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RESEARCH ARTICLE

One Size Does Not Fit All: Multivariant User Interface Personalization in E-Commerce

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ABSTRACT One of the most visible manifestations of the changes brought about by the digitization of everyday life is undoubtedly the spread of electronic commerce. It is difficult to think of the digital economy without considering transactions through electronic channels. In turn, the user interface (UI) is the key to e-commerce, as it is usually the first and primary point of contact between business and consumer. A key trend in e-commerce is the personalization of communications, which can improve the user experience, increase customer satisfaction and deliver tangible business benefits. Today, it is technically possible to base this personalization on an analysis of user behavior using artificial intelligence and machine learning techniques. A common form of personalization in e-commerce is the use of product recommendation systems, but the user interface can be tailored much more extensively. The approach described and discussed in this paper is a multivariant user interface that allows the layout to be tailored to the characteristics, attributes, and behaviors of customer groups generated using machine learning techniques. The results of the research carried out make it possible to verify the practicality of the proposed solution and provide an opportunity to identify development directions that take into account the potential of artificial intelligence. The application of the concept described in the paper is broad, covering all aspects of e-commerce design that require compromises when serving a single UI variant, but allow flexibility and customization for different users when serving a multivariant UI.

INDEX TERMS Artificial intelligence, e-commerce, machine learning, personalization, user interface.

I. INTRODUCTION

The term *digital economy* (DE) [1] combines the terms of *digital computing* and *economy*. It describes the changes taking place in traditional economic activities (such as logistics, production, sales, organizational resource management) as a result of increasing computerization and digitization. Factors currently influencing the dynamics and importance of this direction of economic development are the spread of the World Wide Web, the Internet of Things (IoT), blockchain-related technologies, and technological advances in information and communications technology (ICT).

One of the most important effects of the development of the Internet has been the increased importance of e-commerce. It is highlighted in the definition that recognizes this aspect of business as one of the three key components of the digital economy (along with supporting infrastructure and electronic business processes) [2], but it also appears in others ([3], [4]) definitions. The impact of e-commerce on modern economies cannot be overstated, and successive years show a steady increase in the number and value of ICT-based transactions. Reports from major consulting firms indicate a steady increase in e-commerce's share of retail sales (from 18% in 2017 to a projected 41% in 2027 [5]) and revenues (quadrupling since 2017 to reach $211 billion in 2022 [6]). They inform that in the COVID-19 time e-commerce has grown two to five times faster in every country than before the pandemic [7], but also point to the use of customer data and advanced analytics to deliver personalized communications as one of the key aspects for further development [8].

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Personalization has been a widely used marketing technique in e-commerce since the early days of this distribution channel for products and services. Initially, it relied on decision rules to group customers and target communications. Today, solutions based on machine learning algorithms and artificial intelligence are increasingly used. Because the user interface is the primary point of contact between the business and the consumer in e-commerce, almost all personalization activities are tied to the UI. It is the key to customer acquisition, retention and satisfaction. However, there is usually only one version of UI that is served to all users, regardless of their needs, expectations, and preferences. As a result, what the customer sees is not tailored, but a compromise created by specialists trying to reconcile different requirements. The solution to this problem may be to prepare multiple UI variants and serve them to specific groups (segments) of customers.

However, in order to change the *one UI for all users* approach, it is necessary to develop a solution that fully integrates all necessary components. It should bring together in a single platform the collection of customer behavior data, the grouping based on similarities and differences between them, the design and implementation of modifications tailored to user characteristics, the delivery of dedicated UI variants, and finally the verification of the effectiveness of the changes made and their acceptance or rejection. This is an effort that can both deliver tangible business benefits by tailoring layouts to the specific characteristics of customer groups, and provide a basis for further multi-directional development. The flexibility of this approach makes it possible to address different business needs (e.g., adapting UI variants for specific user groups, such as those involved in sustainability, the elderly, or people with disabilities) and to add components using collected customer data (e.g., preparing content tailored to groups using AI (Artificial Intelligence)-generated content tools, product recommendations enriched with knowledge derived from detailed activity tracking).

The possibilities for multivariant user interfaces are vast. One example is the accessibility of e-commerce systems for the elderly, whose numbers are growing every year. There are many user experience (UX) recommendations for UI design for this user group. However, they are useless if not put into practice, because the available layout variant is tailored to the so-called *average user* and ignores the needs of the elderly. Meanwhile, it is estimated that $16.8 billion in global e-commerce sales are lost each year due to websites that are inaccessible to people with disabilities [9]. The needs and expectations of such users are not fully met because the typical *one (UI) size fits all* approach does not have the capacity to accommodate everyone. However, if it is assumed that there can be multiple *(UI) sizes*, then there is no need to compromise on the design of online stores, and key customer groups can be served with sites dedicated to them. This concept will be discussed in more detail later.

The contribution of this paper is threefold. First, it presents the assumptions and architecture of the system that allows dedicated UI variants to be served to different groups of e-commerce customers. Such a solution can be based on static or dynamic versions of the layout or content, tailored to the identified characteristics of the users and derived from their behavior and choices. Second, it shows the exemplary benefits of implementing the described approach in practice as a result of the experimental studies carried out. Since multivariant UIs are not yet widely used, this business case can provide an important argument for this type of investment. Third, it includes the concept of developing multivariant UIs, both in terms of the range of applications and the tools that can be used with AI/ML (Machine Learning) methods. Their practical application would enable the development of a comprehensive, behavioral data-driven platform for UX optimization in e-commerce.

The paper is organized as follows. Section II presents a literature review on personalization in e-commerce, its importance and the possibilities of using AI/ML methods. Section III introduces a system framework that allows to tailor static or dynamic UI variants to specific customer groups based on collected data about customer choices and behavior. Section IV presents the results of an experimental study to evaluate the business effectiveness of multivariant UIs. Section V describes potential directions for the development of multivariant UI systems, identifies directions for further research. Section VI concludes the paper.

II. LITERATURE REVIEW

A. PERSONALIZATION IN E-COMMERCE

The earliest approaches to personalization, dating back to before the age of information and communications technology (ICT), used demographic (e.g. age, gender, education, etc.), geographic (e.g. country, region), or contextual (e.g. communication or sales channel) data. Today, they are still used to segment customers for targeted communications [10], but are increasingly being supplemented or even replaced by data extracted from automated tracking of customer behavior and decisions [11]. A compilation of selected concepts related to personalization in e-commerce is shown in Table 1. Current popular methods of segmentation include the use of clustering algorithms [18], which use behavioral data to group customers according to characteristics that may not be obvious to experts, or decision rule-based methods [19].

When thinking about personalization, there are three dimensions to consider: what to personalize (content, interface, functionality, channel), who to personalize (individuals or categories of individuals), and what is the basis for personalization (implicit or explicit data) [16]. They all need to be addressed, because only a comprehensive approach has a chance of realizing the potential of tailored communications. At the same time, it is worth asking an additional question - what methods and tools will be used to prepare and implement personalization, as this is crucial from the point of view of available solutions.

TABLE 1. Selected concepts related to personalization in e-commerce.

Concept	Description	Related literature
Objectives of personalization	Reasons for and benefits of personalization in e-commerce.	[12]–[15]
Dimensions of analysis	The scope and method of personalization.	[16], [17]
Segmentation by clusterization	Segmentation of e-commerce customers by specific profile or behavioral characteristics using clustering techniques.	[18]–[21]
E-commerce layout personalization	A form of personalization that results in the customization of a comprehensive UI design, taking into account content and layout.	[22], [23]
Sources of data for personalization	The foundation for implementing data-driven personalization.	[24]–[28]
AI and ML applications in personalization	Applications of AI and ML to personalize user experience.	[29]–[40]

Issues related to the personalization of e-commerce systems, such as recommendations, special offers, customized interfaces, etc., have arisen practically since the beginning of this distribution channel [17]. A review of the literature covering the early stages of the development of this topic reveals a strong focus on user-centered orientation and implementation approaches [41]. It should be noted that the scope of personalization used in practice today has not changed over the years. By far the most popular are product recommendations and special offers [42]. Less popular, due to the complexity of implementation, is comprehensive customization of the entire layout of websites, although efforts are being made in this direction [22], [23].

The primary goal of personalization in e-commerce is undoubtedly the desire to increase customer satisfaction and achieve tangible business benefits [12]. This can be achieved by attracting new customers, but also by increasing loyalty and retaining existing ones. Retention rates are one of the most important factors when analyzing e-commerce performance, so influencing the user's decision to return to the site is a very important area for personalization [13]. The UI-driven perceived usability of e-commerce also influences user preferences for websites, resulting in a propensity for repeat orders [14]. On the other hand, inappropriate and misguided personalization can be ineffective and even counterproductive [15], so decisions should not be rushed based on incomplete or incorrect data.

An important challenge in planning personalization activities is defining the target audience. In the case of systems where the users are known and can be accurately counted (e.g., enterprise resource planning systems, workflow [43]), the personalization recipients can be fairly well defined, although a major inconvenience in this case is the limited data set about their behavior [24]. The case is different for e-commerce systems, where the exact number of users is not known, but it is certainly many more than for typical management information systems. This translates into huge data sets that need to be analyzed to generate recommendations for personalization efforts. Due to the potential volume of data to be processed, it is necessary to optimise the solution for performance, e.g. by sampling and using noise filtering techniques [25]. In addition, solving this problem requires the right approach to preprocessing and preparing data for further analysis [26]. Given the above considerations, in the case of e-commerce systems, personalization will apply to groups (segments) of customers, and for systems used by a smaller number of users, individual or group personalization may be considered.

The primary source of knowledge about customer behavior is their decisions and how they use an online store or other e-commerce system. The most complete picture can be obtained by capturing all of their activities. Such approach is known as *clickstream* [27]. Such data includes every action and decision and its context (including the website visited, browsing time, devices used, geolocation data), so it can be used to tailor communications with great precision. In addition to data derived from customer choices, information provided directly by users, such as product reviews, can also be used for behavioral analysis. In this case, however, four primary determinants must be taken into account: textual content, non-textual content, reviewer-related factors and product-related factors [28].

When deciding on personalization, it is important to note that companies must not only focus on consumers' preference for benefits, but must also consider consumers' privacy concerns and incorporate them into the tailoring of personalized services/products [44]. Striking the right balance between privacy (including information sensitivity) and personalization is critical to ensuring customer satisfaction. Making users aware of the purposes of data collection (especially those resulting from tracking online activity) has a direct impact on subjectively perceived UX [45]. Moreover, the importance of human cognitive factors (i.e., cognitive styles and working memory capacity), which can influence the perception of the quality of the personalization offered, cannot be overlooked [46]. The incorporation of emotional data based on user comments and opinions in the generation of recommendations on e-commerce platforms is also an interesting direction [47].

B. AI/ML-BASED APPROACHES TO PERSONALIZATION

Current recommendation techniques include content-based filtering (CBF), collaborative filtering (CF), and hybrid solutions. Evaluation of their effectiveness can vary widely depending on the context of application, due to their inherent characteristics of each approach [29]. The main problems that arise in CF applications are scalability and sparsity issues. These can be minimized by using a method that combines rough set technology and the nearest neighbor approach [30]. Convolutional Neural Networks, which can minimize problems arising from the local sparsity of user data, are also a potential development direction for product recommendation systems [31]. Another way to improve the quality of recommendations is to use hybrid [32], hierarchical models [33] and multi-agent based solutions [34]. Among other proposed personalization solutions, a recommendation system based on associative classification with four modules is worth mentioning. It includes: Requirement Preprocessing, Classifier Generation, Classification, and System Performance Validation, and leads to the anticipation of heterogeneous customer requirements [35].

AI/ML methods are becoming increasingly popular. They can be used in various ways to personalize e-commerce systems [36]. The concept of Artificial Intelligence-based Personalization (AIP) involves supporting users at five stages of the customer journey through personalized profiling, navigation, incentives and engagement [37]. When using AI, it is undoubtedly necessary to examine potential risks, such as fairness and security issues, but it is also important to understand how each AI service behaves, as this is the basis for rationally choosing the right approach or tool [38]. The widespread use of ML in personalizing human-computer interaction is leading to the popularization of the concept of human-in-the-loop learning [39], which involves continuous adaptation based on the decisions and behaviors of users of information systems, including e-commerce systems [40].

An interesting direction in the development of personalization in e-commerce is the tailoring of the user interface to different aspects of sustainability [48]. Transport issues can also be linked to sustainability [49]. In the case of e-commerce, the problem of *last mile delivery* is particularly noteworthy, which can be solved in various ways (e.g. by using drones [50]) and personalized according to the characteristics of the recipient. The issue is not only the delivery of the e-commerce order itself, but also possible returns due to the legal requirements of distance selling [51].

Although AI/ML methods are already widely used in e-commerce, their rapid development is resulting in new areas where they can support personalization. An interesting example would be Product Question Answering (PQA) solutions that lead to the development of intelligent online shopping assistants that improve the customer shopping experience [52]. According to research, both anthropomorphism and the need to remain consistent significantly increase the likelihood that users will comply with a chatbot's request for service feedback [53]. Moreover, such systems can apply sentiment analysis techniques to better understand the user's queries and emotional state [54]. In this context, the opportunities, but also the consequences and risks of anthropomorphizing such AI-based systems should be kept in mind [55], especially considering the technological developments and the rapidly increasing sophistication of *thinking and feeling* AI. In addition to chatbots or virtual assistants, there are many other applications for generative AI in e-commerce, such as writing product descriptions or marketing texts, search personalization and SEO optimization [56].

In summary, personalization is recognized as a key trend in the development of e-commerce today. Typically, this involves tailoring product recommendations and implementing individualized promotions and pricing offers. A less explored and undervalued avenue for personalization is the customization of the user interface presented to customers. Given the diversity of online shoppers and their different usage patterns, this is an interesting area of research. However, a review of the literature reveals that the topic of providing a personalized user interface using a multidimensional approach in e-commerce is not widely discussed. Consequently, there is a lack of clear evidence to verify the potential impact of the different, personalized user interfaces on the key performance indicators of online shops. This thesis is confirmed by a review of 158 papers on applications of machine learning and deep learning techniques in e-commerce, none of which address extended (beyond product recommendations) UI personalization as a potential venue for ML use [57]. To fill this gap, this paper presents and discusses the issue, starting with a general framework for a multivariant user interface solution. Practical verification of the effects of implementing such a solution allows drawing conclusions and critically discussing opportunities, limitations of potential development directions.

III. BASE FRAMEWORK OF MULTIVARIANT UI PLATFORM

The personalization of e-commerce systems using the concept of multiple UI variants requires the development of a comprehensive solution that addresses all the necessary functional requirements. It should also be open to further expansion as business needs and advances in the use of AI and ML bring new opportunities and challenges.

The basic version of the platform, which allows to prepare and serve dedicated UI variants, personalizing both content and layout, requires four closely related components (modules) (see Figure 1):

- *Data collection*, responsible for gathering data on customer behavior, with special attention to privacy issues;
- *Data analysis*, responsible for multidirectional data analysis;
- *Implementation*, responsible for designing UI variants and serving them to customers;
- *Monitoring and optimization*, combined with data analysis to translate feedback into improved personalization.

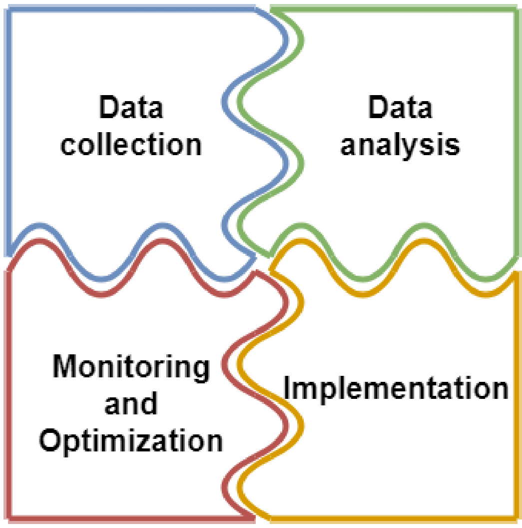

FIGURE 1. General concept of a multivariant UI solution.

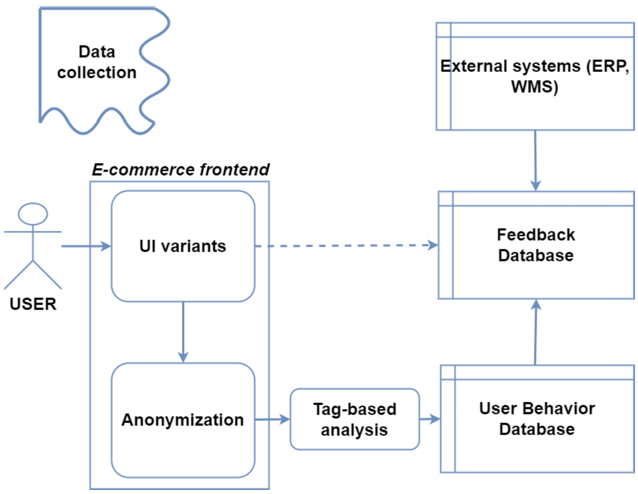

FIGURE 2. Behavioral data collection model.

These components work together to create an ecosystem that not only customizes UI variants, but also ensures the security, adaptability, and quality of the personalized experiences delivered to users.

A. DATA COLLECTION

The basis for the concept of multivariant UI based on customer behavior is the knowledge of how customers use the online store. To obtain this information, it is necessary to analyze the customer journey step by step, with the goal of capturing the entire clickstream. However, there are some important points to keep in mind.

First, with regulatory and market trends emphasizing the importance of privacy, e-shop should obtain customer consent to collect data for personalization purposes and anonymize the information gathered. At this point, it is worth mentioning the limitations in the use of the proposed solution due to the fact that some customers use applications that restrict the use of cookies or block them. Since these files are crucial for the collection of data about the user's behavior (for example, thanks to them it is possible to apply tokenization, which eliminates the use of more private identifiers such as the email address), their deactivation on the customer's device makes it impossible to track them, and therefore there is no basis for recommending personalized communication. Therefore, it can be concluded that a customer who does not allow himself to be known will not be able to experience personalization.

Second, tracking a customer's activity in an online store makes it possible to analyze his or her behavior up to the point of placing an order. However, this is not the last stage of the purchase process, and the remaining steps of the process are also important, especially from the perspective of counting performance indicators. Some of the orders placed may not be paid for, some may not be shipped (e.g., due to incorrect inventory levels), and some of the products purchased may be returned due to regulations that give customers the right to do so. This means that in addition to data from the online store, it may also be necessary to have information from external systems, such as the Warehouse Management System (WMS) [58].

The model of the data collection module, addressing the aspects indicated, is shown in Figure 2. The first element of the solution that customers interact with directly are the UI variants. Their number depends on business decisions and is determined by a fixed number of clusters. However, the number can be increased by adding variants derived from other specific goals, such as older customers or new customers, to those derived from behavioral analysis. Customers are served an interface variant dedicated to their group, and if they are not assigned to a group, they use the default variant or the variant for new users.

Another feature is data anonymization, which is the mapping of identified customer behavior to a unique identifier that contains no private information. The same identifier is used to assign users to clusters and then forms the basis for deciding which UI variant to serve.

In the next step, customer activity information is processed using a tag-based mechanism that allows targeting of the collected data. Available Tag Management System (TMS) applications such as Google Tag Manager, Tealium Customer Data Hub or Magic Pixel can be used to accomplish this task without the need for advanced own software development.

The collected data is stored in a User Behavior Database, which serves as a central repository of information about actions taken during the customer journey. In the adaptation mode of the multivariant UI mechanism, this data is also the basis for analyzing the impact of the introduced changes and for filling the Feedback Database. Optionally, feedback can also be collected directly from customers in an explicit manner (e.g. as an answer to the question *Do you think this version of the user interface is better?*) and used in supervised learning. In addition, the Feedback Database is updated with information from external systems to monitor the status of orders. Thanks to this operation, macro conversion indicators

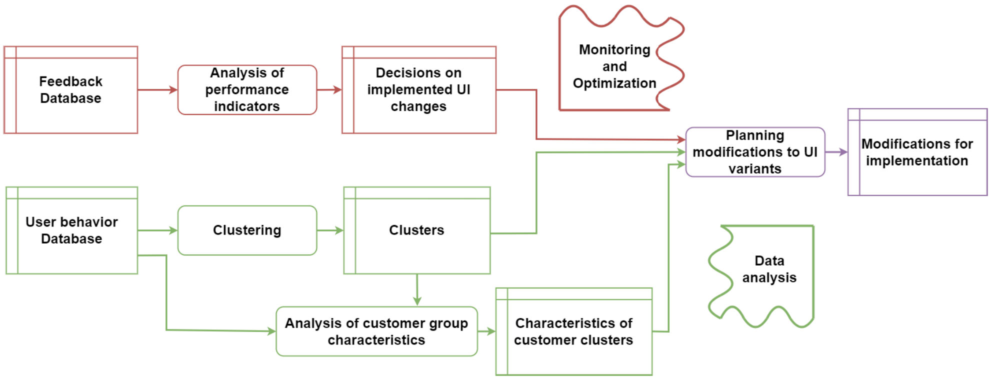

FIGURE 3. Data processing model.

can be calculated with greater precision, which leads to an increase in the quality of the evaluation of implemented UI modifications.

It should be noted that the collection of customer behavioral data applies to all e-commerce users, both returning and first-time visitors. There are differences in how this data is used. For all customers, behavioral data is the basis for clustering (segmentation) and analysis of characteristics that differentiate groups of users. Returning users can also be served a dedicated UI variant, so the information collected also provides feedback for evaluating the effectiveness of the changes made.

B. ANALYSIS AND OPTIMIZATION

The information gathered in the two databases forms the basis for further analysis, which runs in two tracks in the first phase and combines the results in the second phase, enabling feedback-based planning of UI changes (Figure 3). The **data analysis** path aims to identify customer characteristics that can be used to distinguish consistent groups for which dedicated UI variants can be planned. This is done primarily through the use of clustering algorithms, which are classified as unsupervised machine learning methods. The choice of clustering method is an important decision because it affects the performance and efficiency of the platform serving multivariant UIs. When deciding on a clustering algorithm, there are three sets of factors to consider: computational complexity, overall clustering quality, and business context applicability. Among the clustering methods that have been analyzed for the application of multi-variant UI in e-commerce are DBSCAN (Density-Based Spatial Clustering of Applications with Noise), BIRCH (Balanced Iterative Reducing and Clustering using Hierarchies), GMM (Gaussian Mixture Model), Agglomerative Clustering [20], K-means and Spectral clustering [21].

The size of data sets containing information about e-commerce customer behavior forces careful selection of the clustering algorithm due to computational requirements. Some of the available methods (e.g., agglomerative or spectral clustering) are not suitable for processing large data sets, and such options should be discarded. It is also important to consider the resources needed for preprocessing, as this step may require more resources than clustering itself.

A general assessment of clustering quality can be based on commonly used metrics such as the Silhouette Score [59], Calinski-Harabasz Index [60], Dunn Index [61], and Davies-Bouldin Index [62]. Its purpose is to analyze various attributes of clusters, including the degree of consistency and separation between data points, similarity between objects, and cluster density. When selecting indicators to assess the quality of clustering, it is important to keep in mind that their recommendations may vary, highlighting the need for a combined indicator that considers multiple criteria.

The last but not least, the business critical factor influencing the choice of clustering algorithm should be the verification of its suitability to the business context, leading to the practical utility of the resulting clusters. In the case of a multivariant UI, customer groups should be as similar in size as possible, and the number of customers in a single cluster should not be less than the chosen threshold [21]. These requirements arise from the potential cost of designing dedicated UI variants, which is only worthwhile if the UI variant will be served to a sufficiently large number of users.

The second key element of data analysis is to identify the characteristics of the customers in each cluster. The goal is to identify potential directions for UI changes for each cluster individually. These activities can be based on analysis of the frequency of actions taken and the most popular action sequences, which may help identify typical user behavior. This task is aimed at identifying areas of the user interface that should be modified, in order to improve the customer experience.

The **monitoring path** is designed to verify the impact of implemented UI modifications on customer behavior and decisions. In order to assess the quality of the changes, it is necessary to compare the values of selected indicators, calculated for the part of clients from the cluster who received the modified UI variant and the part of clients who received the variant without modifications. It is important that such an analysis is carried out within a single cluster, from which should come the clients who are served both versions of the UI. In practice, it can be assumed that each cluster of

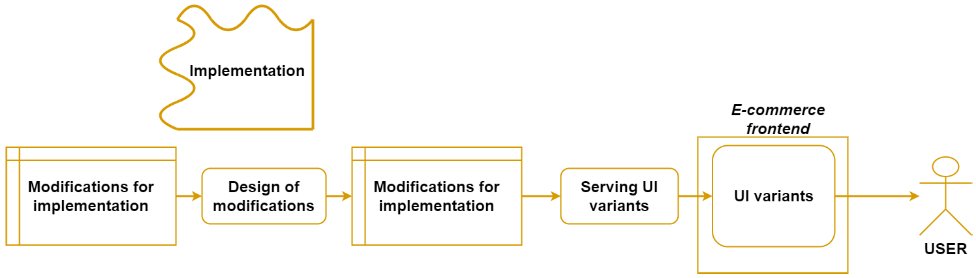

FIGURE 4. **UI variant serving model.**

customers is randomly divided in half and each subgroup is served a version of the UI - either with or without modifications.

Various metrics can be used for analysis, both macro-conversion (such as Conversion Rate - CR, Average Order Value - AOV) and micro-conversion (such as Click Through Rate - CTR, Partial Conversion Rate - PCR). The latter measure allows to verify the compatibility of user behavior with the expected customer journey and can be flexibly adapted to the UI changes under study [23]). It should be noted that the choice of indicators for assessing the impact of changes is very important for two reasons. First, macro-conversion indicators, which in the case of online stores are based on orders placed, require a relatively long time to collect enough data to ensure the statistical significance of the results obtained. Second, macro-conversion indicators are not able to evaluate in detail small changes, their impact on subsequent stages of the shopping process, and identify bottlenecks or steps where customers end their visit without placing an order. Micro-conversion metrics do not have these drawbacks, but are far less significant from an overall business efficiency perspective. For these reasons, decisions to accept or reject proposed UI changes should be based on a combination of macro and micro conversion indicators to ensure maximum reliability.

Finally, the two paths merge in the design phase of new UI changes. These should be driven by both clustered customer features and feedback on previously implemented changes. In the solution discussed, this task is performed by a human UX expert, but may also involve AI/ML-based tools. This phase closes the cluster-specific modification optimization loop and allows iterative exploration of the best configuration of UI variants. Proposals for new changes, once implemented in the e-commerce environment, will be analyzed in the subsequent iterations.

C. IMPLEMENTATION

Implementing the designed changes requires translating the graphic mockups into e-commerce system code (Figure 4).

This is the first strictly technical step in tailoring the UI variants. Its effect is to add modifications to the repository of possible changes. The UI variant can be treated as a set of modifications that adapt the base variant to the specifics of particular customer clusters. This collection may change as a result of the modification acceptance/rejection mechanism and is developed independently for each user group.

The final step is to communicate the UI variant to be served to the customer to the front end of the e-commerce system. A token, given during the first visit and stored in a cookie file, is used to identify users. If it is not found when the customer enters the site (e.g., the customer has cleared the cookie history or the file has expired), it is created and the user is treated as a new visitor. It is worth mentioning that the system does not allow to switch the UI variant during the user's session, so there is no risk of surprising the customer with a change of interface while visiting the e-shop. However, if the customer's behavior changes over time, he or she may move to another group after reclustering and be served with the appropriate UI variant. In this case, the user may experience a change in layout, but this will be the result of the solution adapting to the changed use of the online shop. However, if users do not change their behavior, reclustering will not result in any changes to the UI variant being served.

The described framework of the system allows to prepare, serve and verify multivariant UI in e-commerce. Its use of ML methods enables the analysis of a large amount of user behavioral data and makes it possible to identify characteristics and relationships between groups of customers that could not be found using traditional segmentation methods. However, it is important that the concept of a multi-variant user interface is not just a theoretical consideration, but should also be validated and verified in practice. The potential marketing benefits of personalized UX should be further enhanced by measurable business benefits, so that the investment in such a solution can be translated into increased e-commerce sales. To demonstrate the practical application of the described framework, an experimental study was conducted to answer the question of whether multivariant user interfaces can lead to better macro conversion rates.

IV. EXPERIMENTAL RESEARCH

A. METHODOLOGY

The verification of the concept of multivariant UI in e-commerce was carried out in the form of an experimental study implemented in an online sportswear store. The research was conducted using the AIM^2 platform developed by Fast White Cat (https://fastwhitecat.com/en/), a software company specializing in the implementation of Adobe

Magento-based online stores. It was divided into two parts, which differed in the learning dataset and the chosen clustering method.

The following questions were posed:

RQ1: Can dedicated UI variants improve the values of e-commerce performance indicators based on macro conversion?

RQ2: What are the limitations of using multi-variant UI?

The research began with the collection of learning data. In the first iteration, there were 268,151 user sessions containing customer behavior data collected over 2.5 months. An agglomerative clustering algorithm was used to group users, with the number of clusters (k) set to 4. Such a choice made it possible to obtain clusters with large numbers, so that adequate feedback could be obtained in a short time. Increasing the value of the k parameter can be useful in many cases, and the upper limit determines the cost of designing UI variants.

Among the clusters generated, one was selected that contained the customers most likely to return to the store, increasing the likelihood of repeat purchases during the testing period of the proposed UI changes.

The next step was to analyze the characteristics of customers from the selected cluster for possible UI changes that would match their behavior. Based on the expert analysis, 13 areas were identified that could be changed to match the UI variant. These included the appearance of the home page, listing, and product card. The modifications were implemented and based on them, a dedicated UI variant was defined for further research.

To verify the impact of UI changes, customers from the selected cluster were divided into two groups. One of them was served with the designed dedicated UI variant and the other with the standard UI variant. The CR and AOV metrics, which are key metrics in e-commerce business performance analysis, were used as the basis for evaluation and provided the basis for comparing the two UI variants.

In the first iteration, the verification took 1.5 months. During this time, 162,926 user sessions were identified, of which 7,683 resulted from the activity of clients assigned to the selected cluster. It took 10 minutes and 14 seconds to cluster the first dataset.

The way the study was conducted in the second iteration was analogous to the first. The difference was that the data collection period was extended to 5 months (resulting in a total of 665,256 user sessions in the learning dataset, including sessions from the first dataset) and the clustering method was changed to K-means due to its lower computational complexity and thus the ability to process more data. In this case, the clustering time was 21 minutes and 30 seconds.

The set number of clusters did not change. This time, however, two groups of customers were selected for which 7 and 12 UI modifications were designed and implemented, respectively.

This time the verification took one month and resulted in 180,126 user sessions, of which 6,290 were related to the first studied customer group and 8,924 were related to the second customer group.

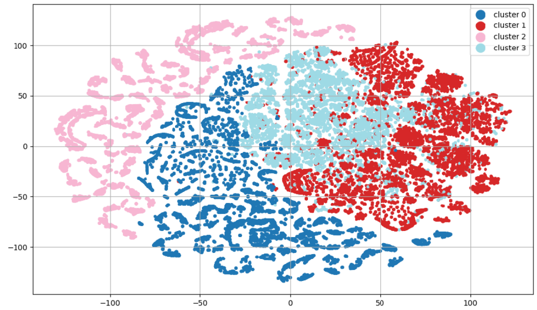

FIGURE 5. Cluster visualization - iteration 1.

TABLE 2. CR and AOV values - iteration 1.

UI Variant	Number of orders	CR	AOV	CR*AOV
Dedicated	163	4.14%	35.63	1.47
Standard	112	2.99%	44.12	1.32
Difference	+45.54%	+38.46%	-19.24%	+11.36%

The experiment described in this paper was designed to verify the effectiveness of UI variants dedicated to specific customer groups and served to returning customers. New customers did not receive dedicated UI variants, so the effectiveness of UI modifications designed for new users was not verified. Such an analysis could be the subject of future research.

B. RESULTS

1) ITERATION 1

As a result of clustering, the following sizes of customer groups were obtained: 10,246, 15,360, 9,960, and 14,745. A visualization of the clusters (using the t-SNE approach [63]) is shown in Figure 5. It should be added that t-SNE is only a technique for visualizing high-dimensional data in a low-dimensional space, so the t-SNE plot cannot be analyzed quantitatively (hence the lack of description on the axes).

A cluster labeled *cluster3* containing 9,960 customers (19.80% of the total analyzed population) was selected for further analysis.

The calculated values of CR and AOV ratios are shown in Table 2. The results show that the implemented changes significantly increased the number of orders placed (and thus improved the conversion rate), but negatively affected the average order value. This suggests that the dedicated UI attracted customers interested in less expensive products. Looking at the aggregated indicator ($CR*AVR$), it can be seen that the implemented changes, in total, resulted in an increase of more than ten percent in the value of this measure.

An important conclusion from this iteration of the study was drawn from the analysis of resource consumption during clustering (Figure 6). It turned out that the computational complexity of agglomerative clustering was so high that it would be impossible to use it with large datasets to

FIGURE 6. **Resources usage - iteration 1.**

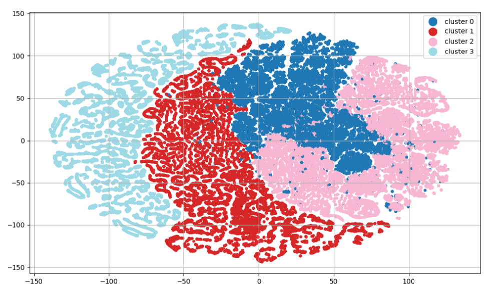

FIGURE 7. **Cluster visualization - iteration 2.**

cluster customers for multivariant UI. Despite the fact that the training set was created using only 2.5 months of data and the online store where the study was conducted has average traffic, agglomerative clustering required the use of half of the available memory and the vast majority of the processors' processing power. Given the characteristics of this algorithm, it would be expected that clustering would not be successful if the learning data set were increased by more weeks. For this reason, in the next iteration, the clustering method was changed to the K-means algorithm, which has lower requirements on available computing resources.

2) ITERATION 2

In this iteration, the learning set contained many more user sessions, resulting in a larger number of clustered clients. In this part of the study, K-means clustering was chosen, without changing the value of the k parameter. With this approach, it was possible to compare the effects of serving dedicated UI variants after applying different clustering techniques and to evaluate their suitability for further research.

Two clusters (labeled *cluster0* and *cluster2*) were selected for further study, with 34,922 (23.39%) and 39,054 (26.16%) users, respectively. A visualization of the clusters is shown in Figure 7.

The values of CR and AOV ratios calculated in this iteration are shown in Table 3. The results obtained this time vary widely among the customer clusters analyzed. The first group of customers is slightly less likely to return to the online store, but the modifications suggested by the UX expert had a positive impact on purchase decisions. The UI-dedicated variant resulted in higher values for both indicators studied, which together resulted in an increase in the value of the aggregated e-commerce performance index by almost 35%.

TABLE 3. **CR and AOV values - iteration 2.**

UI Variant	Number of orders	CR	AOV	CR*AOV
Dedicated-1	109	3.50%	49.83	1.74
Standard-1	90	2.84%	45.45	1.29
Difference	+21.11%	+23.24%	+9.64%	+34.88%
Dedicated-2	164	3.71%	46.53	1.72
Standard-2	159	3.53%	49.73	1.76
Difference	+3.14%	+5.09%	-6.43%	-2.27%

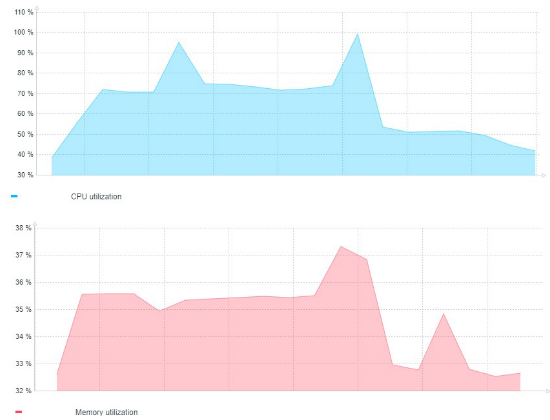

FIGURE 8. **Resources usage - iteration 2.**

For the second group of customers, the results were different. The number of orders (and thus the CR rate) increased, but only by a few percent. At the same time, the average order value fell by a similar percentage, so the value of the overall aggregate index for the dedicated UI variant worsened by 2%.

It is noteworthy that in this case the clustering required less memory (Figure 8), even though the learning dataset was 2.5 times larger, confirming earlier predictions. Given the size of the data sets resulting from the collection of information on e-commerce customer behavior, it is reasonable to assume that the target solution for multivariant UI should be based on the K-means algorithm or its improved versions.

C. DISCUSSION

The research confirmed that user interface variants dedicated to specific customer groups, which were generated using clustering algorithms, can significantly improve e-commerce performance metrics. Thus, it is possible to respond positively to $RQ1$. However, it is not always the case (as research has also shown) that a change project prepared by a UX expert produces a satisfactory result. It's important to remember that expert-based matching of UI variants to customer groups is an iterative process that can be done by trial and error. An alternative might be to break the set of planned changes into individual modifications and analyze them one by one. This would be a kind of A/B testing that could be automated, creating a mechanism for auto-adaptation of the UI. However, there are potential limitations to this approach. The most important is the concern that implementing individual modifications may not affect macro conversion rates enough to affect changes in observed CR or AOV values. Wanting to develop the system in this direction would be more likely to rely on micro-conversion metrics to identify the impact of small modifications on customer behavior. The problem, however, may be that from a business owner's perspective, micro-conversion may not be important if it does not translate into measurable macro-benefits.

In addition to the problem of determining the granularity of the set of modifications and the associated need to select performance measures, other limitations of the proposed solution can be also identified (*RQ*2).

Undoubtedly, the issue of customer retention rate is very important. Serving dedicated UI variants only makes sense if users revisit the online store. If customers rarely return to your online store the business is based on attracting new customers rather than on increasing loyalty. In such case the described approach should not be implemented. On the other hand, if the goal is to increase loyalty (and this is usually the case when taking action to personalize communications), then multivariant UIs can add significant value. In the research presented in the paper, the return rate allowed for 5-10% session coverage with dedicated UI variants for the clusters studied, although it should be noted that the experiments were conducted over a relatively short period of time (4-6 weeks). This problem can be minimized in two ways - by increasing the scope of learning data to analyze as many customers as possible, and by encouraging visitors to use the online store as often as possible, particularly through effective UX personalization.

However, there is still the problem of new, non-clustered customers. In practice, they can be treated as a kind of supercluster, not directly resulting from clustering, but complementing it. It is worth designing a special UI for this group as well. Knowing that a user is coming to the site for the first time (either at all or for a long time) can be used to encourage them to stay in the online store, showcase the brand or products, show a tutorial, etc. This leads to the conclusion that a hybrid approach to serving multivariant UIs may be a worthwhile option to consider. Dedicated variants can be tailored to clusters of customers based on behavioral data (as is the case in the framework described), but they can also be prepared for specific pre-defined groups of customers, to which users can either be assigned by the clustering mechanism or can decide themselves that they want to be served a specific UI variant (e.g., designed for the elderly, for those engaged in sustainability, etc.).

V. FURTHER DEVELOPMENT

Verification of the introduced concept of serving a multivariant UI based on customer groups generated through the use of ML methods showed that it has potential to be used to fully personalize layouts in an online store, going beyond the *one UI for all* scheme. However, the identified limitations planning for further development and enhancement. It is worth noting the value of the collected customer behavior data. In the basic version of the solution, it is used to group users, but thanks to increasingly better AI/ML mechanisms, it can have a much wider application in e-commerce personalization. Expanding the customer profile data through additional surveys could also be considered. However, such an approach would require in-depth analysis to identify the issues and the quality of the responses.

AI-based systems can be generally categorized into three main groups: *mechanical AI*, ideal for standardization; *thinking AI*, optimal for personalization; and *feeling AI*, most effective for fostering a sense of connection [64]. The second group in particular has potential in described applications, developing the approach to improving UX in e-commerce.

Undoubtedly, one direction for further development should be the optimization of algorithms used for preprocessing and data analysis, including clustering methods. The current solution suffers from performance problems that limit the possible range of learning data that can be processed. Adding an *intelligent* preprocessing function and optimizing the chosen clustering algorithm could significantly speed up the performance of the system and thus its business value.

Another possibility for the application of AI could be tools for cluster prediction based on the first identified e-commerce actions of a new user. As mentioned above, non-clustered customers are a very large group of visitors. Their specificity can be addressed by offering them a dedicated UI variant, but one could also try to pre-assign them to one of the existing clusters using knowledge of initial activity. This is both an algorithmic and a performance challenge, but if solved effectively, it can significantly improve the effectiveness of the platform.

There is also potential in the implementation of self-adaptation. While some steps of the described UI customization process cannot (yet?) be automated (e.g. the design of mock-ups and their implementation), it is possible to organize the process of evaluating changes in such a way that decisions to accept or reject changes are made autonomously. Additional possibilities in this regard are provided by allowing feedback directly from the customer, as this is the basis for the use of supervised learning algorithms. A combination of unsupervised and supervised learning methods could have a positive impact on business outcomes, perceived usability, and customer perception of personalized layouts.

Analysis of customer behavior can lead to conclusions about their involvement in various types of initiatives, such as sustainability. The right UI modifications can reassure customers that their purchases are in line with this approach. This can be done in a variety of ways, from serving simplified graphics that result in a lower carbon footprint due to the amount of data transferred, through adding features that support customer involvement in sustainability initiatives, to recommending products, payment methods, or delivery methods (including *last mile delivery*) that fit with this concept. It is worth noting that a dedicated UI can not only serve to meet customer expectations for sustainability support solutions, but can also have an awareness-raising and engagement-building effect on users. This direction is driven by the fact that e-commerce customers often exhibit unsustainable consumer behavior due to a lack of basic knowledge or motivation, making it difficult for them to make environmentally conscious choices [65].

An very interesting direction for the development of multivariant UIs seems to be the use of AI generated content (AIGC) tools. To achieve comprehensive personalization, it is possible to personalize the content communicated to e-commerce customers, in addition to the commonly used in practice product recommendation engines and dedicated layouts discussed in this paper. Te range of potential applications is wide and includes both real-time communication solutions (e.g. virtual assistants, Product Question Answering - PQA systems, etc.) and static content such as product descriptions and applications, company information, etc. In this case, it is worth mentioning the integration with backend systems provided in the discussed framework. This is crucial if AIGC is to be used to personalize communications, especially if integrated systems include Product Information Management (PIM) class solutions. Data from external systems can be the basis for further text generation by AI, both in real-time communication (virtual assistants) and in the creation of descriptions. The latter application, taking into account the possibility of serving multivariant UIs, offers the possibility of generating dedicated product descriptions based on the identified characteristics of each cluster. However, the scope of such a solution depends largely on the nature of the products offered. For goods with identical characteristics that are well described in publicly available sources (e.g. consumer electronics, books, music), generating descriptions is not a problem, even using publicly available Large Language Model (LLM) class tools such as ChatGPT. The situation is slightly different if descriptions are to be generated for non-standard products, because then it is necessary to train the model using, for example, inside information, catalogs, or advertising brochures. And don't forget about the information gathered about customer behavior - this knowledge can also be used to train AIGC models, providing the opportunity to better personalize the content presented to specific groups of customers.

When analyzing the prospects of using AI/ML for UI personalization in e-commerce, potential risks and limitations cannot be overlooked. Security challenges, which include economic, cultural, social, and military aspects, as well as ethical concerns and qualitative issues related to artificial hallucination, pose significant obstacles. Potential threats include unintentional invasions of privacy, prejudice, discrimination, copyright concerns, and the adverse effects of intentional harmful actions on personal privacy, social equilibrium, and national security. The importance of these issues underscores the plans for implementing regulations that establish standards and strengthen the security of artificial intelligence and generative content systems for their continued advancement. An example of this is the so-called *AI Act*, a European Union regulation on artificial intelligence [66]. Its reach extends to all sectors, except the military, and applies to all categories of artificial intelligence. The regulation would apply to vendors of artificial intelligence systems as well as companies that use them in a commercial capacity. After more than two years of negotiations, the document was agreed upon in December 2023, paving the way for further proceedings. Admittedly, there are planned grace periods for the new regulations (from 6 months to 2 years), but it will undoubtedly be a big step towards standardizing AI applications. However, it can be assumed that the potential applications of personalization in e-commerce will not remain unaffected by the new law.

VI. CONCLUSION

Digital Economy is associated with various economic developments and is now a key trend, driven by the growing technological capabilities to collect, process and use data. One of its most visible and widely noticeable manifestations is the expansion of various forms of e-commerce. Billions of people worldwide use this form of shopping, and the ability to shop online has become an essential aspect of the digitalization of modern life.

On the other hand, it should not be forgotten that the competitiveness of e-commerce makes it necessary to look for tools that will not only attract new customers, but will also be able to retain the existing ones. Potential solutions include all aspects of personalizing the user experience. Because the user interface is the fundamental connection between businesses and consumers in e-commerce, personalization efforts focus primarily on it. This approach is not new, having been used practically since the early days of e-commerce, but technological advances are significantly changing its basis, which is customer behavioral data. New data collection and processing capabilities, including the use of AI and ML solutions, mean that UI personalization can be more complete, accurate, and effective.

The e-commerce personalization approach presented in this paper goes beyond standard product recommendations. The use of multi-variant user interfaces moves away from the compromises that characterize solutions that use a single variant for all customers. Because the grouping of users and the design of dedicated variants are based on machine learning methods, it is possible to capture characteristics and behaviors that would be impossible to identify using traditional decision rules. The research presented here shows that tailored UI variants can deliver measurable benefits, which is just as important from a business perspective as ensuring customer satisfaction and personalized experiences.

While offering dedicated layouts is a big step toward full UI personalization in e-commerce, there are opportunities for further development of this concept. In particular, the broader use of AI-based tools offers great promise. One example is automatic content generation, because different versions of the layout are served to different groups of customers, and personalized content can be added to these versions. The information collected about e-commerce usage can be an excellent basis for generating messages that personalize communications.

However, potential limitations should not be overlooked. While customers expect personalization in e-commerce, they are increasingly concerned about privacy. At the same time, good personalization requires knowledge of the user, and broad restrictions on the collection of data about their behavior and choices can make personalization difficult or ineffective. The introduction of user privacy regulations has forced major changes in the approach to personalization, and future changes in the use of AI may change the rules of the game again. The evolution of tools that use AI to personalize customer communications in e-commerce will depend as much on technological developments, user needs and requirements, as it will on future regulations governing AI applications.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could appear to influence the work reported in this paper.

DATA AVAILABILITY

The datasets used in the study described in the paper are available for download from [67].

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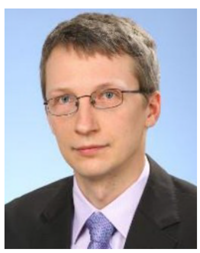

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