The role of multimedia in e-commerce: An analysis of Czech e-shop websites

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***Abstract*—E-commerce has revolutionized the way businesses interact with consumers and emphasizes the importance of online presence and sales strategies. This study explores the evolving landscape of e-commerce and focusses on the essential role of multimedia content in increasing user engagement and satisfaction in the web application of Czech e-shops. Multimedia elements, including audio, video, animation, and interactive functions, offer unique opportunities for attracting consumers and influencing their purchase decisions. The study analyses data from surveys conducted between Czech online shopping platforms to determine the impact of multimedia integration on user perception of website design and overall satisfaction. The study examines the decision tree algorithm as tools for classifying the attributes of electronic shops and predicting user perceptions of graphic interest. Despite the challenges of data complexity and classification accuracy, the insights generated from these analyses provide valuable guidance to companies looking to optimize their multimedia strategies and improve consumer e-commerce experiences. It is assumed that the user's first impression is closely related to the presence and quality of multimedia and content elements in the user interface of a website. However, based on the results of the survey, it turns out that while the user's first impression is closely related to the evaluation of the graphical attractiveness of the e-shop, the presence of the specific observed multimedia and content elements on the website's user interface is not significant.**

Keywords—website content, e-commerce, media richness, user satisfaction, decision trees, classifier, decision rules

I. Introduction

With the evolution of the Internet from a technology communication tool to a customer relationship channel, sales companies must change their online presence and sales strategies. With the rapid increase in global Internet access and adoption, with more than five billion Internet users worldwide, the number of people shopping online continues to grow[1]. E-commerce has already become an indispensable part of global retail. Along with the increase in the number of e-customers and e-shops, today's e-commerce is changing the way consumers communicate with businesses and forcing e-shops to offer a wider range of services. To satisfy their customers, they offer convenience, a wide range of products, and the ability to compare prices and read reviews [2]. As more transactions are made online, understanding the factors influencing consumer satisfaction becomes a key to the success of electronic stores. Consumers on the Internet cannot be contacted with real goods, so online sellers are trying to provide more complete, clear and transparent product information to reduce consumer risk perception and increase satisfaction and purchase intentions [2]. Companies are looking for new and innovative ways of attracting and satisfying their target audience [3], [4]. Consumer satisfaction in the e-commerce context is influenced by various factors such as website design, ease of use, quality of product information, perceived value, customer service and emotional engagement [5].

As competition in the online space intensifies, the quality of the user experience becomes a major factor of differentiation. The success of websites is mainly achieved through increasing the media richness, from text and graphics to interactive virtual experiences, and increasing the satisfaction and confidence of buyers.

Recent research on the use of multimedia in the e-commerce can be summarized in two directions: research on the use of individual multimedia elements within the web presentation of an e-shop and research on the influence of media richness on customer satisfaction.

A. *Multimedia content in e-commerce*

Unlike traditional stores, online stores can offer few contacts with humans during the purchase process. Also, very often, e-commerce owners don't spend enough time preparing their product pages. But creating an attractive product page is a kind of art. Each detail can mean the difference between a sale and a missed opportunity. Content must be useful, meaningful, and compelling for the target audience [6]. Putting emphasis on the creation of quality content is crucial to creating another way of gaining customers.

Creation of customer-centric digital content consists of two broad activities, customer acquisition and customer optimization. Both are of fundamental importance to the company's economic result. Acquiring customers means activities that generate traffic - attracting visitors to the online store; customer optimization refers to activities that improve the user experience and convert more visitors into customers.

Product page optimization is a process of examining and improving product sales website design, content and functionality. This involves optimizing elements such as product descriptions, images, prices, reviews, and call buttons to create personalized shopping experiences, increase brand trust among customers, and drive sales on ecommerce product pages [7].

The use of multimedia can help capture attention, better communicate information, and create memorable and engaging experiences for website visitors. Another undeniable benefit of multimedia is that it provides the best medium to faithfully represent what users see, hear, and experience in the real world [8].

Creating multimedia rich digital content involves creating content that is highly interactive, engaging, and dynamic, typically with elements such as audio, video, animation, and interactive features (see Fig. 1). Unlike static text and images, rich media enable user interaction and provide a more immersive experience. It is often used in digital contexts to attract users' attention and convey information in a more compelling and interactive way.

In e-commerce, rich media can be used to provide detailed product descriptions, demonstrations, and customer testimonials. Studies have shown that rich media can increase consumer engagement, improve product understanding, increase confidence in product quality, and reduce perceived risk [9]. Rich media offer opportunities for sales growth. The significance of media richness in e-commerce lies in its ability to transcend the limitations of traditional text-based content, providing users with a more visually stimulating and interactive environment. By incorporating elements such as product videos, audio, 360-degree views, interactive product tours, and customer reviews presented in multimedia formats, e-commerce websites can effectively convey information, enhance the user experience on a website [7], evoke emotional responses, and facilitate informed purchasing decisions.

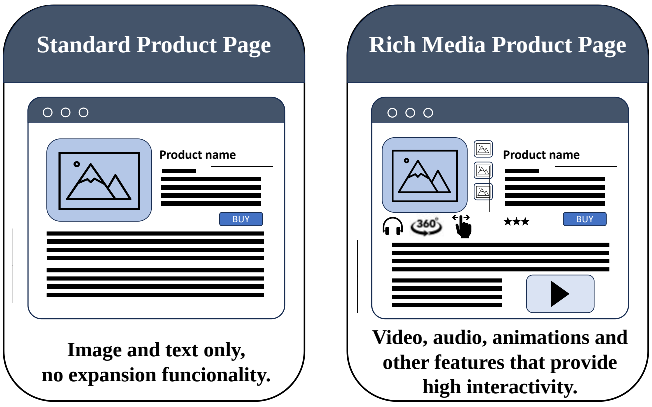

Fig. 1 The difference between a standard product page vs. product page using rich media.

B. *The impact of media richness on customer satisfaction*

Consumers' make decisions based on information gathered from sources that vary in the richness of the medium. As stated in [8], [9], [10], the quality of product information together with engaging content design elements, including the use of rich media, have a positive impact on user satisfaction, improved product understanding, and increased purchase intention (see “Fig. 2”).

The theory of media richness [13] assumes that the effectiveness of communication depends on the richness of the

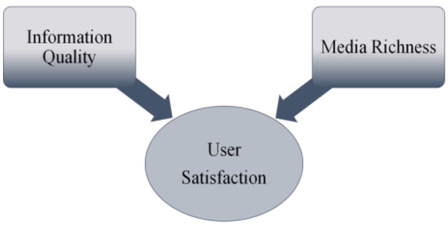

Fig. 2 The impact of information quality and media richness on customer satisfaction

media, which is characterized by the ability to convey more stimuli, the ability to provide immediate feedback, the number of cues and channels utilized, personalization and natural language support. When used in e-commerce, rich media are considered a highly rich communication medium that allows rich, vivid, and compelling information to be conveyed to consumers, and it can be assumed that websites with richer media should lead to higher consumer satisfaction [14].

This theory highlights that different media hold varying information richness [10]. Several empirical studies [15], [16] have developed a framework to explain consumer satisfaction and purchase intention based on the quality of information offered and the use of rich media in online shopping and found that higher involvement of these components increases the likelihood of purchasing a product.

However, we must remember that the scope of the information search in the selection task may depend not only on the media richness, but also on the characteristics of the product category [15] and the information quality of the webpage content [16].

Information quality when choosing and buying online emphasizes the fact that the product presentation contains all the information about the product, especially a sufficiently long and accurate product name. All product details should be clear and useful for product selection. Finally, specific product attributes should be easily comparable to other product variants even across another retailer's website [17].

Good websites provide greater satisfaction, improve quality perception, and inspire positive attitudes [18]. The integration of rich media elements has a significant impact on the user's attitude towards web applications, particularly in terms of graphical interest and engagement.

II. Methodology of the Case Study

In this paper, we focus on Czech e-commerce for several reasons. Although the Czech Republic does not have as big a market as Germany, France or the United Kingdom, it has a significant position within the EU and is one of the leaders in e-commerce in Central Europe. The Czech Republic has one of the highest internet penetration rates in the EU – according to Statista.com [1], e-commerce penetration reached 85% in 2023 (the EU average is 68%) and with more than 50,000 e-shops, it has the highest number of e-shops per inhabitant. In Central and Eastern Europe, Czechs spend the second largest amount of money on the Internet. At the same time, we can point to one of the most dynamically developing markets, where the Czech Republic achieved an increase of 41 percentage points from 2012 to 2022 (the EU average was 20 percentage points).

In our research, we have decided to check whether the first impression of e-shop visitor is related to their graphic interest, content that incorporates rich media. This paper deals with an analysis of data from the data surveys from the area of e-shops based on selected data mining methods. The objective of this paper is to describe relationships based on multimedia elements of online shopping web applications and on the attitude of users with regard to the graphic interest of these web applications.

A. *Data collection and data preparation*

The analysis is based on data from two large-scale surveys conducted in 2023. The first survey focused on specific multimedia features and examined the presence of media richness. The second survey explored the user experience and information quality. Both surveys focus on selected e-shops, whose list was obtained from the largest public database e-shopy.cz [19], which provides robust and reliable data for analysis and research purposes. The database includes an overview of established and well-known Czech online shops and includes a wide range of product categories.

The first survey included 22 questions to explore the presence of graphical elements such as 2D and 3D icons, product photos, illustrations, product videos, alongside interactive features designed to increase user engagement (e.g., dynamic button changes, product card highlighting, and interactive button color shifts). Data were obtained from 632 e-shops. These data from this questionnaire were previously used in a study [20] aimed at identifying the competencies of business students to create effective multimedia content using association rules.

Based on previous research, a new questionnaire has been designed, this time focussing on the content of the website presentations of selected e-shops, especially on product page processing. This second survey consisted of 31 questions and was conducted among the same group of Czech electronic stores [19] examined in the first questionnaire. This subsequent questionnaire sought detailed insights into various aspects of e-shop operations including the type of e-shop (sale of goods, sale of services, combination of the above types) and classification in a specific category (e.g. food and beverages, hobby and leisure, health and wellness, etc.), first impression of the given e-shop, the presence of a chatbot, ease of use of the e-shop and its clarity, the possibility of searching and comparing products, the breadth of the assortment, information available on the product page, methods of delivery and payment, etc., including an overall assessment of the e-shop and its graphics attractiveness/interest. Data were obtained from 853 e-shops. A sample of the obtained data is the “Table I.” and “Table II.”.

TABLE I. A SAMPLE OF DATA FROM THE 2ND SURVEY (1ST PART)

Time	0_ID	URL	1_eshop_type	2_eshop_category
03.10.2023 8:25	1	https://www.enii-nails.cz	combination	cosmetics_beauty
03.10.2023 8:35	2	https://dronpro.cz	combination	electronics_technology
03.10.2023 8:44	3	https://www.tetadrogerie.cz	sale_of_goods	cosmetics_beauty
13.11.2023 9:22	4	https://www.flagranti.cz/	sale_of_goods	fashion_clothing
03.10.2023 8:51	5	https://www.anareus.cz/cs/	combination	sports_outdoor
03.10.2023 8:59	6	https://www.svet-koupelny.cz/	sale_of_goods	household_furniture
03.10.2023 9:05	7	https://www.tescoma.cz	sale_of_goods	household_furniture
03.10.2023 9:11	8	https://www.stonegallery.cz	combination	other
03.10.2023 9:19	9	https://www.earplugs.cz	sale_of_goods	electronics_technology
03.10.2023 9:25	10	https://www.outletexpert.cz	sale_of_goods	fashion_clothing
03.10.2023 8:35	21	https://www.rajapack.cz/	sale_of_goods	other
03.10.2023 8:47	22	https://www.oxe.cz/	sale_of_goods	electronics_technology
03.10.2023 8:55	23	https://funbaby.cz/	sale_of_goods	childrens_goods_toys
03.10.2023 9:03	24	https://www.zaparkorun.cz/	sale_of_goods	electronics_technology
03.10.2023 9:10	25	https://www.mybesthome.cz/	sale_of_goods	household_furniture

The data from the first questionnaire was taken from [20] and was already ready for further use. Data from the second questionnaire was examined, cleaned, corrected and reclassified. Data was merged into one final data file.

TABLE II. A SAMPLE OF ACHIEVED DATA FROM THE 2ND SURVEY (2ND PART)

0_ID	3_previous_visit	4_previous_purchase	5_first_impression	6_cookies pop-up window
1	no	no	I_really_like_the_eshop	yes
2	no	no	not_bad	no
3	yes	no	I_like_the_eshop_but	yes
4	no	no	I_like_the_eshop_but	yes
5	no	no	I_dont_like_the_eshop	yes
6	no	no	not_bad	yes
7	yes	no	I_really_like_the_eshop	yes
8	no	no	I_like_the_eshop_but	yes
9	no	no	I_like_the_eshop_but	yes
10	no	no	not_bad	no
21	no	no	I_like_the_eshop_but	no
22	no	no	I_like_the_eshop_but	yes
23	no	no	I_really_like_the_eshop	no
24	no	no	not_bad	no
25	no	no	I_really_like_the_eshop	yes

Because there were the same but also different e-shops in both questionnaires and there were also errors in the records, the final collection contained 484 e-shops, which were described by 61 attributes.

For modeling purposes, only those attributes that appeared to be suitable for solving the given task were selected. These were the attributes from the first questionnaire: Anim_PopUp_R, Carousel_R, Anim_Text_R, Anim_Logo_R, Changing_Logo_R, 2D_icon_R, 3D_Icon_R, Prod_Zoom_R, Prod_High_R, Butt_Act_R, Mob_Vers_R, Mob_Anim_Ham_R, Prod_Illust_R, Prod_Photo_R, Prod_3D_R, Prod_3D_Anim_R, Anim_2D_3D_object_R, Anim_Illust_R, Video_R, Sos_Net_R. The following were selected from the second questionnaire: 1_eshop_type, 2_eshop_category, 5_first_impression, 15_clarity_product_page, 17_quality_product_graphics and 30_graphicall_interesting. Description of these attributes is in the “Table III.” and “Table IV.”.

TABLE III. ATTRIBUTES DESCRIPTION – 1ST PART (SELECTED ATTRIBUTES FROM THE 1ST SURVEY)

Attribute	Question	Values
Video_R	Do the e-shop pages contain product videos?	yes/no
SoNet_R	Is there a link to social networks on the entry page of the e-shop?	yes/no
Prod_Zoom_R	Does the product zoom when hovering the mouse?	yes/no
Prod_High_R	Does the product card get shaded or highlighted after hovering the mouse?	yes/no
Prod_Illust_R	Are there illustrations (i.e. drawings or paintings) of the products on the e-shop pages?	yes/no
Prod_Photo_R	Are there product photos on the e-shop pages?	yes/no
Anim_PopUp_R	Will an animated pop-up window/windows appear after opening the e-shop (or later)?	yes/no
Carousel_R	Is there a carousel at the top of the e-shop homepage?	yes/no
Changing_Logo_R	Does the e-shop logo change (e.g. color or other graphics) after hovering the mouse?	yes/no
Butt_Act_R	Do the buttons change color or do other actions when the mouse is hovered over?	yes/no
Mob_Vers_R	Is there a mobile version of the e-shop?	yes/no
Mob_Anim_Ham_R	Does the mobile version of the e-shop have an animated hamburger menu?	yes/no
2D_Icon_R	Are there 2D icons on the e-shop pages?	yes/no
3D_Icon_R	Are there 3D icons on the e-shop pages?	yes/no
Prod_3D_R	Are there examples of the offered products in 3D (static 3D object) on the e-shop pages?	yes/no
Prod_3D_Anim_R	Are there examples of the offered products in 3D motion on the e-shop pages - e.g. around their axis (animated 3D object)?	yes/no
Anim_Text_R	Does the e-shop homepage have text animation?	yes/no
Anim_Logo_R	Is there an animated logo on the homepage of the e-shop?	yes/no
Anim_2D_3D_Object_R	There are animated 2D or 3D icons on the e-shop pages (e.g. in the menu or in the footer of the page), or other animated 2D or 3D objects?	yes/no
Anim_Illust_R	Are there animated product illustrations on the e-shop pages?	yes/no

TABLE IV. ATTRIBUTES DESCRIPTION – 2ND PART (SELECTED ATTRIBUTES FROM THE 2ND SURVEY)

Attribute	Question	Values
1_eshop_type	1. What type of this e-shop is it?	sale_of_goods, sale_of_services, combination
2_eshop_category	2. In which category would you classify the selected e-shop?	food_beverages, other, pet_supplies, household_furniture, book_music_stores, cosmetics_beauty, electronics_technology, health_wellness, hobby_free_time, childers_goods_toys, sport_outdoor, fashion_clothing
5_first_impression	5. What is your first impression of this e-shop?	I_like_the_eshop_but, I_really_like_the_eshop, I_dont_like_the_eshop, not_bad
15_clarity_product_page	15. How would you rate the clarity of the product page?	very_clear_product_page, moderately_clear_product_page, slightly_confusing_product_page, very_confusing_product_page
17_quality_product_graphics	17. How would you describe the quality of the graphic description of the products on the product page?	1_photo_or_0_photo, few_photos_and_details, good_photo_quality_no_video_and_3D_view, high_quality_photos_and_videos
30_graphically_interesting	30. Do you find the e-shop graphically interesting?	definitely_yes, definitely_no, rather_yes, rather_no

Since we focused on monitoring the graphical attractiveness of the e-shop from the user's perspective in relation to the selected multimedia and content elements, the attribute related to the overall evaluation of the e-shops was not included. The basic attitude of the website visitors with regard to these two variables is shown in “Table V.”

This table shows the relationship between the overall evaluation of the e-shop (29_satisfaction) - the question examined in the second survey focused on the content quality of the website, and the evaluation of its graphical interest (30_graphically_interesting) - the question examined in the first survey focused on the graphic presentation of the website. Respondents who said that they liked the e-shop but that some things could be improved (I_like_the_eshop_but) rated the e-shop as rather interesting (value rather_yes refers to 114 rated e-shops; 23.55%). Those who like the rated e-shop very much also consider the e-shop to be graphically very successful (value definitely_yes; refers to 94 rated e-shops; 23.55%) or rather graphically interesting (value rather_yes; refers to 47 rated e-shops; 9.71%).

TABLE V. THE RELATIONSHIP BETWEEN THE OVERALL EVALUATION OF THE E-SHOP AND ITS GRAPHICAL INTEREST

	30_graphically_interesting_in [%]			
29_satisfaction in [%]	definitely_not	rather_not	rather_yes	definitely_yes
I_dont_like_eshop	**6.20**	4.34	0.21	0.00
not_bad	0.83	**17.36**	5.79	0.21
I_like_the_eshop_but	0.41	7.85	**23.55**	3.51
I_really_like_the_shop	0.41	0.21	9.71	**19.42**

In the data preparation phase, it was necessary to perform data selection, categorization of respondents' answers, and reclassification of answers into values usable for modelling.

Some loss of information occurred during the data pre-processing phase, when the least frequent e-shop categories were grouped together under the category 'other' (these were the categories gifts (0.62%; 3), luxury goods (1.03%; 5), work_office (1.24%; 6), arts_craft (0.83%; 4), gardens (1.24%; 6), food_supplements (1.86%; 9). After the changes, the category "other" contained 60 shops (12.4%).

In data exploration, five attributes were excluded due to the prevalence of one value in the data (e.g. the attribute Prod_Photo_R: value “yes” in 97.31% (471 e-shops) and value “no” in 2.69% of e-shops (13 e-shops), the attribute Prod_3D_Anim_R: value “yes “ in 6.4% of cases (31 e-shops) and the value “no” in 93.6% of cases (453 e-shops).

Attributes 2_eshop_category, Mob_Vers_R, Prod_3D_R, Anim_Logo_R were evaluated as partially significant (marginal) from the given set of attributes.

From the total number of attributes, the final dataset contained only significant attributes with respect to the defined goal. These significant input attributes are the following: 5_first_impression, 15_clarity product_page, 17_quality_product_graphics, Prod_Zoom_R, Prod_High_R, Prod_Illust_R, 3D_Icon_R. The attribute 30_graphically_interesting was in the role of the output variable.

This data was used to create classification models based on selected decision tree algorithms.

B. Decision trees

The representation of knowledge in the form of decision trees is a well-known method in many fields [21], [22], [23]. A decision tree [24] is a predictive model that can represent classifiers and regression models. Classification trees, also known as classifiers, are used to solve classification tasks where we deal with classification of an object into a predefined set of classes based on its attribute values. These trees can be useful as an exploratory technique.

Data classification is a two-step process. The first step involves building a classifier that describes a predetermined set of data classes or concepts. A classification algorithm constructs the classifier by analysing a training set consisting of database tuples (in the context of a classification task, data tuples can be referred to as examples or objects) and their corresponding class labels [26].

A tuple, $\boldsymbol{X}$, is represented by an n-dimensional attribute vector $\boldsymbol{X} = (x_1, x_2, ..., x_n)$, which depicts n measurements made on the tuple from n database attributes, respectively, $A_1, A_2, ..., A_n$. Each attribute represents a 'feature' of $\boldsymbol{X}$. It is assumed that each tuple, $\boldsymbol{X}$, belongs to a predefined class, as determined by another attribute called the class label attribute (i.e. the predefined class is one from values of an output attribute). This step is also known as supervised learning [26].

The initial stage involves learning a mapping or function, $x = f(\boldsymbol{X})$, which can predict the associated class label y for a given tuple X. The aim is to learn a mapping or function that separates the data classes. This mapping is usually represented as classification rules, decision trees, or mathematical formulas [26].

The model is used for classification in the second step and the accuracy of the classifier's predictions is estimated. In this step, the test set is used consisting of test tuples and their associated class labels. These tuples are not used to construct the classifier [26]. Further information on decision trees can be found in [24], [25], [26].

C. Selected algorithms of decision trees

Decision tree induction is a supervised learning technique. It involves the use of algorithms that automatically construct a decision tree from a given data set. The goal is typically to find the optimal decision tree by minimising the generalisation error. However, it is also possible to define other target functions, such as minimising the number of nodes or the average depth of the tree [24].

The CART, CHAID, C5.0, and QUEST are examples of decision tree algorithms. The algorithms selected are further explained, for example, in [24], [25], [26].

III. Results: Data Analysis by the Decision Trees Selected Algorithms

This section of the paper analyses decision trees created by using selected algorithms for classifier creation, namely C5.0, CRT, QUEST, and CHAID. The results are described.

Experiments were realised on the given dataset with the above-mentioned significant variables (input variables: 5_first_impression, 15_clarity product_page, 17_quality_product_graphics, Prod_Zoom_R, Prod_High_R, Prod_Illust_R, 3D_Icon_R; output variable: 30_graphically_interesting.).

Unsatisfactory classification results were obtained, including differences of more than 10% between the training and test data sets.

Adding the marginal variables mentioned above (2_eshop_category, Mob_Vers_R, Prod_3D_R, Anim_Logo_R) did not improve the results.

Therefore, a selection was made of e-shops that focus only on the sale of goods (the most common group in the available data) - see “Table VI.”.

TABLE VI. Attribute Frequency 1_eshop_type

Value	Frequency in [%]	Frequency
combination	6.82	33
sale_of_goods	88.43	428
sale_of_services	4.75	23

Further experiments were carried out with different sizes of training and test datasets. There was a slight improvement in the classifier results (but the accuracy was still around 50 to 60%). The results obtained are shown in “Table VII.” and “Table VIII.”.

TABLE VII. Training to test set ratio 60:40

Algorithm	Accuracy in [%]	Accuracy in [%]	Difference in [%]	Number of decision rules
	Train data	Test data		
C5.0	61.6	53.37	8.23	8
CRT	52.8	52.81	-0.01	2
CHAID	57.2	55.6	1.6	4
Quest	57.2	54.49	2.71	3

TABLE VIII. Training to test set ratio 70:30

Algorithm	Accuracy in [%]	Accuracy in [%]	Difference in [%]	Number of decision rules
	Train data	Test data		
C5.0	62.41	54.35	8.06	12
CRT	62.76	55.07	7.69	7
CHAID	62.07	54.35	7.72	9
Quest	53.1	52.17	0.93	2

The CRT-based classifier rules consisted of the attributes 5_first_impression, 5_first_impression and Prod_High_R or attributes 5_first_impression and 17_quality_product_graphics. A total of 7 rules were found (see “Table VIII”). An example of rules is shown below:

R1: IF 5_first_impresion = I_like_the_eshop_but THEN 30_graphically_interesting = rather_yes

R2: IF 5_first_impresion = I_really_like_the_eshop AND 17_quality_product_graphic = high_quality_photos_and_videos THEN 30_graphically_interesting = definitely_yes

R3: IF 5_first_impresion = I_dont_like_the_eshop AND Prod_High_R = no THEN 30_graphically_interesting = rather_not

R4: IF 5_first_impresion = I_dont_like_the_eshop AND Prod_High_R = yes THEN 30_graphically_interesting = definitely_not

The relative importance of the variable 5_first_ impression was high (0.73). The other variables in the rules were almost insignificant (17_quality_product_ graphics, 3D_Icon_R, Prod_Zoom_R and 15_clarity_product _page: importance from 0.02 to 0.04), except for the attribute Prod_High_R, whose relative importance was 0.17.

Rules generated by the classifier using C5.0 were also very often constructed using the attribute 5_first_impression or 5_first_impression and Prod_High_R, 5_first_impression, and 15_clarity_product_page. Only attribute 5_first_impression was considered highly significant (relative importance 0.86). The other variables in the rules were again almost insignificant (Prod_Hight_R (0.07), Prod_Zoom_R and 15_clarity_produt_page, 3D_Icon_R: significance values from 0.02 to 0.07). A total of 12 rules were found (see “Table VIII”).

The classifier generated by the CHAID algorithm found 9 rules (see “Table VIII”). As with the previous rules, the 5_first_impression attribute was the most significant. The relative importance of the predictor in building the model was 0.81. The other variables in the rules (Prod_Illust_R, Prod_High_R, 3D_Icon_R, 17_quality_product_graphics and 15_clarity_product_page) were almost insignificant. Their relative importance was between 0.02 and 0.05.

For the classifier based on the QUEST algorithm, only 2 rules were found (see “Table VIII”). Again, the attribute 5_first_impression with a relative importance of 0.95 played a crucial role.

IV. CONCLUSION

The use of rich media in e-commerce platforms provides a multifaceted approach to the presentation of products and services and allows companies to create an immersive and compelling digital experience for their customers.

Looking at the rules found, it is obvious that some rules were found that correspond to reality (e.g. rule R1: If the first impression of the e-shop is that it is nice, but a few things could be improved, then the e-shop seems quite graphically interesting. Other rules are more interesting, e.g., rule R4: If the first impression is not good, highlighting graphic elements can increase the negative rating of an e-shop. Other rules of classifiers imply that although the e-shop is rated as very nice according to the first impression, the final rating of the graphical interest of the e-shop is rather negative due to the considerable lack of clarity of the product page and the difficulty of navigating it, etc.

Based on the results of the models, it can be concluded that the monitored web elements and their graphical representation have only a small influence on the graphical evaluation of the e-shop. The first impression of the website visitor plays a crucial role in the evaluation of the e-shop, as shown by the relative importance of the predictor in the estimation of the models. The relationship between the graphical interest of e-shops and the first impression of visitors in this data set shows the Fig. 3.

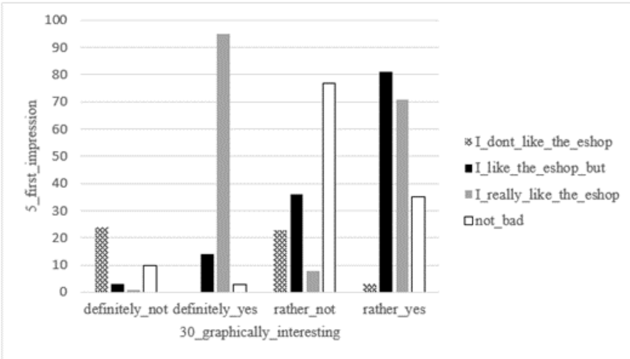

Fig. 3 The relationship between the graphical interest of e-shops and the first impression of visitors

In further experiments, it would be advisable to extend the data matrix to include other observed e-shops and to focus on improving the accuracy of the classification models, e.g. by using other suitable algorithms to generate classifiers.

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