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# ARCHITECTURE OF THE PLATFORM FOR SELF-ADAPTATION OF E-COMMERCE INTERFACES

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**Purpose:** Personalising the e-shop content is one of the marketing methods used in e-commerce. However, it has been limited to product recommendations, advertisements, and prices. Meanwhile, layout personalisation also offers great, but underestimated, opportunities.
**Design**: The analysis of existing solutions, the research and development work allowed for the design, implementation and practical verification of a platform that enables serving multiple interface variants to e-shop customers.
**Findings:** One of the results achieved is a solution architecture that can be successfully used for customer segmentation and allows for dedicated interface variants to be served.
**Research limitations/implications**: The research conducted was aimed at practical verification of the effectiveness of the proposed architecture and was therefore limited in scope. Further work should include more in-depth research, including elements of self-adaptation of the user interface.
**Practical implications:** The proposed architecture can be applied to e-commerce solutions that combine the ability to analyse customer behaviour using machine learning methods with a personalised approach to the user interface. Such approach has already found its practical implementation in the e-shop of a major sportswear brand.
**Social implications:** Personalisation of the e-commerce interface also has social impact. Recipients of a dedicated interface, served on the basis of the described architecture, can also be customer groups requiring non-standard solutions, such as the elderly or people with disabilities.
**Originality/value:** Serving customers with dedicated interfaces, resulting from analysis of their behaviour and preferences, is not yet a common practice. The proposed solution presents a proposal for an innovative, but already field-verified, solution architecture that can provide a significant competitive advantage in a very demanding e-commerce market.

**Keywords:** e-commerce, user interface, recommendation, clusterization.

**Category of the paper:** Research paper, Case study.

## 1. Introduction

E-commerce has become an important part of the modern economy due to its convenience, cost-efficiency, increased reach, data-driven insights, improved customer experience, and flexibility. As technology continues to advance, e-commerce is likely to become even more important in the years to come. Such solutions can provide a more personalised and streamlined customer experience. With features such as product recommendations, personalised offers, and easy checkout processes, e-commerce platforms can improve customer satisfaction and loyalty. One of the critical aspects of e-commerce that can significantly impact customer satisfaction and retention is user interface (UI) and user experience (UX). By creating a positive user experience, businesses can increase user engagement, build trust with customers, increase loyalty, reduce bounce rates, and generate more revenue.

In order to provide an appropriate and personalised interface to an e-commerce customer, a series of activities must be carried out to gather information about user behaviour and preferences, analyse the data, group customers, prepare a dedicated interface, serve it, and verify the results, so that the solution can then be optimised in a feedback loop. This is important for commonly used approaches such as product recommendations, as well as for more advanced solutions that could deliver a personalised layout.

Preparing an end-to-end solution capable of supporting different models for delivering a multi-variant e-commerce user interface is not a trivial matter. The complexity of the challenge and the services required to solve it makes it crucial to have the right solution architecture to achieve the business goal while meeting the non-functional requirements. This problem was tackled in the design, implementation and refinement of the AIM$^2$ - the platform for self-adaptation of e-commerce interfaces. This solution - an intelligent system that allows e-commerce platforms to optimise their user interfaces automatically – is described in the paper. This is a unique approach that has only been signalled in a few publications, but without any practical verification of the concept. The architecture of the platform consists of several components that work together to provide a seamless user experience:

- User model - a representation of the user's behaviour and preferences.
- Designer module - that let to generate different versions of the UI, which are tested against the user model to determine which version performs best.
- Adaptation engine - provides UI variants and uses artificial intelligence (AI) algorithms to group customers based on actions, events, purchases, and other factors.
- Monitoring - provides feedback on performance of various UI versions, which is used for improving the effectiveness of the adaptation engine and UI variants.

An important element of the evaluation of the proposed architecture was putting it into practice and verifying its effectiveness by analysing the impact of dedicated interfaces on e-commerce KPIs. The pilot implementation has confirmed that the AIM$^2$ platform can improve the e-commerce user experience and has a positive impact on the conversion rate.

## 2. Literature review

Studies on the effect of UI design on the user experience in e-commerce can be found in the literature. The design of a user interface (UI) in e-commerce can have a significant impact on the user experience (UX) of a website or an application. The UI design can influence how users perceive the usability, efficiency, and satisfaction from the e-commerce platform (Gunawan, 2021). Guidance and examples in designing web interfaces of e-commerce applications that are good and easy to use are presented by a number of authors (Heriyandi, 2021; Polewski, 2022; Syafrizal, 2022).

At the beginning, user interface recommendation services for e-commerce systems did not use artificial intelligence methods (Baraglia, 2007; Kopel, 2013). Today, solutions that make extensive use of various AI algorithms, e.g. collaborative filtering (Laksana, 2023) and different methods of clusterization, such as K-means (Zhao, 2022), DBSCAN (Yang, 2015), BIRCH (Jabade, 2023), etc. are applied in practice.

Automatic optimization of e-commerce user interface (UI) can be achieved using various techniques based on traditional approaches or on artificial intelligence (AI) and machine learning (ML) algorithms. It may be the implementation of a computational method that supports the design, revision, and amendment of web e-commerce GUI, streamlining the overall process and minimising the need for HCI experts (Fasciani, 2018). Three interaction approaches in e-commerce UX optimisation are possible: adaptable, semi-adaptable and fully adaptable (Alotaibi, 2013). The first involves manual adaptation by the user or an expert, the second manual adaptation supported by system recommendations, and the third fully automatic adaptation.

The involvement of users and the analysis of their behaviour when using the information system are of great importance in order to achieve the desired result of an effective UI (Evers, 2014). It has been taken into account in a three-phase approach for modelling and developing dynamically adaptive systems based on the combination of the runtime models technique and the AOSD (Aspect Oriented Software Development) paradigm (Loukil, 2017).

The analysis of the architecture of selected digital platforms in e-commerce allowed to propose a tailored four-layers platform architecture for the e-commerce context (Wulfert, 2022). Solutions based on the SOA (Service Oriented Architecture) paradigm can also be used to implement e-commerce platforms (Li, 2019). The next-generation e-commerce platform with the personalised portal, instead of the traditional trading platform, can make better use of the opportunities offered by modern technology (Huang, 2019).

The architecture of a recommendation system in e-commerce typically involves multiple components working together to provide personalised product recommendations to users (Ricci, 2022). At the highest level of generality, the individual elements are responsible for: the acquisition of source data, processing of this data, generation of recommendations and their delivery to the final recipient and can be found in various applications of recommendation systems, such as purchasing recommendations (Oldridge 2022), educational hypermedia targeting (Kristofic, 2005), image recommendation (Melo, 2018), media recommendation (Amatriain, 2013), but also for recommending website personalization (Baraglia, 2007).

The analysis of existing solutions has made it possible to propose an initial architecture to collect customer behaviour data, analyse it using selected machine learning methods and serve a dedicated interface to specific customer groups. Practical verification of the implemented solution enabled the evaluation of the proposed architecture and its iterative improvement.

## 3. Proposed architecture

The AIM[2] platform architecture has four general components, that are typical for AI-based recommendation system (Figure 1).

| | |
|---|---|
| **Monitoring** | User behavior analysis<br>UI variants efficiency measurement |
| **Adaptation engine** | AI based clustering<br>UI variants providing mechanism |
| **UI Designer** | Possible changes to the interface<br>Variants of UI |
| **User model** | User actions and activities<br>Tokenization<br>User behavior patterns |

**Figure 1.** Components of the recommendation system for e-commerce multi-variant UI.

Source: own study.

The detailed architecture refers to the main components, but allows it to be divided into functional modules, identify relationships and define a rough process to achieve the platform's goals (Figure 2).

It contains all the elements necessary to deliver a dedicated user interface in different business models:

– personalised UI for customer groups defined by rule-based methods (e.g. different interfaces for new users, VIPs, loyalty-club members, etc.), with manually designed layout,
– personalised UI for customer groups generated by AI-based algorithms (clusterization), with manually designed layout,
– self-adaptive user interface, a solution that can operate autonomously, without the supervision of a UX specialist, with automatically designed layout.

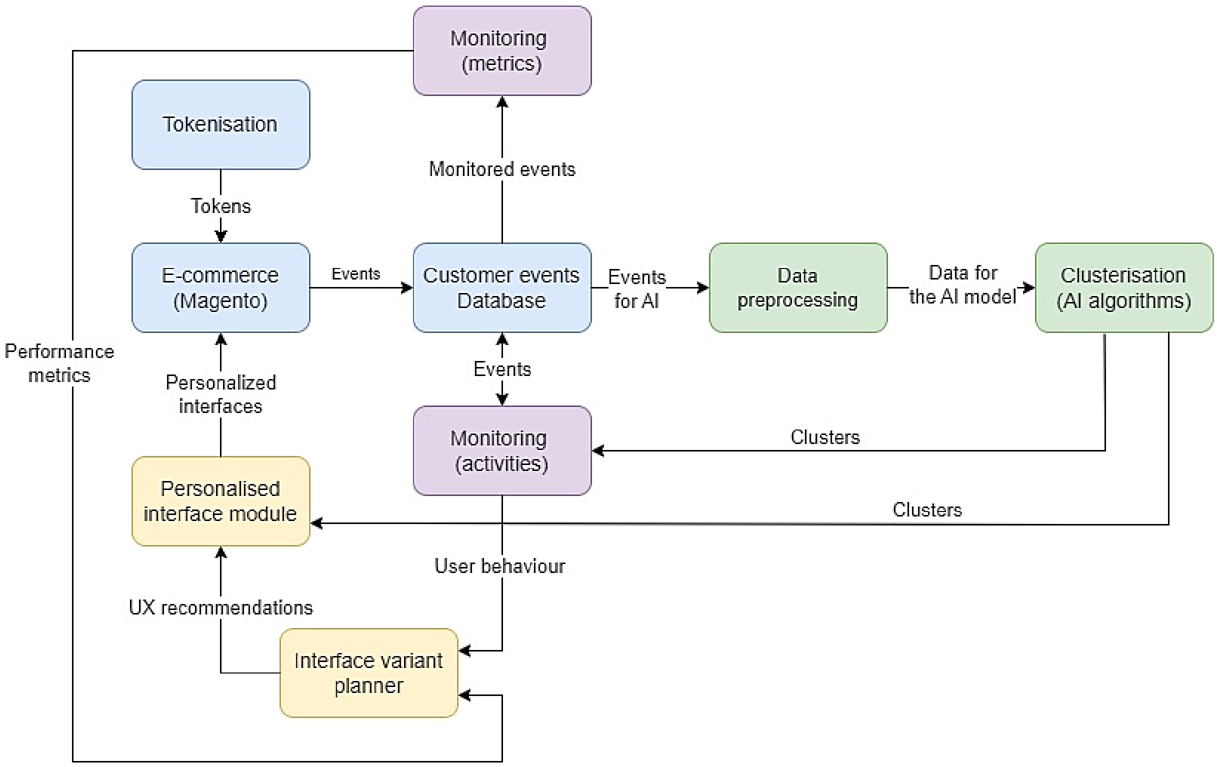


**Figure 2.** Detailed architecture of the platform for e-commerce multi-variant UI.

Source: own study.

### 3.1. User model

The collection of reliable data on e-commerce user behaviour is crucial to the functioning of the platform. It is important that the data collected reflects the actual actions taken by the e-shop customers, but with a high level of anonymity guaranteed. This component includes 3 modules:

– Tokenisation.
– User profiling.
– Data collection.

The first of them is responsible for ensuring privacy and compliance with the legal conditions for the protection of personal data (GDPR). Before the user activities observed in the e-shop are stored, a process of deletion or anonymization of personal data takes place and the observations are assigned to unique tokens associated with e-shop customers. Tokens can be generated using existing standards, e.g. UUID (ISO-9834, 2014).

The CattyFingerStrike module, developed within $AIM^2$ platform, is responsible for ensuring the anonymity of the data collected. It generates UUID token which is stored as *cookie* file on the customer's device.

The original solution involved the use of three tokens:

- *deviceToken* - based on the relevant parameters when a device is used the first time,
- *customerToken* - generated for the logged-in user only,
- *lastToken* - the token generated after entering a valid e-mail address in the observed fields.

Such approach proved to be impractical and insufficient, so it was replaced by a single unique token.

Tokens are sent to the e-shop and stored in the database together with events resulting from customer activity and allow to create user profile. Such profiles include pairs: user ID and theme ID (identifier of the interface variant to be served to the client) and are used to show the correct interface variant in the customer's browser**.**

Data collection is achieved through a combination of two solutions - Tag Management System (TMS) and a Web Analytics System (WAS). TMS is software that can be used to manage tracking tags. A *tag* is a snippet of JavaScript code put into website's source code to gather data about visitors' activity on the website. Such systems can simplify the deployment and maintenance of tags, used in online content to interface with applications such as web analytics, personalisation, and advertising. Top TMS vendors include Google Tag Manager, Tealium iQ Tag Management, Adobe Experience Platform Launch, Qubit and Signal Customer Intelligence Platform (TTC, 2019). WAS is used to track and analyse user behaviour on the website using cookies, log files or hybrid solutions. The most popular system in this class is Google Analytics (GA), with a market share of more than 50%. Other popular tools are: Facebook Pixel, WordPress Jetpack, Yandex.Metrica, Hotjar, MonsterInsights and Matomo (W3TECHS, 2023). The collected information on user behaviour is used to group customers and to analyse the differences between generated clusters.

### 3.2. UI Designer

The UI Designer component includes two modules: *Interface variant planner* and *Personalised interface module*. The first is responsible for management of layout areas that can be modified within the user interface.

Examples of the website design modifications may include, (but are not limited to:

- Menu - changes in the order of categories, changes in the location of tabs, placing the menu in the mobile version.
- Listing - buttons with levels of sales or changes in product categories.

– Product card - larger images, tabs at the bottom, change in content, collapse descriptions, larger price.
– Page footer - collapse/expansion.
– Pop up in the login and registration.
– Search - magnifying the search icon.
– Shopping cart - repositioning of the bar with information about free delivery.
– Filters - changes in order of: category, price, size, colour and other, collapse/expansion of attributes, horizontal filters, category as dropdown, categories in sidebar, filters on top.

Examples of the different search engine design options are shown in Figure 3.

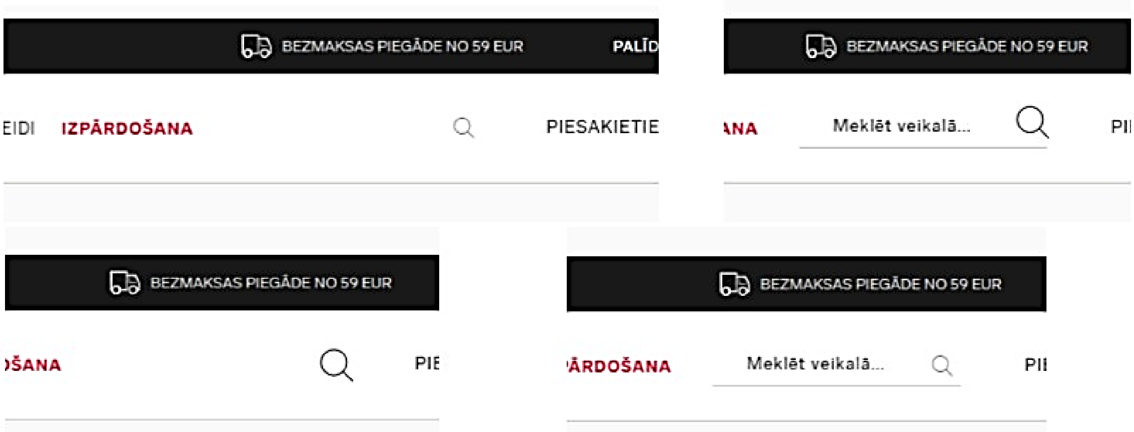


**Figure 3.** Different variants of the search engine in e-shop.
Source: own study.

The second module allows an interface variant to be configured as a collection of changes in individual areas. The choice of modification depends on the characteristics of each customer cluster. A dedicated interface variant can be prepared, and then served, for all or only selected customer groups.

### 3.3. Adaptation engine

The first part of data analysis is preprocessing. For the purposes of clustering, data is aggregated by customer identifiers, with a particular focus on those with registered accounts. As characteristics of each visitor, the dates of the first and last visit and the purchase amount are included, among others. The most important activities should be predefined. All types of stored activities are then counted. In addition, key statistics on the most frequently viewed products, sizes and categories, are taken into account.

The resulting matrix is subjected to a PCA (Principal Component Analysis) transformation for data dimension reduction and information extraction. This involves constructing a linear space basis in which successive dimensions explain the data variance in the best possible way. The algorithm successively maximises the variance after the first coordinate, the second, and so on. The transformation of the data obtained in this way is easier for further analysis.

The second part of the data analysis is grouping of the e-shop customers. One of the possible options is to use machine learning approach - clusterization (also clustering or cluster analysis). It is an unsupervised learning technique that groups a set of objects (e.g. customers) in such a way that objects in the same group (cluster) are more similar (in defined sense) to each other than objects in other groups (clusters). The aim is to identify groups of users with similar behaviour in order to provide them with dedicated user interface variants (Everitt, 2011).

It is difficult to explicitly categorise clustering algorithms because the categories may overlap, so that a method may have features from several categories. One popular approach to classifying clustering algorithms includes (Han, 2011):

- Partitioning methods.
- Hierarchical methods.
- Density-based methods.
- Grid-based methods.
- Model-based methods.
- Spectral methods.
- Model evaluation-based methods.

The choice of clustering method and its parameters depends on the specific requirements of the e-commerce in which the self-adaptation mechanism is implemented. For this reason, it is important that a platform for serving dedicated interfaces has several different clustering algorithms implemented. The preparation of a set of clusters of users to whom dedicated interface variants will be served should be preceded by an analysis of the effects of clustering by various available methods.

A preliminary analysis of the efficiency of different clustering methods showed that two methods - K-means (Li, 2022) and hierarchical (agglomerative) clustering (Ah-Pine, 2018) - exhibited the most promising results. Therefore, both of these methods have been firstly implemented within the described platform and could be selected to generate customer clusters. In the next stages of development, six more clustering methods were added, which could potentially be used to group e-commerce customers.

### 3.4. Monitoring

Monitoring within the platform involves two modules - analysing the behaviour of users assigned by AI to clusters and verifying the performance indicators of the served dedicated interfaces.

The aim of user behaviour analysis is to identify user patterns that can be used to make changes to dedicated interfaces. The basis for this analysis is an overview of actions and action sequences (predecessor - action - successor) and their occurrence frequency. An additional element of this study is the analysis of the values of indicators describing cluster differentiation (Figure 4).

| | label 0, mean/mode | label 1, mean/mode | label 2, mean/mode | label 3, mean/mode | label 4, mean/mode |
|---|---|---|---|---|---|
| action | 13.9553 | 123.5409 | 85.5175 | 44.3444 | 17.5494 |
| event | 3.9731 | 33.5366 | 28.9879 | 11.0461 | 3.3089 |
| firstTimestamp | 2023-05-31 01:22:11 | 2023-05-24 02:54:48 | 2023-06-04 06:47:30 | 2023-05-31 21:12:59 | 2023-06-02 22:17:12 |
| lastTimestamp | 2023-06-01 07:17:28 | 2023-06-06 07:28:55 | 2023-06-15 21:24:42 | 2023-06-07 03:46:33 | 2023-06-06 22:23:01 |
| revenue | 0.413 | 13.0102 | 9.8347 | 4.1907 | 0.0771 |

**Figure 4.** Sample clustering summary.

Source: own study.

The efficiency of the dedicated interfaces is verified by calculating the values of selected indicators - partial conversion rate (PCR), conversion rate (CR) and average order value basket (AOV) of orders placed.

The first assesses the consistency of expected customer journey within e-shop with preferred actions (e.g. homepage - listing - product card - add to cart).

The PCR can be calculated according to the formula:

$$PCR_c = \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{s} EPP_{ij} \tag{1}$$

where:

*n* is the number of sessions related to a customer from the cluster *c*.

*s* is the number of activities within the session *n*,

$PCR_c$ is the calculated PCR metric value for the cluster *c*,

$EPP_{ij}$ is the score of an activity *j* during a session *i*.

For the purposes of the solution evaluation, it was assumed that points are added if the activity was compliant with the expected customer journey, such as going from the homepage to the listing weighted 10 points, adding to the shopping cart weighted 20 points, and moving between product pages weighted 5 points.

CR and AOV are typical and the most important KPIs that help organizations measure and track their business performance (Saleh, 2010). CR is defined as the number of orders a website captures to the number of visitors:

$$CR_c = \frac{O}{n} \tag{2}$$

where O is the number of orders placed by customers from the cluster *c*.

AOV represents the average amount a customer spends when placing an order:

$$AOV_c = \frac{\sum_{i=1}^{O} V_i}{O} \tag{3}$$

where $V_i$ is the value of *i*-th order placed by customers from the cluster *c*.

It is worth noting here that the PCR metric can be calculated for all customer sessions, while the other metrics require the customer to complete the visit with placing an order.

This difference is important because only a few percent of visits result in an order, meaning that a much longer study period is needed to obtain statistically significant results when it comes to CR and AOV indicators.

## 4. Evaluation of the architecture

### 4.1. Research methodology

The research was conducted using the AIM$^2$ platform, developed by Fast White Cat. S.A. The platform includes modules that address collecting information about customer behaviour in an e-shop, grouping customers using different clustering algorithms, designing different user interface variants, serving these variants to selected groups of customers and monitoring of effectiveness of these interface variants.

The evaluation consisted of the following stages:

- gathering information about customer behaviour of the e-shop,
- dividing customers into groups based on the selected clustering method,
- analysing characteristics differentiating the customer behaviour in the groups,
- designing a variant of the interface on the basis of the behaviour of users from the selected group,
- serving of a dedicated interface variant to half of the customers in each group, while the other half of the customers was provided with a default interface,
- collecting information about the purchasing behaviour of the customers when studying the impact of the delivered interface and analysing the results obtained.

The analysis was carried out twice to increase the reliability of the results obtained.

In the first iteration information was collected for 73 days, in the second for 96 days. Actions taken by the customer were recorded for each session, in particular those related to navigating the e-shop, selecting options and filters, adding products, using the search engine. The above constituted learning datasets that allowed customers to be divided into groups.

The learning dataset was processed using the agglomerative clustering algorithm. The clustering method was selected based on the results of previous studies, as its use allowed for clusters with the least variation in abundance. In addition, it was assumed that the size of a single group should not be less than 10% of the total number of clustered customers.

An analysis of customer behaviour in each of the designated clusters was then carried out during which the values of the indicators describing each group, such as number of actions and events, completed purchases, use of the search engine and the most frequently executed action sequences describing how customers navigate the e-shop, were compared. This analysis formed on the basis for the design of a dedicated user interface variant.

The designed interface variant included 13 modifications to the default interface. Changes were made in the following components of the e-shop: the homepage, category page, product page and search engine. These were chosen to match as closely as possible the customer behaviour of the cluster containing the most active users. In both iterations, the dedicated interface was the same and was provided to the cluster of users with the highest activity.

Each customer group was split in half and for the next 21 days (during both iterations separately) one half was served a dedicated interface variant and the other half the default interface. Customers from each cluster were served the same dedicated interface variant. Customers who visited the e-shop for the first time during the study, which means they did not belong to any cluster, were served the default interface.

The efficiency of the dedicated interface was verified based on three indicators: CR, AOV, and PCR. At the time of the study, the expected customer journey (necessary to calculate the PCR value) was defined as the sequence of homepage - listing - product card - add to cart. Any activity that conformed with the expected journey was scored to allow verification of the impact of the dedicated interface on customer behaviour.

### 4.2. Results of the evaluation

In the first iteration the learning dataset included 261,774 customer sessions, and 333,637 customer sessions in the second iteration. The number of sessions was influenced by the fact that during the second iteration of the research, there was a large promotion in the e-shop, which significantly affected the number of sessions and the number of orders.

In both cases, agglomerative clustering was carried out, with the number of clusters set at 4. It allowed to achieve clusters with the size exceeding 10% of the total population. The size of clusters in the first and second iterations is shown in Table 1.

**Table 1.**
*The size of customer clusters*

| cluster | | 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|
| Iteration 1 | size | 14870 | **18080** | 9966 | 5873 |
| | percentage | 30.4782% | **37.0575%** | 20.4267% | 12.0375% |
| Iteration 2 | size | 22190 | **23644** | 13909 | 10830 |
| | percentage | 31.4426% | **33.5029%** | 19.7087% | 15.3458% |

Source: Own study.

Scatter plot of the 2nd iteration clustering along the dimensions of low-dimensional representation produced by the UMAP algorithm (McInnes, 2018) is shown in Figure 5.

It was decided to prepare a dedicated interface variant based on the behaviour of customers from **cluster 2**. The results indicate that this is the group of users who make the most use of the e-shop which means the highest number of actions and events and buy the most often, meaning the highest revenue value. Therefore, it can be assumed that providing them with a dedicated interface, could bring the greatest benefit to the e-shop owner.

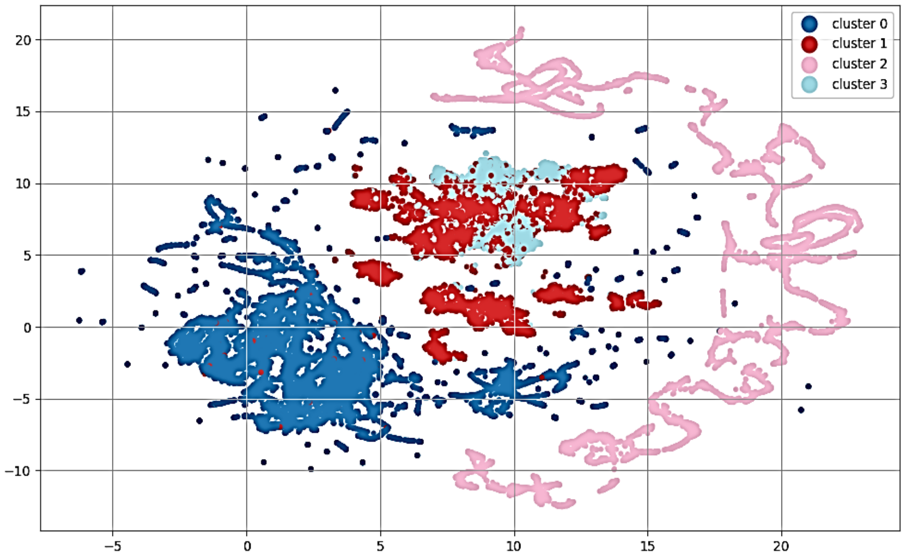


**Figure 5.** Scatter plot of the clustering.

Source: own study.

The PCR, CR and AOV values obtained in the first iteration of the study are shown in Table 2, while those from the second iteration of the study are shown in Table 3.

**Table 2.**
*Comparison of metric values (iteration 1)*

| cluster | interface | sessions | orders | PCR | CR | AOV |
|---|---|---|---|---|---|---|
| 1 | default | 970 | 18 | 30.49 | 1.86% | 26.49 |
| | dedicated | 1077 | 10 | 30.79 | 0.93% | 42.60 |
| **2** | **default** | **2440** | **71** | **46.71** | **2.91%** | **43.38** |
| | **dedicated** | **2582** | **110** | **45.77** | **4.26%** | **48.41** |
| 3 | default | 270 | 5 | 35.07 | 1.85% | 42.62 |
| | dedicated | 282 | 9 | 28.21 | 3.19% | 33.77 |
| 4 | default | 778 | 29 | 38,76 | 3.73% | 27.95 |
| | dedicated | 799 | 26 | 44.10 | 3.25% | 38.63 |

Source: Own study.

**Table 3.**
*Comparison of metric values (iteration 2)*

| cluster | interface | sessions | orders | PCR | CR | AOV |
|---|---|---|---|---|---|---|
| 1 | default | 1548 | 33 | 33.64 | 2.13% | 44.60 |
| | dedicated | 1604 | 30 | 31.01 | 1.87% | 44.97 |
| **2** | **default** | **2799** | **86** | **44.47** | **3.07%** | **41.25** |
| | **dedicated** | **2930** | **129** | **46.28** | **4.40%** | **36.18** |
| 3 | default | 385 | 21 | 41.38 | 4.91% | 45.69 |
| | dedicated | 428 | 23 | 46.66 | 5.97% | 38.92 |
| 4 | default | 1926 | 83 | 56.14 | 4.31% | 41.52 |
| | dedicated | 2015 | 75 | 52.77 | 3.72% | 40.36 |

Source: Own study.

It is worth noting that the clusters in both iterations of the study may have contained different customer groups, but the characteristics of the clusters (number of actions, events, revenue, etc.) were similar so the results obtained can be considered comparable.

## 5. Discussion

The research carried out allowed verification of the correctness of the developed platform architecture for serving a multi-variant e-commerce user interface. The selection of the solution components as well as their interrelationships made it possible to prepare the study by collecting and preliminary analysing data, grouping (clustering) customers and designing a dedicated interface variant for one of the clusters. It was also possible to collect data on the behaviour of users who were served a dedicated interface and compare them with customers from the same cluster who were served the default interface.

The results also verified the effectiveness of the dedicated interfaces and their business value. The interface variant designed for a selected group of customers confirmed its superiority over the default interface, above all in terms of conversion rate, but showed no significant impact of the dedicated interface on the other performance indicators. In both iterations of the study, customers from the selected cluster who had a dedicated interface served achieved a higher CR - by 46% and 43% respectively. From an e-commerce efficiency perspective, this is a significant difference that can be converted into tangible financial benefits. Analogous benefits of a dedicated interface did not occur for the other clusters, supporting the hypothesis that it is worth serving different interface variants for different customer groups. For the other performance indicators tested (PCR and AOV), no clear results could be observed. While the AOV for the dedicated interface was significantly higher in the first iteration, it was lower in the second iteration than for the customers in cluster 2 who were served the default interface. The PCR value was similar for the client subgroups in cluster 2 in both iterations, so it was not possible to conclude on the impact of the dedicated interface on this indicator.

The study also identified some limitations in the application of the proposed approach. Firstly, the short period of learning data collection meant that only about 20% of the customers visiting the shop during the research period were returning customers, i.e. recognised and allocated to any of the clusters. This means that in order to collect information on as many customers as possible, the learning data collection time should be extended, and the clusters should be regularly updated with new customers. In addition, treating new (unclustered) customers as a separate supercluster, which can also be served a dedicated interface, tailored to customers who have not visited the e-store in a long time.

The second limitation is the relatively long time required to gather feedback to assess the effectiveness of the interface variant in terms of CR and AOV indicators. This means that in the case of interfaces served to less active customers, one has to expect long waiting times for orders to assess the quality of modifications.

The third limitation is related to the preparation of interface variants for customer clusters. In the proposed solution, this is the task of a UX specialist, who proposes a set of modifications to the interface variant on the basis of knowledge and collected characteristics of the clusters.

Such a solution can be inefficient, as the specialist works by trial and error. Therefore, it is necessary to consider expanding the proposed architecture with modules that will automate the process of tuning interface variants, thus eliminating the need for human labour.

The research carried out made it possible to confirm the correctness of the proposed solution architecture, to prove the economic efficiency of dedicated interface variants in e-commerce, and to confirm the theoretical considerations on the subject. As no analogous experiments have been conducted before, the results obtained during the study represent an important step towards the commercialisation of multi-variant UIs, providing evidence of the tangible benefits of their implementation.

Taking into account the findings of the research, further work should focus on optimising dedicated interfaces and on preparing a solution that extends the use of dedicated UIs to new users whose behaviour is unknown and therefore cannot be clustered.

## 6. Conclusion

The primary objective of the research described in the publication was to propose and verify the correctness of a platform architecture that allows serving multiple variants of the e-commerce user interface. The correct implementation of all the steps foreseen in the process of providing a dedicated interface allows to conclude that the proposed architecture is suitable and can be used in the design of analogous solutions. Based on the analysis of publications and existing applications on the market, the results of the research carried out provide a unique validation of the sense and the way in which dedicated UIs should be served to e-commerce customers.

In addition, the hypothesis that designing a dedicated interface variant for a selected group of customers may increase the conversion rate (by more than 40% in both studies) has been confirmed. This is a key achievement that confirms the business value of the implemented platform and provides the basis for further practical implementations. The implementation of new solutions requires an analysis of their effectiveness (e.g. ROI), and the results of the studies provide a measurable assessment of the benefits of the proposed approach.

The research carried out provides a basis for further work, particularly related to the need to minimise identified limitations and weaknesses, such as the possibility of serving dedicated interfaces only to returning customers and the need to prepare interface variants by trial and error. It also allows to identify directions for further development of the solution architecture - the problem of a large group of new users should be addressed, and consideration should be given to expanding the platform with modules that allow self-adaptation of interface variants.

In conclusion, it can be said that layout personalization in e-commerce has great potential and can be an important part of gaining competitive advantage in e-commerce. The development of technology allows for the effective collection and processing of a large amount of data, including on user behaviour, and thus for far-reaching personalization, of which the described platform is an example.

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Credit authorship contribution statement:

- Adam Wasilewski: Conceptualization, Methodology, Formal analysis, Investigation, Writing - Original Draft.
- Elżbieta Pawelek-Lubera: Project administration, Writing - Review & Editing.

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