Personalization of User Interface and Clustering of Users

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Adaptive user interfaces (AUIs) are defined as user interfaces that can change according to user activities. They are designed to adapt to the needs of individual users or groups of users based on their preferences, behavior, and context. These interfaces provide an optimal user experience by adapting interface elements, including layout, content, and functionality, to align with users' needs and goals.

Keywords: e-commerce ; personalization ; clusterization ; adaptative user interface

1. Introduction

In today's digital world, where users interact with a wide range of devices and platforms, each with different capabilities and limitations, AUIs play a crucial role in ensuring a sophisticated and personalized user experience (UX) [1]. This approach fosters consistency and personalization across devices, thereby elevating user engagement, satisfaction, and productivity. However, it is essential to acknowledge certain limitations, particularly in situations that involve repetitive or familiar user experiences [2]. This problem can also occur with new e-commerce customers who are unfamiliar with the site's structure, navigation, or products [3]. In such cases, the creation of a dedicated interface variant for this specific user group can encourage prolonged site engagement and facilitate continued shopping.

Web-based systems, including e-commerce solutions, can benefit from personalized user interfaces that automatically adapt their presentation, content, and structure based on user characteristics, needs, or preferences [4]. AUIs offer numerous advantages over nonpersonalized systems. They enhance usability and effectiveness by adjusting to the user's expertise level, providing relevant guidance and feedback. Additionally, AUIs reduce cognitive load, minimizing user fatigue and the likelihood of errors. The provision of pertinent, personalized information further contributes to an improved UX, ultimately boosting user satisfaction and motivation [2]. However, the design and implementation of such a solution can be a complex task requiring the application of interdisciplinary knowledge [5].

While there are various approaches to creating adaptive user interfaces, one of the most effective appears to be the use of artificial intelligence (AI)-based clustering to divide clients into groups and provide those groups with a dedicated interface [6]. AI clustering is a technique that groups similar data points (e.g., e-commerce customers) based on certain characteristics. In the context of e-commerce user interfaces, clustering can consider actions, events, purchases, and other relevant factors [7]. By implementing AI clustering, companies can tailor different versions of the user interface for each cluster, ensuring that every customer enjoys an optimized browsing and shopping experience.

Today, e-shops commonly use various mechanisms for product recommendations that rely on advanced data analysis, including AI [8], but there is also considerable potential in AI-assisted user interface personalization.

To implement the AUI concept using machine learning (ML) mechanisms, it is crucial to establish an architectural and functional framework. This framework should efficiently collect customer behavior data, process it while considering the business context, and translate resulting recommendations into the final user interface design. Despite the prevalence of studies on various approaches to generating recommendations in e-commerce [9][10], it is challenging to find comprehensive research on personalizing user interface design. Existing studies, such as those on product recommendation systems, primarily focus on personalized content like lists of recommended products rather than addressing the website layout (e.g., the location of components on the website).

2. Personalization of the User Interface

The historical context of UI personalization is briefly discussed, noting that attempts to provide dedicated user interfaces predate the dominance of artificial intelligence in recommendation services [11]. Previous efforts were often linked to the service-oriented architecture (SOA) paradigm [12]. Today, various approaches are commonly used for personalization in adaptive web shop interfaces, including AI-based methods such as collaborative filtering (CF) [13], CF based on deep learning [14], and its modification that uses the relationships between items rather than users (item-based CF—IBCF) as the basis for inference [15], case-based reasoning (CBR) [16], the RFMT (recency, frequency, monetary, time) model [17], data mining [18], and clustering [19]. UI personalization is applicable across diverse IT systems, whether within organizations (e.g., enterprise resource planning—ERP [20]), supporting interorganizational collaboration (e.g., workflow [21]), or dedicated to customers (e.g., e-commerce [22]).

The practical implementation of the AUI concept faces a fundamental challenge concerning the collection of data used for making inferences and recommending interface options to users. This challenge involves the necessity for capabilities to capture customer data, algorithms to identify similarities and differences in user behavior, and strategies or processes to use the extracted information to achieve specific business objectives [23].

Recommendations based on customer characteristics and behavior can rely on either explicit or implicit data collection methods. In the case of explicit data collection, customer characteristics, including demographic factors, social factors, and location, are directly obtained. In theory, collecting this type of data is not a problem for web-based e-commerce systems [24]. However, challenges arise when considering the quality of such datasets. Some customers may be unwilling to provide demographic data, prefer to browse anonymously, or even deliberately provide false information. Moreover, demographic information is subject to change over time, introducing uncertainties that are challenging to assess accurately [25]. On the other hand, implicit data collection involves tracking user activity without direct interaction with the customer. This approach is generally more reliable, as it does not depend on customer willingness to provide information. However, it faces increasing limitations due to legal restrictions, such as the GDPR [26] or privacy policies, and evolving e-commerce development trends that restrict the use of third-party cookies [27].

In the realm of e-commerce, user segmentation, borrowed from classic marketing techniques, is a common approach that involves dividing the customer population into groups with similar characteristics relevant to the objectives of the process [28]. The effectiveness of segmentation techniques can vary depending on the specific e-commerce business, its objectives, and the available data. Generally, segmentation can be described as an unsupervised learning process that utilizes different grouping approaches to create sets of objects (customers) based on target functions derived from selected measures of similarity or differentiation [29]. Given the dynamic nature of customer behavior, needs, and perceptions in e-commerce, segmentation techniques should be flexible, adaptable to large input datasets [30], and capable of handling rough sets [31].

While traditional customer segmentation methods have been used for decades, artificial intelligence, particularly machine learning, is increasingly playing a crucial role in this domain. Clustering algorithms are one example of such segmentation approaches [32].

3. Clustering of Users

Clustering, especially using the K-means algorithm, is a prevalent research topic in customer segmentation applications in e-commerce. Gomes and Meisen's analysis of academic articles published between 2000 and 2022 on segmentation for customer targeting in e-commerce indicates that K-means is the most frequently cited clustering method, holding a 39% share [23]. This approach is known for its efficiency, although its computational complexity is influenced by factors such as dataset size, the number of clusters, and the initialization of cluster centroids. The combination of K-means with recency, frequency, monetary (RFM) analysis has been used for generating product recommendations [33]. Additionally, K-means has been applied to predict customer churn in B2C scenarios [34]. The pure K-means algorithm is often used for the segmentation of e-commerce users to create groups with different characteristics [35]. Similar goals have been explored using the particle swarm optimization algorithm [36]. Such a goal coincides with the potential use of clustering to create groups of customers to be served with a specific UI. Undoubtedly, K-means is an algorithm with many advantages, but it should be noted that within the framework of the aforementioned study, modifications of this approach, such as K-medoids (partitioning around medoids—PAM [37]) and K-medians, were also understood under the term K-means. It is worth noting that despite their similarities, these K-… approaches can lead to significantly different results when applied in practice [38].

To a lesser extent, there are studies on using other clustering approaches in e-commerce. Hierarchical clustering (of which agglomerative clustering is a subset) in e-commerce applications is discussed [39]. It is worth noting that the standard algorithm for hierarchical agglomerative clustering (HAC) has a time complexity of $O(n3)(3)$ and requires $\Omega(n2)\Omega(2)$ memory, making it slow even for medium-sized datasets. This is a major limitation from the point of view of clustering on detailed e-commerce customer behavior data, as such learning datasets can be very large [40]. In turn, fuzzy C-means clustering, which is a version of K-means where each data point has a fuzzy degree of belonging to each cluster, can be modified to improve the clustering analysis effect of e-commerce user behavior [41].

A comparison of the performance of the K-means and DBSCAN (density-based spatial clustering of applications with noise) algorithms in e-commerce applications showed slightly better results with the second method [42].

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