Factors Affecting the Use of Online Recommendation Systems in E-Commerce in Croatia

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***Abstract* - The concept of utilizing IT for recommendations has existed since the inception of computer science, but it has become more prevalent in recent years as e-commerce has grown significantly. Because recommendation systems are effective at simulating customer behaviour and offering users personalisation, they have helped numerous e-commerce and content providers expand. In order to determine what influences customers' adoption and usage of online purchase recommendation systems, this research explores the factors affecting recommendation systems' adoption and use in e-commerce in Croatia. The structural model of partial least squares and the Unified Theory of Adoption and Use of Technology (UTAUT) were employed to accomplish this goal (PLS). 130 users of online recommendation systems made up the sample. Research has shown that users will only utilize recommendations if they are given supplementary goods that improve their purchasing experience. Users trust recommendation systems (43%), but they have reservations about whether they deliver on their promises which is related to the fact that only a small number of retailers track and evaluate the effectiveness of recommendation systems in their online stores.**

Keywords - e-commerce; recommendation systems; artificial intelligence

I. Introduction

The rapid growth of media, information and network technologies, trading platforms and social networks has generated a massive amount of data that people find difficult to process and comprehend daily. This proliferation of primarily repetitive information places a strain on the human brain and falls short of delivering the desired level of efficiency. The combined effects of this information overload negatively impact productivity and satisfaction with its use. To put it simply, the speed at which users can respond to specific information is slower than the speed at which the information is being transmitted, and the increased availability of information options results in a decreased rate of utilization. This phenomenon is referred to as information overload and is a result of the ongoing and rapidly evolving technological revolution. According to Toffler [1], information overload refers to the difficulties an individual may encounter when trying to comprehend a problem or decide due to the overwhelming presence of information. Information overload places information professionals in a constant state of mental overload or stress, affecting them on a global scale. It has a significant negative effect on the psychological well-being of individuals [2]. Due to a considerable amount of information, the decision-making process in purchasing is under immense pressure [3]. In light of this, recommendation algorithms have a significant impact on the shopping experience in e-commerce. These systems leverage consumer-purchasing patterns to learn about and help users choose the things they should buy, which helps reduce information overload. Furthermore, recommendation systems (RS) lower the time of searching for and choosing products by making recommendations based on the user's profile, and they are critical due to their primary function: predicting whether the user will be satisfied with a particular product [4].

II. Theory and Previous Research

An online RS is a type of information filtering system that provides personalized recommendations to users based on their preferences, interests and behaviour. It is intended to make pertinent suggestions to consumers while they utilize an online platform, such as an e-commerce website, social-media or an online streaming service, in real-time. RS use a combination of user data, machine learning (ML) algorithms, as well as artificial intelligence (AI), to make personalized recommendations. The data used by these systems includes user profiles, browsing and purchase history, ratings and reviews, social network data, and other behavioural data. The ML algorithms analyse this data to identify patterns, make predictions, and recommend items that are likely to be of interest to the consumer. Online RS come in a variety of forms, including content-based filtering, collaborative filtering, and hybrid methods that integrate both approaches [5]. In recent years, these systems have gained popularity as a means of improving user experience and raising user engagement on online platforms. With the rise of social media, social elements have become important part of RS [5].

The importance of RS in consumer journey are studied in numerous researches, in contrast to prior study that concentrated on technological elements [6]. In context of RS in consumer journey, the focus of researches varies, from efficiency of RS to consumer satisfaction and trust towards RS [7]. To be used by consumer in the purchase process, RS have to be perceived as trustworthy, as well as relevant. Using RS showed positive impact on the shopping process satisfaction level [8] and those consumer who consulted product suggestions chose suggested products twice as frequently as those who didn't [9]. Perceived RS information quality and system quality, two important characteristics of efficient RS, have a significant effect on consumers' satisfaction and trust [5]. Consumers' perception of the importance of quality and relevant information often leads to neglecting other business related factors, as the relevance of suggested content is top priority focus for RS designers. RS must benefit consumers, but also, they are great way for sellers to increase profitability. Research [10] showed that the RS systems designed by balancing both profit and relevance, compared to those that are oriented to recommending relevant content, generate higher profit, while not influencing the consumer' trust and profit gains were due to balance of consumer's trust and the diversity and relevance of RS. Development of social media increased the social component of RS. Researches [7][11] have shown that consumers most frequently utilize recommendations coming from other consumers. Also, consumers tend to trust more third party RS than RS coming from the seller [7]. Some of the recent researches, such as [12] has investigating connection between the level of psychological ownership (PO) and RS designed preferences, showing that users with high PO prefer user-centric RS approach. Furthermore, consumers learn through their purchase process and apply the weights they ascribe to different product attributes. The RS that learns user preferences through the purchase as even if a recommender system fully understands consumer utility, the highest utility product might not be the greatest advice if the customer needs to discover his or her own preferences [13].

With the development of the technology and more complex consumer journey with information overload as important factor that influence consumer's purchase decision, RS becomes more and more relevant in a practice, as well as in scientific research. With that in mind, and the fact that research of adoption and usage of RS by consumers in Croatia has not been conducted and published in major scientific databases, this research conducted.

III. Research Methodology

The research conducted in this paper was influenced by similar research studies [14][16].The methodology used in this research is The Unified Theory of Acceptance and Use of Technology (UTAUT) is one of the most comprehensive technology acceptance models, integrating eight influential acceptance models regarding individual acceptance of newly introduced information technologies. [15]

UTAUT model uses three determinants: performance expectancy (PE), effort expectancy (EE), and social influence (SI). PE refers to the user's expectation that using the system will lead to improved job performance. Research suggested that this is one of the most important predictors of the intention to use technology [15]. EE measures the degree of ease of use or complexity of the technology associated with the use of the technology. SI is the perception of an individual that important others think he should adopt a new system.

UTATU 2 model is often extended by more determinants: facilitating conditions (FC) are the resources and support that a consumer perceives as available to engage with technology; price value (PV) refers to the value that a consumer perceives in relation to the price paid for using the technology and trust (TR) which a crucial variable as it plays a significant role in shaping a person's perception [15].

The UTAUT model was deemed most appropriate for this study, which aimed to assess the behavioural intention and use of RS among customers in Croatia. Data was gathered through an online survey. Snowball methodology of recruiting respondents was applied. N=130 surveys from respondents who indicated they utilize online shopping, made up the analysed sample. A 5-point Likert scale was used to measure all determinants.

Based on previous researcher's findings, UTAUT model was extended and adapted for the purpose of this research (Fig. 1) and hypothesis are formed as follows:

- Hypothesis 1 (H1): PE is expected to have a positive effect on the behavioral intention to use RS in e-commerce.
- Hypothesis 2 (H2) EE positively influences the behavioral intention of RS in e-commerce.
- Hypothesis 3 (H3) SI positively influences the behavioral intention of RS in e-commerce
- Hypothesis 4 (H4) PV positively influences the behavioral intention of RS in e-commerce
- Hypothesis 5 (H5) T positively influences the behavioral intention of RS in e-commerce
- Hypothesis 6 (H6) Behavioral intention of RS in e-commerce positively effects the use

PLS statistical software was used to statistical data analysis.

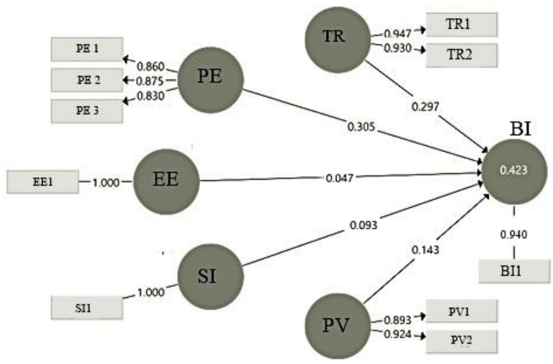

Figure 1. Research model

IV. Discussion

The scales were adopted from the original UTAUT model from [16]. To test the proposed structural model, we used partial least squares–structural equation modelling (PLS-SEM). We checked the absence of measure bias error or common method bias (CMB) as recommended in [17].

In this model, the occurrence of a VIF greater than 3.3 is preferable as an indication of pathological collinearity. To do so, we conducted a full collinearity test in order to rule out CMB. We used data from our original PLS algorithm report. In first step we took results from latent variables and paste them in first free row in our original data set. In a second step, we added a new column called Random V populated with random values that represents all values of that original data set. From that point we created new canvas/model in our structural model. In that model all variance inflation factors (VIFs) extracted by this method must be lower than 3.3 to confirm that the sample has no CMB as in Table 1.

PLS SEM model tries to ensure the reliability and validity of the measurement scales. Factor loading show how well an item represents the underlying construct. Loadings over 0.70 are recommended as in [15]. In our work we eliminated Si3 and Ee3 from the scale.

TABLE I. TEST COMMON METHOD BIAS, VARIANCE INFLATION FACTORS

	Random V
Social influence	1069
Effort expectancy	1505
Performance expectancy	1097
Behavioral intention	1403
Trust	1140
Price value	1008

TABLE II. MEASUREMENT SCALES AND LOADING S

Construct	Items	Loadings
Social influence	Si1	0.804
	Si2	0.903
	Si3	
Effort expectancy	Ee1	
	Ee2	0.89
	Ee3	
Performance expectancy	Pe1	0.86
	Pe2	0.875
	Pe3	0.83
Trust	T1	0.947
	T2	0.93
Price value	Pv1	0.893
	Pv2	0.924
Behavioral intention	Bi	1

The results are presented in Table II.

We analyzed the reliability of the constructs with two indicators: Cronbach's Alpha and composite reliability. The values obtained were over the 0.7 suggested. In terms of convergent validity, the average variance extracted (AVE) was used. The results were over the 0.5 as in Table 3. [15] Fornell–Larcker's test (Table 4.) was used to test discriminant validity of model, which compares the square roots of the AVE (shown in the diagonal in bold) with the correlations of each variable (shown in rows and columns). The first value must be greater than those in their respective rows and columns as in [18]. To check the statistical significance of each of the coefficients or paths (Table 5) we carried out bootstrapping with 10,000 subsamples and used the Standardized Root Mean Square Residual to assess the model's goodness of fit [15]. The

TABLE III. COMPOSITE RELIABILITY AND CONVERGENT VALIDITY

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
PE	0.817	0.823	0.891	0.732
PV	0.79	0.805	0.904	0.826
SI	0.81	0.836	0.912	0.839
Trust	0.865	0.876	0.936	0.88

TABLE IV. FORNELL-LARCKER CRITERION

	EE	PE	PV	SI	Trust	pn
EE	**1**					
PE	0.551	**0.855**				
PV	0.402	0.628	**0.909**			
SI	0.202	0.217	0.228	**0.916**		
Trust	0.524	0.665	0.652	0.299	**0.938**	
pn	0.483	0.578	0.519	0.236	0.584	**1**

TABLE V. STRUCTURAL MODEL

Hyoptesis	Path coefficiens	Rsquare	Fsquare	Validate
EE on BI	0.121		0.031	Supported
PE on BI	0.284		0.041	Supported
PV on BI	0.116		0.019	Supported
SI on BI	0.045		0.004	Not supported
TR on BE	0.228		0.043	Supported
BI		0.437		
srmr				0.051
Q²predict				0.386

value obtained was 0.051, less than the 0.08, suggesting a good fit of the complete model. The model results in Table 5. also show both the verified hypotheses and the size of their effect. Four of five relationships formulated are significant, of which only the results for expectations–intention to use ratio exceed the minimum 0.2 recommended by [15]. In all cases where the ratios were significant, the effect size (Fsquare) was between 0.015 and 0.35, except in scenarios Si on Bi which were below it. However, the model has a very good fit as the SRMR obtained is only 0.051, well below 0.08. Stone–Geisser's Q2 was calculated to evaluate the predictive capacity of the model. Result is 0.386, value greater than 0 so it is conclude that model has a relevant predictive capacity [15] (Table 5)

From the total number of respondents (N130), there were 70 women and 60 men; 85% or 65% were between the ages of 25 and 54. Of the respondents, 56% declare they have a bachelor's degree or higher, and 41% have completed secondary school. In this context, to the question 'How often do you shop online,' the vast majority, or almost 87% of respondents, answered that they shop one to several times a month. More precisely, 37% of the surveyed shop once or more times a month, and 40% once or more in three months. A significant increase in shopping frequency compared to 2018 research confirms the post-pandemic statements about the rise in sales in e-commerce in Croatia [19].

As we stated previously, the aim was to investigate how the mentioned constructs influence the use of RS in e-commerce. The measurement model that evaluates the validity of the construct and the structural model that evaluates the connection of the variables after application showed a positive result. Survey results showing composite latent variable concordances ranging from 0.860 to 1. The Cronbach's Alphas of the five constructs are displayed in Figure 4. All CAlphas are above the threshold of .70 (Nunnally, 1978), meaning that the reliability is confirmed. Composite reliability indicators for all latent variables must be between the value of 0.7, also called the critical value, and the value of 0.99, representing a very high degree of internal consistency [16]. In this model, the reliable composite values range from the minimum value of 0.890 to the maximum value of 1, in complete accordance with the previously defined interval. It represents a high degree of internal consistency or reliability of the model for the variables. Discriminant validity is a measure that is compared with different but related concepts. It should not be correlated with measures that measure another concept.

When it comes to trust 'in' and expectations 'from' RS - two factors that are incredibly high on the list of users - respondents say that they will use them only when the solutions offered by the systems make sense to them, i.e., when they are shown to them complementary products, similar products but with a better price, products that complement and enrich their shopping experience. According to the answers, 66% of the respondents agree that they can trust the system's recommendations, but almost 30% of the respondents are neutral on this issue (neither sure nor unsure that RS should be trusted). On the next question, their skepticism stands out. Namely, less than half, or 43%, agree that the systems 'fulfill what they claim' and 29% are undecided. In short, users trust recommendation systems but are skeptical about the statement that they live up to what they claim (that is, in what they do, which we could relate to the fact that a tiny number of retailers monitor and analyze data on the performance of RS. Namely, RS often display or link completely non-complementary/irrelevant products and the like). RS are part of our everyday life, and it is almost impossible to avoid them. Accordingly, most respondents, 48% of them, declare that they will use them to the same extent as before, and even 30% that they will use them more often. Only a more minor number declare that they will use them less (4%) or that they will stop using them (1.5%), which, in today's context of the general spread of the Internet and various smart devices, would be an almost impossible mission.

V. Conclusion

When an individual is surrounded by constantly changing mass media and new information contexts, their ability to make accurate predictions decreases significantly. To restore their prediction accuracy to an average level, they must rapidly process more data. Recommender systems are a specialized type of information filtering system that attempt to anticipate a user's evaluation or liking for a specific item, product, or service. This prediction is then displayed to the user as recommendations and suggestions based on the results. In this context, the user will be satisfied if three parameters are met: how much the recommendation is focused on his needs (personalized), how interesting it is and how useful it is to him. The primary goal of any recommendation system is to build a quality and objective mathematical model that will be able to measure these three. Their acceptance is wide because they facilitate the processes in the store, but also more broadly: it is used by customers who find it easier and faster to shop, and by merchants in e-stores to increase the value of their basket, make it easier for customers and make shopping as high-quality as possible. After the collected data, the test was carried out through the UTAUT model in the already mentioned SmartPLS 3.0 software tool, which determines the success of the research using various calculation measures. Based on the results all hypotheses from the test are above the limit values and were accepted. The high predictive ability of the model was established for most variables. All selected constructs have a positive influence and the greatest role on the behavioral intention to use the RS in e-commerce. All except the construct: Social impact (what others think about the use), which was to be expected. Namely, recommendation systems are practically impossible to avoid, they do not represent a novelty, and the interest is about how much someone uses it or what opinion they have about the use of the recommendation system - for other users, it is a less important question. Users and customers in e-commerce believe in what the systems recommend to them but express skepticism when they answer whether these systems fulfill what they do. However, almost 80% also state that they intend to use the recommendation systems equally or even more than now. That is important information for store owners and managers: customers and users recognize the importance of systems in everyday life, are aware of them, and use them almost equally, regardless of whether they buy utilitarian or hedonistic products. On the other hand, e-merchants should pay more attention to the monitoring and analysis/analytics of referral systems because it is proved that these systems have a very measurable impact on revenue growth, customer satisfaction, purchase intentions, time spent on the site, which are all key indicators of success when it comes to e-commerce.

REFERENCES

[1] S. Galloway, Post Corona, Penguin Random House, 2020

[2] W. D. Hoyer, “An examination of consumer decision making for a common repeat purchase product,” Journal of consumer research, vol. 11(3), 1984, pp. 822-829.

[3] N. Zeldes, D. Sward, and S. Louchheim, Infomania: Why we can't afford to ignore it any longer. First Monday, 2007

[4] T. Manos, T. H. King, S. Kallumadi, V. Murdock, and M. de Rijke. "Challenges and research opportunities in ecommerce search and recommendations," ACM Sigir Forum, vol. 54, no. 1, 2021, pp. 1-23.

[5] X. Yang. "Determinants of consumers’ continuance intention to use social recommender systems: A self-regulation perspective." Technology in Society, vol. 64:101464, 2021

[6] C. Yin, Y. Guo, J. Yang and X. Ren, "A new recommendation system on the basis of consumer initiative decision based on an associative classification approach." Industrial Management & Data Systems, vol. 1118, 2018, pp. 188-203.

[7] E. Lepkowska - White, "Are they listening? Designing online recommendations for today's consumers." Journal of Research in Interactive Marketing, vol. 7, 2013, pp. 182-200

[8] G.N. Punj, R. Moore, “Smart versus knowledgeable online recommendation agents,” Journal of Interactive Marketing, Vol. 21, 2007, pp. 46-60.

[9] S. Senecal, J. Nantel. "The influence of online product recommendations on consumers’ online choices," Journal of retailing, vol. 80, 2004, pp. 159-169.

[10] U. Panniello, H. Shawndra, and M. Gorgoglione. "The impact of profit incentives on the relevance of online recommendations." Electronic Commerce Research and Applications, vol. 20, 2016, pp. 87-104.

[11] Y.F. Chen, "Herd behavior in purchasing books online," Computers in Human Behavior, vol. 24, 2008, pp. 1977-1992.

[12] B.G. Seo, D.H. Park, "The effective recommendation approaches depending on user’s psychological ownership in online content service: user-centric versus content-centric recommendations," Behaviour & Information Technology, 2022, pp. 1-13.

[13] D. Dzyabura, J. R. Hauser, "Recommending products when consumers learn their preference weights." Marketing Science vol. 38, 2019, pp. 417-441.

[14] P. Silva,. “Davis' technology acceptance model (TAM)” Information seeking behavior and technology adoption: Theories and trends, 1989, pp.205-219.

[15] J.P. Cabrera-Sánchez, I. Ramos-de-Luna, E. Carvajal-Trujillo, A. F. Villarejo-Ramos, “Online recommendation systems: Factors influencing use in e-commerce,” Sustainability 12, Vol. 21:8888, 2020

[16] V. Venkatesh, M. G. Morris, G. B. Davis, F. D. Davis, “User Acceptance of Information Technology: Toward a Unified View,” MIS Quaterly., vol. 27, 2003, pp. 425–478.

[17] N. Kock, “Common Method Bias in PLS-SEM: A Full Collinearity Assesment Approach”. International Journal of e-Collaboration (ijec), vol 11, 2015, pp. 1-10

[18] D. Barclay, R. Thompson, C. Higgins, ”The Partial Least Squares (PLS) Approach to Causal Modeling: Personal Computer Adoption and Uses as an Ilustration” Technol. Stud. 1995, vol. 2, pp. 285–309.

[19] C. Kramarić, V. Šebek and N. Kaurin Knežević, “Croatian E-commerce Market: Overview, Potentials and Challenges”, Oeconomicus, vol. 13, 2020, pp. 22-30