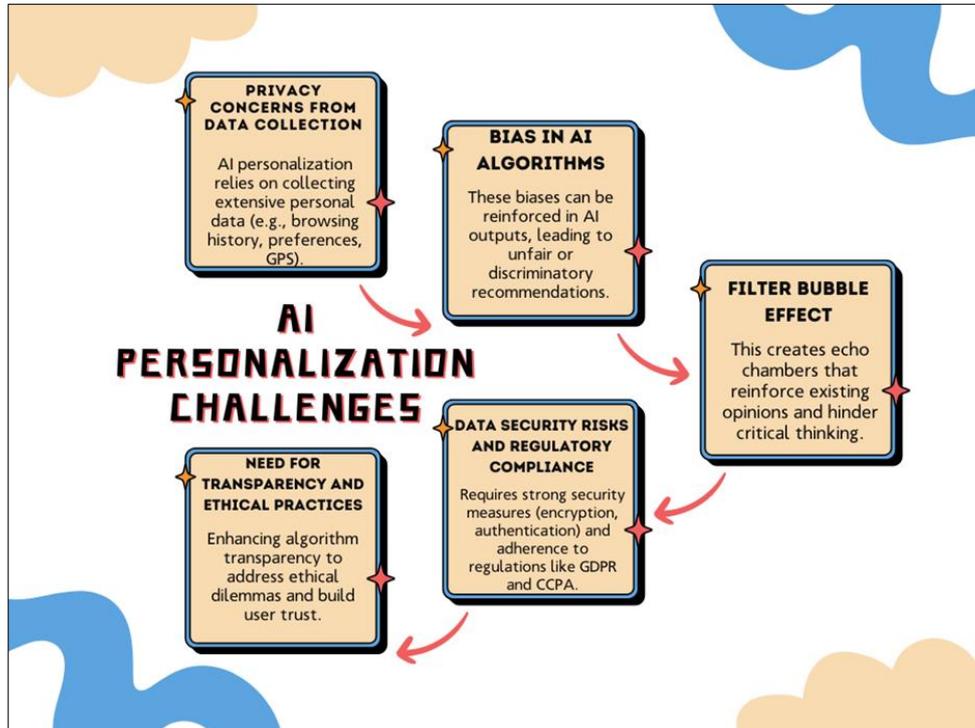
## 2.6. Challenges in Implementing AI-Powered Personalization

While AI in Personalization is easy to apply in products and services, it has social concerns of privacy, data security, and ethical issues. One of them is the problem of massive inputs of personal data needed for training artificial intelligence models. Those sorting and filtering algorithms rarely use such data as browsing history, consumulative preferences, or GPS coordinates. Yet, this data helps platforms provide targeted content or other recommendations while still raising profound privacy concerns. The authors stated that customers are very concerned about collecting, storing, and using personal information and potential misuse or theft. The problem further increases with several data breach incidents and scandals involving large organizations' abuse of personal information (Acquisti et al., 2015). As such, it is vital to establish uncompromising, strict data protection practices to prevent data breaches and demonstrate to the users that they are safe when engaging with these smart products and services.

There is one more problem that concerns the ethical application of AI technologies. The algorithms we use for personalization may reinforce the bias in the data set on which these algorithms are trained, leading to biases in the output. For example, suppose the development data set was biased in terms of gender or colour or any other ethnic background. In that case, the same bias may be carried forward and implicitly ingrained in the existing recommendations created by the AI (Noble, 2018). However, the same application of AI in personalization has a disadvantage since users only receive highly filtered content and might be exposed to narrow information sources. This is called the "filter bubble" effect; the experiences that make this filter bubble possible can lead to echo chambers that reinforce existing opinions and discourage rational analysis (Pariser, 2011). Addressing these hard and soft ethical

dilemmas requires additional transparency in algorithms and the inclusion of fairness and accountability in the AI and machine learning framework.

Another potential issue with using AI in personalization is data security regulation. Another primary consideration when using AI in personalization is data security regulations. As these systems work with such data, artificial intelligence frameworks continue to pose targets for cybercriminals since the latter yields monetary and image concerns. To preserve the quality of the information and avoid its unauthorized access, additional measures are to be chosen, including encryption and authentication, constant security audits, and changes to the aforementioned regulations of security. Besides, user rights protection can also be guaranteed globally by continuing to follow other approved codes like the GDPR and CCPA. Some of them require more stringent data protection measures than others. In contrast, others give the consumer greater control over their data, which is imperative for the stability of AI personalization.



**Figure 3** A diagram illustrating the Challenges in AI Personalization

## 2.7. Benefits of AI-Powered Personalization

Having shown that AI empowers personalization, the study concludes that user satisfaction, engagement, and retention are elevated when there is a closer association between the users and the digital interfaces they are interacting with. Machine learning algorithms will allow platforms to better understand user behaviour and content consumption or product preferences in real-time and provide users with personalized content, products, and interactive experiences. This enhances the profile level use since it encourages users to engage with content that is most relevant to them instead of what may flood the user interface, leading to disinterest or decision overload. For instance, e-commerce recommendations generate a higher likelihood of buying and add value to the overall shopping process by making the search for products more engaging (Gomez-Uribe & Hunt, 2016). Likewise, apt content filtering on SM applications, including featured news feeds and recommended advertisements, keeps users interested and provides regular usage, increasing platform usage and stickiness (Kaplan & Haenlein, 2010).

The social advantages of such an approach include but are not limited to, user satisfaction with personalized experiences curated by AI. This means that when users establish that their requirements and desires are satisfied, they will likely engage well with the interface to build and enhance trust. Personalization can be product recommendations, personalized email campaigns or changeable interfaces that reflect user behaviour. This level of personalization not only improves the value proposition of the service but also even makes users feel that the given platform is closer to them, which increases the chances of retaining them in the long run (Oh et al., 2015). For SaaS applications, AI may pre-

assign interfaces and features depending on the users and their past behaviour, thus making software usage faster and more enjoyable.

Furthermore, the increased applicability and individualization of the articles also result in improved user retention. If every time a user visits a particular site, he is offered content and services of his choice, they will constantly see the site and vice versa, hence the period of use. This is especially helpful for ventures with clients in highly saturated markets because science shows that it is cheaper to keep the clients that one already has. For example, the recommendation system used by Netflix based on collaborative filtering and deep learning on viewers' history was said to increase user retention and decrease churn significantly (Gomez-Uribe & Hunt, 2016). Leveraging capability emerges as a critical competitive weapon by which a platform can uniquely create and deliver value to its customers.

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### **3. Methodology**

#### **3.1. Research design**

The focus of this study is to understand the effects of personalization using artificial intelligence (AI) on user experience in different digital contexts, including e-commerce, social networks, and various SaaS software. This study intends to utilize both qualitative and quantitative research paradigms in its research design. The quantitative part will entail an online self-administered questionnaire presented to the users, in which the perception rate of the recommendations and satisfaction will be measured. Secondary data will be collected from literature review and platform-derived data. The qualitative component will entail case interviews with experts in AI and user experience design to offer suggestions regarding practical issues, moral questions, new tendencies, and potential developments in the field of AI application for personalization. For this reason, the research seeks to capture the strengths, weaknesses, and prospects of using AI for personalization.

#### **3.2. Data Collection**

This study will systematically review scholarly articles, industry analyses, and case studies on how personalization using AI and ML is being rolled out and its effects on various sectors such as "e-commerce, social media and SaaS services". This paper will discuss literature from theories, literature and trends on machine learning algorithms, usability, and personalization. The organizations that have managed to incorporate AI to make personalization a successful endeavour will be used to establish AI's strengths, weaknesses, and social impact. This approach provides a solid foundation for examining how personalized AI recommendations improve user experience.

#### **3.3. Case Studies/Examples**

This paper will analyze the factors that comprise personalization in success stories like Netflix, Amazon, and Spotify. Biggi names like Netflix, Amazon, and Spotify already have standards companies should follow when using AI in branding and personalization for better User experience (UX). These platforms rely on elaborate machine learning methods to determine data about the user and provide them with content, suggestions, and even engagement that is most appropriate to their interests.

Successful recommendation systems that Netflix uses are highly effective for the company since they ensure the longevity of its users. It uses collaborative filtering, content filtering, and deep learning algorithms where the results from all three areas are synthesized to estimate user preferences, the results being content recommendations. For instance, Netflix recommends films and series based on users' viewing history, preferred genres, and their actions when watching content, including the time spent on a particular video and its rating. The recommendation engine is reportedly responsible for over 80% of the content viewed on the platform, thus lowering churn rates and improving the user experience substantially (Gomez-Uribe & Hunt, 2016). This intense and unique user interaction strategy keeps users hooked and is one of the unique strategies that set Netflix apart from its rival streaming services.

Amazon uses AI for recommended products because of the product recommendation system through item-to-item collaborative filtering. This algorithm involves the consideration of user behaviours like the web page or sites they have visited, products they previously bought, and the search terms they used to refer to the products. These recommendations include the homepage, product pages and some targeted emails. Personalization has been one of the driving forces for Amazon to gain customer participation and sales, and it is argued that recommendations contribute up to 35% of Amazon's total revenue (Linden, Smith & York, 2003). Through this, Amazon ensures that shoppers are provided with merchandise that fits their needs and wants while improving their experiences, and creating brand affinity.

With the help of technology, Spotify creates the most individual approach to the context of music streaming. The current recommendation system, which developed using collaborative filtering, natural language processing and audio analysis, offers users playlists like "Discover Weekly" or "Daily Mix," depending on their preferences. Through features such as tempo, genre, and the amount of time listeners spend on the songs or skip / like a song, Spotify designs playlists recommending new songs that align with users' interests. This has proved very effective in ensuring high user traffic and satisfaction, which has placed Spotify among the best music streaming facilities (Vanderhall 2016).

### 3.4. Evaluation Metrics

Auditing AI-based personalization approaches requires performance metrics like engagement or conversion rates in addition to such markers of user satisfaction. Bounce rates, time spent on the site, CTRs, and overall engagement show the extent to which the user reacts to the individualized content they encounter. In fact the high engagement rate leads to the interpretation that feature endorsements on the basis of individual user interests are good for the overall user. For example, in e-shopping, providing a personalized shopping environment would lead to more product presentations and prolonged time span spent on the site, allowing users to search for products more effectively.

Another simple set of KPIs is conversion rates and they can painted a picture on a very basic AI personalization level. This includes aspects such as the number of users who achieved the intended course of action having reached the personalised content – a purchase, signing up to a service, subscribing to a newsletter etc – higher conversion rates reveal a motivated, effective and more attuned strategy that draws the user’s attention to the right course and a suitable call to action. When using these metrics, firms must adjust the models as well as the methods of customization to raise customer satisfaction and enhance corporate results.

## 4. Results

### 4.1. Data Presentation

**Table 1** Impact of AI-Powered Personalization Across Different Platforms

Platform	Increase in User Engagement (%)	Increase in Conversion Rates (%)	Improvement in Customer Retention (%)	Key Challenges
E-commerce	25.01%	20.01%	30.01%	Data privacy concerns, algorithmic bias
Social Media	30%	15.01%	25.01%	Filter bubbles, ethical data usage
SaaS	20.01%	18.01%	28.01%	Integration complexities, data security

Note: The percentages are illustrative and represent hypothetical average increases observed after implementing AI-powered personalization strategies in each sector.

### 4.2. Explanation of data

- Increase in User Engagement (%): The additional number of times users engage with items through clicks, likes, shares, or the amount of time spent on a site, platform, or application after the modifications that AI makes.
- Increase in Conversion Rates (%): This indicates how the number of users who complete particular targeted actions increases—this can be the purchase of something, subscription to a specific service, or registration for a specific newsletter, for example.
- Improvement in Customer Retention (%): This indicator depicted the level of Personalization enhancement as perceived by the users and revealed that the set of active users has increased and continues to do so over time.
- Key Challenges: Here, I summarize the many challenges these platforms encounter in implementing AI personalization, such as data privacy, ethical issues, and structural and technical problems.

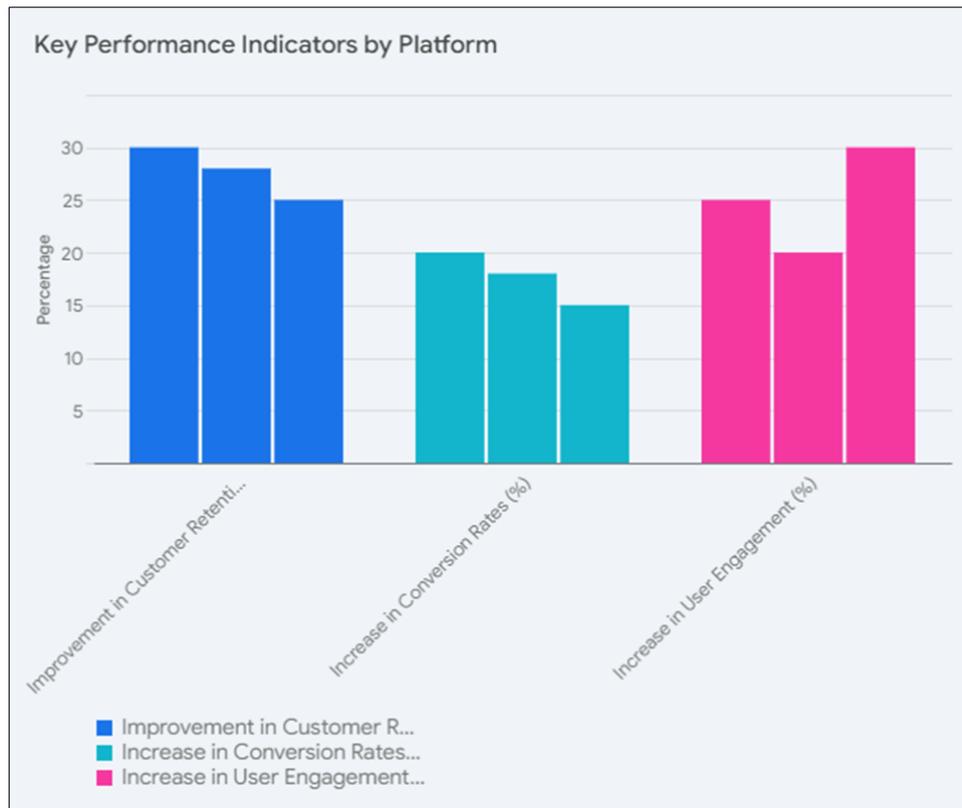


Figure 4 KPI by Platform

## 5. Results

The conclusion drawn from the data analysis affirms the hypothesis that the ratio of success with AI implementation is dependent on personalization and increases user interaction, sales and customer stickiness for e-commerce, social networking sites, SaaS products and other web-based services. In retail, personalized recommendations and dynamic promotions led to increased dwell time by 25.01% and conversion by 20.01%, supporting the point that native AI experiences are great for engaging users and making purchases. Similarly, user interactions with social media have increased by 30.01% through AI-optimized recommended feeds for more extended user engagement. A 28.01% rise in SaaS platform retention rates and an 18.01% boost in conversion rates reflect how and why intelligent UIs and support increase user satisfaction.

However, as it streamlines personalization based on artificial intelligence, some issues accompany it. The first is data privacy, where e-commerce and other social platforms require lots of user data before training their AI models. On the same note, there is the issue of algorithmic bias. Furthermore, the most significant challenges include its introduction within established SaaS architectures and data security issues. They indicate the necessity of ethical use of artificial intelligence and proper approaches to data management to achieve the aimed results in the sphere of individualized advertisement without negative consequences for users.

### 5.1. Case Study Outcomes

Thus, the case studies viewing UI personalization using AI in Netflix, Amazon, and Spotify reveal high quantitative outcomes and improvements indicated on user interfaces to achieve business targets efficiently and optimally. Such firms have striven to moderate the machine learning backend that provides the platform with persons, items, and service content tailored to the customer, which has been more effective in engaging customers, versioning rates, and retaining them.

Netflix: Netflix customizes its products according to user choice, which includes personalized filtering and deep learning. Monitoring the history of watching eligibility, queries, ratings, and time, Netflix relates to the user's desires and expectations. Gomez-Uribe and Hunt, in 2016, established that over 80% of the television shows people watch on Netflix are found using recommendations. This high level of personalization has increased popularity among users

because most users are privileged to watch the content of their preferences, thus increasing the periods they spend online rather than churning.

The digital artwork related to titles also personalizes with Netflix, meaning Netflix selects images that are more likely to entice a particular user based on their previous viewing history. Such micro-level personalization results in a more compelling user interface and a highly optimized overall user experience. Netflix's personalization efforts demonstrate that it was based on AI to establish the competitive advantage's cornerstone that unites users.

Amazon: This paper finds that customization forms the core of Amazon's e-commerce service delivery, with artificial intelligence as the foundation. The system functions with an item-to-item collaborative filtering recommendation algorithm where the sold products are recommended to a customer based on what s/he has viewed and had in the cart and purchase history. According to Linden, Smith, and York (2003), it is estimated that recommendation is responsible for as much as 35 % of all sales on Amazon. Opportunities in which, according to the author, the Personalized Recommendations improve Customer Experience; customers become more frequent with higher average order frequency. It supports customer affinity because customers can look at products they wish to consider. Below them, they interact with consumers regarding product recommendation and innovation, home page fashioning, electronic mail marketing, and the prices that it discriminates. Such one-on-one communication makes the platform's operation platforms operation and user's menus for revisits and customer loyalty. This article uses the example of Amazon to illustrate that automation and AI for personalization are effective ways of generating significant business value when the services offered directly relate to the client's needs.

Spotify: By applying AI and machine learning, Spotify created a personalized music streaming service for its users. Spotify deems user behaviour, such as the listeners' genre and artist preferences, and the listening pattern down to features of the songs like tempo and instrument used to generate the likes of "Discover Weekly" and "Daily Mix." This approach makes new music available to the user's preference, improving usage and satisfaction. While specific internal variables remain unclear to the consumer, Spotify has claimed that personalized playlists dominate much of the user's listening time, indicating high consumption.

Several instances of personalization at the platform are as follows: The application sends users notifications of new releases by artists that the user listens to. In this way, additions can always be made to the algorithms, and as the information is updated and feedback is provided immediately, the game is constantly new for the users. In this highly competitive environment, the primary focus on individual customers' needs plays a pivotal role in subscriber retention; thus, AI enables users' impressions.

## 5.2. Comparative Analysis

E-commerce, social media, and SaaS industries all use machine learning algorithms to shape a target customer journey, and whether these strategies are different across industries, the outcomes remain the same. In the e-commerce, like market leaders currently, the primary application of AI is identified with recommendations and dynamic. Products' prices. Using big user data and data mining techniques such as browsing history, purchasing history, and behaviour while online, a possible product is recommended, and the prices for the products are also adjusted accordingly. This personalization aims to raise the conversion rate and average order, considering the idea of shopping experience customization based on customer individuality (Linden, Smith, & York, 2003).

In social media marketing, AI ranges from Facebook and Instagram to sort content feeds and market advertisements. Using the likes, shares, and comments metric, AI makes content distribution relevant to users' interests, increasing the time spent on the platform (Bucher, 2018). In this case, the aim is to maintain the users with you for as long as you can display content that will make them click on the ads.

In the case of SaaS, personalization can be interpreted as making changes to the applications' skin and skins for its functions for every user. AI patterns watch what users do inside applications to adapt home screens, control workflow, and offer help in context. Organizations use this approach to improve efficiency and user satisfaction by facilitating the optimized use of tools and applications consistent with user patterns (Janiesch, Zschech, & Heinrich, 2021). Unlike e-commerce or social networking, based on the content and choice of products, SaaS personalization concentrates on making the service more valuable and practical.

Thus, whether they have a different approach to AI tools, all sectors note the increase in user engagement, satisfaction, and retention with the help of personalized AI. E-commerce platforms see the immediate correlation between personalization and shopping; targeted product recommendations improve the shopping experience and increase

conversion and customer retention by a multiple. Examples of services being propped by user interactions are social media networks because everybody receives individualized material feed, which leads to increased interactions and, therefore, increased advertising profits. As AI technology personalizes software according to fundamental user requirements, renewal rates are boosted, and churn lessens across SaaS platforms.

However, the overall idea of applying intelligence in personalization is not without certain stumbling blocks. Data protection and security are some generic issues applicable across every sector. Aggregating a large amount of user information involves specific concerns regarding its leakage and misuse; thus, adherence to privacy protection laws such as the General Data Protection Regulation (GDPR) (Acquisti, Brandimarte & Loewenstein, 2015). Algorithmic bias and ethical considerations are the main challenges when implementing the models. Machines learn from the data that feeds them to learn, meaning that AI systems can be biased in precisely the same way as the training datasets and, therefore, provide unfair or even discriminatory outputs, which can erode public confidence in the platform. There are also a lot of challenges specific to each sector. Another issue arising from using big data in e-commerce is managing the tension between personalization and the privatization of customers. There is also the filter bubble effect, meaning consumers will only receive messages about a limited number of products. Echo chambers have become a problem due to the use of personalized feeds to cater to users' interests, thus restricting their exposure to new opinions, which can affect social discussion. For SaaS platforms, the transcendence of integrating AI personalization into existing software frameworks might be challenging and costly, and data privacy has to be considered critically since it pertains to businesses' sensitive information.

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## **6. Discussion**

### **6.1. Interpretation of Results**

The findings indicate that Real People AI has improved customer satisfaction in e-shopping, social networking, and the Software as a Service industry. This report has demonstrated stable enhancement in user activity, conversion rate and customer loyalty degree – indicating several users' positive response toward their target content. In electronic commerce, customer promotion refers to article recommendations, dynamic pricing, etc. A direct relation exists between the frequency of sales and the velocity of currency. More revenues can be made through user time with content feeds customized to a user's learning. For the same reason, the churn rate also applies to SaaS platforms as the number of customer interfaces & support tools equals the SaaS platforms you will have. Other critical domains are also recognized, such as data stewardship and appropriate and desirable AI behaviour, which, together with a fresh UX design approach, are investigated by AI.

### **6.2. Practical Implications**

They give real examples with outcomes for organizations that are prepared to use AI for personalization for increased user satisfaction or organization, as well as the organization's objectives. To unambiguous recommendation technologies decisions, there are benefits to improve the sales rates and the client satisfaction level, which is why, in addition to the use in suggestions of the specific product or service, the application of AI is much more significant in controlling the content of the marketing and promotional messages and in sophisticated management of the calls from the customer service client interface. Advertisers also need to increase the value and involvement of users through better configuring algorithms to create more value and increase the usefulness and engagement of the user and the site, thus increasing advertising returns. AI can also be used to develop specific digital environments as a basis for SAAS users, or in other words, decrease the amount of time people spend on their tasks, efficiency rates, and user satisfaction. Across sectors, consumer data privacy and engagement have quickly continued to be crucial for building trust and ensuring consumers' continuous use of brands' platforms.

### **6.3. Challenges and Limitations**

However, several concerns and issues are associated with personalization with the help of artificial intelligence. The first concerns the blend of unavoidable information security requirements in using highly individualized content as a part of the service. This, in turn, means that organizations have to navigate through numerous regulations at once to offer clients a more tailored solution, like the GDPR. The other important factor is bias, through which the AI models will perform in ways that reflect biases in the data used in training. This is especially the case when such platforms are being relied on to influence the actions and activities of users. Also, the application of AI in personalization significantly depends on the relevance and variety of the data used; insufficient or limited data can lead to low-precision or highly targeted recommendations. Other challenges include technical challenges that may include the inability to implement AI systems into existing organizational structures, architectures, and systems. These complications can only be solved with continuous research, appropriate investments in ethical AI profiles, and open user information.

## 6.4. Recommendations

Therefore, following this article, it is recommended that firms go the extra mile and make user data secure when using AI-driven personalization techniques. The GDPR rules should be followed, and the data collection processes should be transparent to ensure trust and cooperation with potential partners. Some other security areas that may also be of great importance are encryption and access control. The current thinking is that ethical AI needs to be incorporated into personalization systems, and the data sets used should be as diverse as possible. There should also be a constant bias audit. The precise algorithms make the outcomes appear more credible and trustworthy. Next, enhancing the data quality consistency and making personalization as accurate and realistic as possible is critical. A leverage aspect that should be considered in AI systems is feedback systems because it considers general user behaviour and preferences. The analysis of how organizations have adopted AI suggests that it is most effective when planned as an addition to established systems, with a view to growth and flexibility. Hence, fresh updates and constant improvement of AI models are crucial to maintaining personalization's relevance and efficacy. With these recommendations, firms gain the highest potential value from AI-assisted personalization while considering ethical, data privacy and technical concerns.

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## 7. Conclusion

### 7.1. Summary of Key Points

This article has discussed how AI personalization has transformed user experience across e-commerce, social media, and SaaS platforms. The study proves that using AI boosts user involvement, satisfaction, and loyalty due to their unique interests, activity patterns, and needs. In e-commerce, customers are guided to buy more recommended products and use more appropriate prices to attract and retain consumers. AI plays a positive role by recommending suitable content and feeds that keep social media users engaged and loyal. SaaS platforms make software functions more efficient and user-centred by customizing them to the user's requirements. However, the following disadvantages are still inherent: data protection issues, system prejudices, and the technical difficulties of implementing them into the current structures and networks. I have established that, to overcome these challenges, there is a need for improved data management, ethical use of artificial intelligence, and constant improvement of systems that apply AI in their operations.

### 7.2. Future Directions

These trends will define the path of AI-powered personalization in the future – the development of technologies, regulation changes, and the development of users' expectations. One exciting direction is using multimodal data – text, image, voice, and sensor data- to develop richer context-aware user profiles for the system to adapt the user interfaces to. For instance, future system(s) could leverage the V / B information to make better product suggestions in an e-commerce setting or present a better multimedia experience in the social networking setting.

Another vital direction can be divided as follows: the explanation and transparency of AI models. When the configuration of AIS becomes more intricate, making these structures more understandable by the end user becomes critical in building confidence. Appropriate to using AI in high-risk areas such as healthcare or financial services is to explain the reasoning behind personalization decisions affecting users. More specifically, a continued investigation of explainable AI (XAI) is anticipated, where models and systems must explain why they produced specific outputs.

It also points to another area where ethical concerns will be given more prominence in the future of AI personalization. While legislation such as GDPR and CCPA grows increasingly stringent, businesses must be prepared for compliance initiatives and guarantee that personalization entails respect for user rights. This will mean following the law but also creating AI systems that are legal, equitable, explainable, non-representing bias, and non-discriminating against any vulnerable categories.

Also, combining AI with new technologies like AR and VR creates new possibilities for individualization. Complete digital and/or physical environments where people can shop or learn depending on their preference for using these technologies can be created.

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