J Inno Sci Eng, 2024, 8(2): 251-265
https://doi.org/ 10.38088/jise.1308353

Research Article

Impact of Recommender Systems in E-Commerce – A Worldwide Empirical Analysis

Ayse Cilaci Tombus [1*], Ergin Eroglu [2], Ibrahim Halil Altun [2]

[1] *Department of Industrial Engineering, Faculty of Engineering, Gebze Technical University, 41400, Kocaeli, Turkey*

[2] *Segmentify, 34718, Istanbul, Turkey*

Cite this paper as:
Tombus Cilaci, A., Eroglu, E., Altun, I.H. (2024). *Impact Of Recommender Systems in E-Commerce – A Worldwide Empirical Analysis.*Journal of Innovative Science and Engineering. 8(2): 251-265

*Corresponding author: Ayse Cilaci Tombus
E-mail: acilaci@gtu.edu.tr

Received Date: 01/06/2023
Accepted Date: 24/06/2024

Abstract

Recommender systems in the industrial sector are experiencing a growing application within e-commerce platforms, focusing on tailoring customer shopping experiences. This trend has led to increased customer satisfaction and enhanced sales outcomes for businesses operating in this domain. Despite the widespread prevalence of e-commerce globally, there exists a noticeable gap in the empirical assessment of recommender system performance for business objectives, particularly in the context of utilizing data mining methodologies and big data analytics.

This research aims to address this gap by scrutinizing authentic global e-commerce data that spans diverse countries, industries, and scales. The primary objective is to ascertain the impact of recommender systems, measured in terms of contribution rate, click-through rate, conversion rate, and revenue, by leveraging advanced big data analytics and data mining techniques. The study utilizes average values derived from an extensive dataset comprising 200 distinct e-commerce websites, representing a spectrum of 25 countries distributed across five different regions. Notably, this research represents a pioneering initiative in the literature as it harnesses and analyzes empirical data on such a comprehensive scale derived from various global e-commerce platforms.

Keywords: Recommender systems, E-commerce, Big data, Data mining, Data analysis.

1. Introduction

The global economy has been greatly affected by the COVID-19 pandemic, leading to notable changes in consumer behavior and a rapid expansion of e-commerce on a global scale. E-commerce has gained heightened significance in the lives of consumers, resulting in shifts in their buying patterns and motivations. Key drivers for online shopping now include affordability, time efficiency, and a wide range of product options [1]. According to Cramer-Flood's research, there is a projected 8.9% growth in retail e-commerce sales globally this year, as depicted in Figure 1 [2].

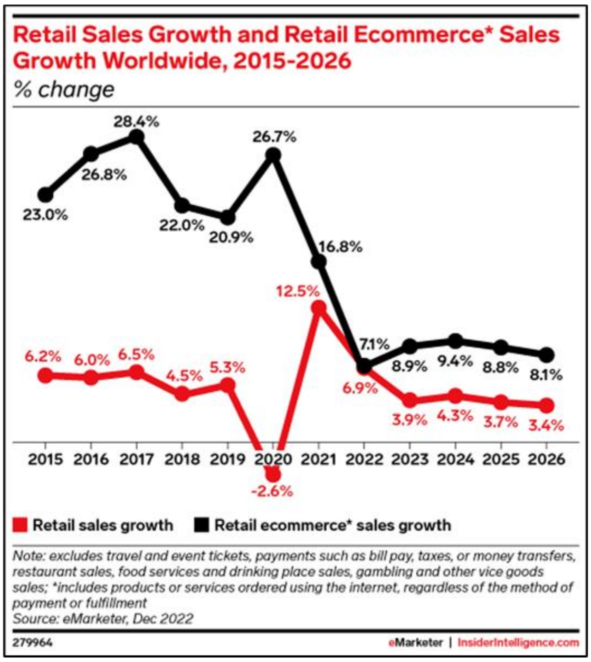

Figure 1: Retail Sales Growth and Retail Ecommerce Sales Growth Worldwide, 2015-2026

As reported by Forbes [3], online transactions are projected to account for 20.8% of all retail purchases in 2023. Looking ahead to 2026, it is anticipated that 24% of retail purchases will occur online. The e-commerce sector is expected to experience a 10.4% growth in sales during 2023. Figure 2 illustrates that the global e-commerce market is estimated to reach a total value of $6.3 trillion in 2023. Furthermore, by 2026, the e-commerce market is forecasted to surpass $8.1 trillion, representing a significant increase in market share within a relatively short time frame.

Figure 2: The Growth in Retail Ecommerce Sales Worldwide 2021-2026

In this context, it is very competitive, and e-retailers are looking for more productive and effective ways of selling through their e-commerce websites. Therefore, recommender systems (RSs) are becoming more prominent for them.

Automated recommendations have become ubiquitous in today's online landscape, permeating various platforms. Online shops routinely offer suggestions for additional shopping items, music streaming services like Spotify, recommend new tracks or artists, and social media news feeds are personalized to individual preferences. The primary purpose of such recommendations is to assist users in discovering items of relevance and prevent decision fatigue. Concurrently, these systems align with the organizational objectives of providers, aiming for increased sales or heightened user engagement. The widespread acceptance and success of recommendation technology in practical applications strongly indicate the efficacy of modern RSs, which significantly influence the choices and decisions of consumers. Consequently, these systems hold the potential to generate substantial business value, as evidenced by the studies conducted by Adomavicius et al. [4], Gomez-Uribe and Hunt[5], Jannach and Jugovac [6], and Lee and Hosanagar [7].

The research in information systems and computer science has predominantly concentrated on algorithmic design and enhancing the performance of recommender systems, as extensively reviewed by Adomavicius and Tuzhilin in 2005 [8]. However, there has been relatively limited exploration into the impact of recommender systems on consumer behavior and decision-making. Given the crucial role that recommender systems play as decision aids in online commerce, there is a recognized need to delve into their influence on consumer behavior. Adomavicius and et al. [9] showed that personalized recommendations also impact consumers' willingness to pay for those items.

RSs aim to provide personalized product recommendations to website customers by learning from their behavior and suggesting relevant products. These systems strive to personalize the user experience and cater to their interests.

In general, there are three primary approaches to product recommendations: (i) based on the top overall sellers on a website, (ii) tailored to the customer's demographics, or (iii) personalized according to the customer's previous purchase history.

Implementing a Recommender System (RS) enables websites to personalize the user experience by adapting to the preferences of each individual customer. Additionally, RSs can contribute to the growth of e-commerce sales in three key ways. Firstly, by presenting relevant recommendations to users, RSs have the potential to convert mere visitors into buyers who might have otherwise browsed without making a purchase. Secondly, through cross-selling techniques, RSs can suggest complementary products, thereby increasing the average order size over time. Lastly, RSs facilitate customer loyalty by personalizing the website for each user, fostering a stronger user-site relationship.

As customers interact with the system more frequently, the quality of recommendations improves, leading to increased customer loyalty towards the site. Furthermore, RSs are employed to target customers and provide tailored offers, as search engines and advertising companies rely on presenting effective suggestions based on users' behavior. Industrial recommenders are optimized for revenue generation. Important evaluation criteria besides accurate predictor are coverage of the product catalog, utility, and serendipity of recommendations, adaptivity and scalability of the algorithm, and more.

In this research, an investigation was conducted into 200 e-commerce websites utilizing Recommender Systems (RSs). Research focus centered on comprehensively evaluating the impact of RSs in the e-commerce domain, considering various perspectives such as geographical location, industry classification, and the size of e-commerce websites: Are there any significant differences between tier, region, industries, and localization of companies in terms of contribution rates and other metrics resulting from usage of RSs?

The evaluation metrics encompassed contribution rate, click-through rate (CTR), conversion rate, and revenues.

The dataset for this study was sourced from a Software as a Service (SaaS) RS provider. The selected websites spanned 27 diverse sectors, including Accessories, Alcoholic Beverages/Spirits, Apparel & Fashion, Arts & Entertainment, Auto Parts, Baby & Kids, Books/Music/Art, Cosmetics & Pharmacy, Electronics, Fashion, Food, Hobby & DIY, Home Depot & Furniture & Appliances, Industrial Equipment, Jewelry, Lingerie, Luxury Goods, Marketplace, Pet Store, Shoes, Sports Equipment, Sports Fashion, and Supermarket.

Furthermore, the websites were chosen from 25 different countries: Argentina, Azerbaijan, Bosnia and Herzegovina, Brazil, Bulgaria, Canada, Chile, Colombia, Croatia, France, Germany, Greece, Ireland, Italy, Macedonia, Mexico, Montenegro, Pakistan, Poland, Romania, Serbia, Slovenia, Turkey, the United Kingdom, and the United States. To add granularity, the study categorized the websites into four different sizes based on revenue: small, medium, large, and extra-large.

2. Theoretical Background

Online retailers are increasingly using online recommender systems and consumer feedback mechanisms. They reduce consumer search costs and uncertainty associated with the purchase of unfamiliar products.

According to the findings of Pathak et al. [10], their recommendations not only enhance sales but also offer retailers increased flexibility to adjust their prices. Their comparative analysis reveals that recommendations have a greater impact on sales compared to consumer feedback. In other words, the study suggests that implementing recommendations is more influential in driving sales than relying solely on consumer feedback.

In the research conducted by Fleder and Hosanagar [11], it was discovered that certain commonly used recommendation systems can result in a decrease in the overall variety of sales. However, the study also identified the presence of path dependence, meaning that in specific cases, the same recommender can either enhance or diminish sales diversity. This implies that the impact on sales diversity is contingent on various factors and cannot be generalized across all instances of recommender systems.

According to Rafeh [12], recommender systems play a crucial role in assisting users in finding the most suitable items quickly and easily. Recommender systems are widely employed by e-commerce companies as a strategy to boost their profitability. These systems serve as valuable tools in increasing sales and revenue by providing personalized recommendations to users. By suggesting relevant and tailored products or services to customers, e-commerce companies can effectively engage users, increase conversion rates, and drive repeat purchases. Using recommender systems, companies can tap into the power of data analytics and algorithms to deliver targeted recommendations, ultimately enhancing the overall profitability of their business operations. Additionally, Schafer [13] provides an analysis of how recommender systems contribute to increasing sales on e-commerce platforms, examining six specific sites that have implemented such systems. Overall, both papers suggest that recommender systems are an effective tool for driving e-commerce sales.

In another study conducted by Li and Karahanna [14], they examined existing empirical research on recommender systems and presented a comprehensive overview of the relationships and variables explored in the literature across all three stages of the recommendation process. This information is summarized in Figure 3, providing a coherent view of the research conducted in the field of recommender systems.

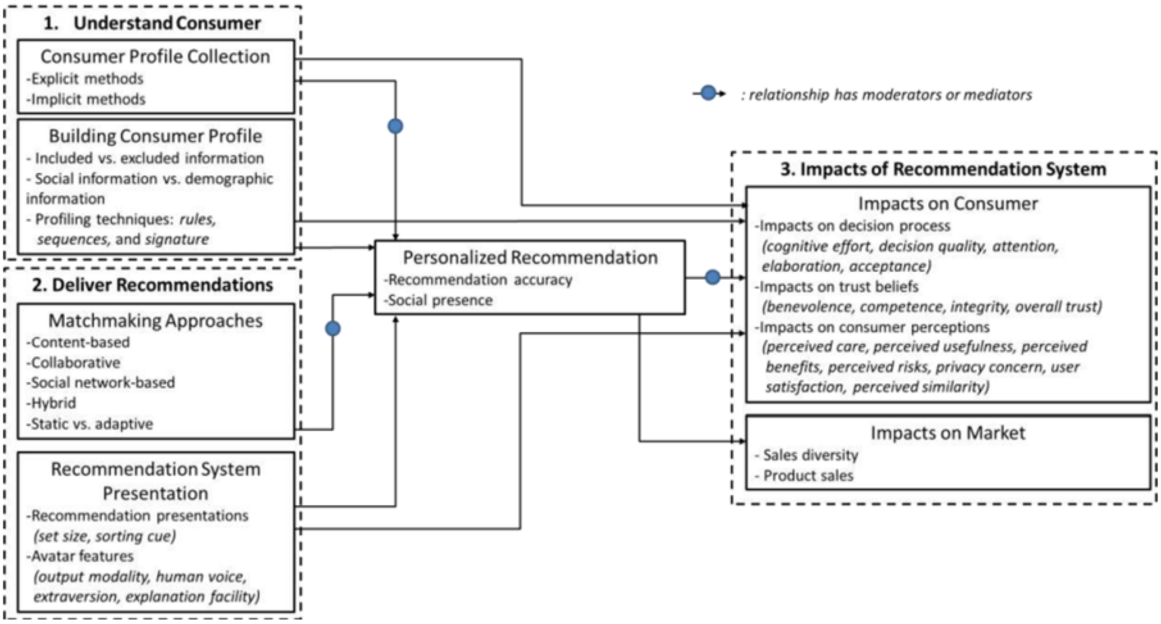

Figure 3: Recommendation Process

The central inquiry revolves around understanding the impact of recommender systems on sales, considering the intricate relationships among recommendations, sales, and pricing. Using a robust empirical model applied to data from two online retailers, the study finds that the strength of recommendations positively influences sales, with a moderation effect based on the recency of recommended items. Additionally, recommender systems contribute to the long-tail phenomenon and impact cross-selling positively. Notably, recommendations also affect prices, providing retailers with flexibility in adjusting pricing strategies. The empirical results suggest that these value-added services, especially recommendations, not only enhance sales but also empower retailers to charge higher prices by offering more information about product quality and suitability. A comparative analysis indicates that recommendations have a more substantial impact on sales compared to consumer feedback, emphasizing their significance in online retail strategies [15].

Senecal and Nantel's [16] experimental findings highlight the significant influence of online recommendations on choices, surpassing the impact of human recommendations. Studies by Cooke et al. [17], De et al. [18], and Hinz and Eckert [19] further emphasize that this impact extends beyond mere product substitution, contributing to a noteworthy increase in overall sales.

The literature, encompassing insights from various sources [20,21,22,23,24], collectively affirms the positive business impacts of recommender systems, though the precise magnitude of these effects remains uncertain. Reported figures range widely, spanning from incremental revenue effects [25] to transformative improvements measured in terms of "Gross Merchandise Volume" [26]. Complicating matters, determining the most meaningful metric for assessment can be challenging in certain application domains. While increases in click-through rates are commonly employed, their direct correlation with the long-term business value of a recommender system is, at times, subject to questioning [27].

Pathak et al. [28] showed that recommendations improved sales. However, their empirical analysis focused on the recommendations of amazon.com and books only.

Although it is not easy to measure the effect of online value-added services such as recommender systems [29,30], in this study the differences between different countries, industries, and sizes of the companies by using empirical data of 25 different countries through 200 different e-commerce web sites from 27 different sectors were evaluated.

There is no doubt that RSs help users to make correct decisions in their online transactions [31] and the shift to online shopping has made it incumbent on producers and retailers to customize for customers' needs while providing more options than were possible before [32].

3. Materials and Methods

Average values of 200 different e-commerce websites among 25 different countries in 5 different regions: 7,072,648,753 page views, 2,078,481,801 widget views, 5,796,781,099 impressions, 221,460,248.3 items, 998,465,646 users, 1,465,312,969 sessions, 19,918,845 purchase orders, and 162,803,439.7 purchase items in total were included in this study.

Data was grouped according to the sizes of the companies (small, medium, large, and extra-large) and according to regions (USA, Balkans, UK-Ireland, Turkey, Rest of All). Also, the industries were grouped into 10 main categories. The data have been produced from August, 2022 to March, 2023.

Kruskal-Wallis test has been used instead of ANOVA to compare the groups’ medians because sample sizes and variances are different.

The following comparison metrics have been used to evaluate the impact of recommendation algorithm usage in e-commerce websites:

Contribution Rate (USD): Total revenue (USD) from recommended items / Total Revenue (USD) from the whole website

Contribution Rate Purchase Orders: Total number of purchase orders including recommended items / Total number of purchase orders in the whole website.

Contribution Rate Purchase Items: Total number of purchased recommended items / Total number of purchased items in the whole website.

AOC/AOV: Average purchase order value (USD) of recommended items / Average purchase order value (USD) for the whole website

ABS Rate: Average number of items in the purchase orders for recommended items / Average number of items in the purchase orders for the whole website

AVG Price Rate: Average price per purchased recommended item / Average price per purchased item.

View Rate: Number of Widget Views / Number of Impressions

CTR: Number of Clicks / Number of Widget Views

Basket Rate: Number of Basket Items / Number of Clicks

Widget View: Recommendation widget which has been seen by the user

Impression: Recommendation widget which has been served to the user

Click: Number of clicks on Recommendation widget

Purchase Orders: Number of purchase orders (PO)

Purchase Value: Total revenue from purchase orders (USD)

Basket Items: Number of items in the basket

Basket Value: Total monetary value of items in the basket

4. Results and Discussion

4.1. Tiers

When the companies were grouped as small, medium, large, and extra-large according to their revenues, most widget views, impressions, clicks, purchase orders, purchase values, and basket sizes except basket values were observed in large companies as shown in Table 1.

Table 1: General Statistics (Average) According to Tier

Tier	Widget View	Impression	Click	Purchase Orders	Purchase Value (USD)	Basket Items	Basket Value
Small	4,860,686.96	12,424,605.69	459,904.13	6,218.27	141,107.27	51,269.44	2,984,459.51
Medium	4,657,483.73	14,940,452.94	382,177.99	5,218.47	179,921.30	37,105.08	128,767,792.13
Large	33,600,697.13	81,960,652.50	1,716,655.03	100,549.09	1,640,898.85	664,040.53	70,198,658.80
Extra Large	13,905,224.83	31,824,393.17	1,173,765.75	12,941.17	1,189,596.45	116,928.08	11,221,690.23

However, CTRs are smallest for large companies compared to other tiers although they have highest purchase value in total (Table 2).

Table 2: Rates According to Tier

Tier	View Rate	CTR	Basket Rate	AOC (USD)	Purchase Value (USD)
Small	0,41	0,10	0,15	55,40	2.215.902,01
Medium	0,42	0,10	0,13	79,13	2.247.392,16
Large	0,43	0,08	0,22	112,72	17.413.246,95
Extra Large	0,50	0,10	0,12	129,81	15.760.448,04

There is not any significant difference between tiers according to Contribution Rate (Kruskal Wallis test: statistic=5.45920, p value=0.141099)

4.2. Regions

When the countries were grouped according to regions, Turkey has two times of average number of basket items with recommendation (ABS-RS) in comparison to other regions. Turkey has the least average order value for sales with recommendation and from the whole site, and also has the lowest average number of basket items rate with recommendation over the whole site.

American region countries have the highest CTR, average price, and average price rate with recommendation over the whole site.

Ireland-UK region has the highest average order value with recommendation and the Balkans have the highest average order value throughout the whole site. (Table 3)

Table 3: General Statistics According to Region

Region	ABS-RS	CTR	AOC (USD)	Average Price (USD)	ABS	AOV(USD)	AOC/AOV	ABS Rate	AVG Price Rate
Ireland-UK	1,56	5,77%	102,47	58,88	5,97	151,49	0,68	0,66	1,05
Turkey	3,16	6,27%	74,27	55,51	3,59	87,72	0,72	0,64	1,13
Rest	1,36	8,51%	88,87	58,67	2,70	142,46	0,73	0,66	1,10
Americas	1,21	11,32%	91,88	61,90	3,31	120,65	0,74	0,65	1,84
Balkans	1,70	7,76%	82,60	252,70	3,38	427,50	0,65	0,65	1,08

There is not any significant difference between regions according to the Contribution Rate (Kruskal Wallis test: statistic=4.28244, p value=0.36913)

4.3. Turkey vs. Global

When investigated, AOC and view rate are lower whereas CTR, basket rate and value of purchase in average are higher in Turkey.

Table 4: General Statistics (Average) According to Turkey vs Global Comparison

	View Rate	CTR	Basket Rate	AOC (USD)	Purchase Value (USD)
GLOBAL	0,44	0,09	0,13	91,75	4.290.250,94
TURKEY	0,41	0,10	0,17	73,03	6.388.524,34

4.4. Industries

It can be seen from Kruskal Wallis test that there is significant difference between sectors according to the Contribution Rate. So, it is essential to differentiate the services according to industry (statistic=21.64041, p value=0.01009).

When the industries in Turkey are evaluated, there is no significant difference between sectors (statistic=11.15174, p value=0.26545).

When the industries are evaluated globally, there is no significant difference between sectors (statistic=13.05951, p value=0.10982).

4.5. Insights

We also investigated these factors from different perspectives. When we look at the tiers, extra-large companies have the highest CTR and the lowest average basket size compared to other tiers as shown in Figure 4.

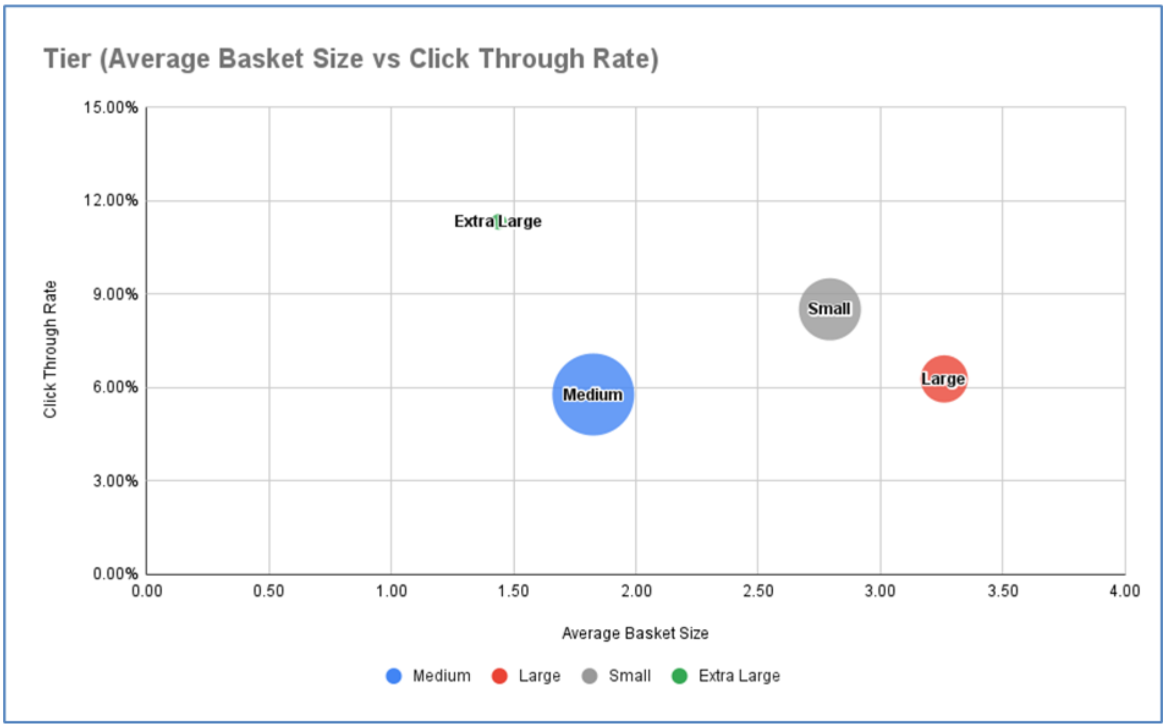

Figure 4: Tiers according to Average Basket Size vs. Click Through Rate

American countries have the highest CTR, the Balkan countries have the highest CR and Ireland-UK and Turkey have close CTR and CRs according to Fig. 5.

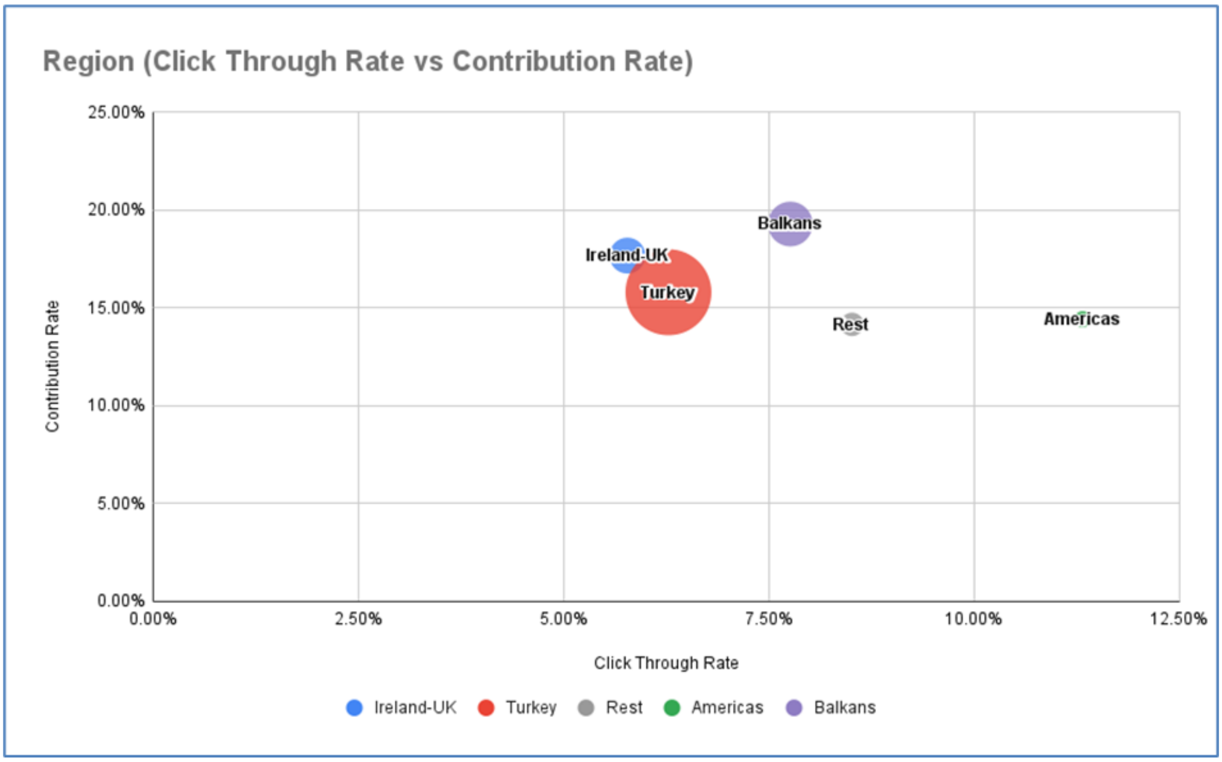

Figure 5: Click Through Rate vs. Contribution Rate According to Regions.

When we compared Turkey with other countries Turkey has higher ABS but lower average product price as it can be seen in Fig. 6.

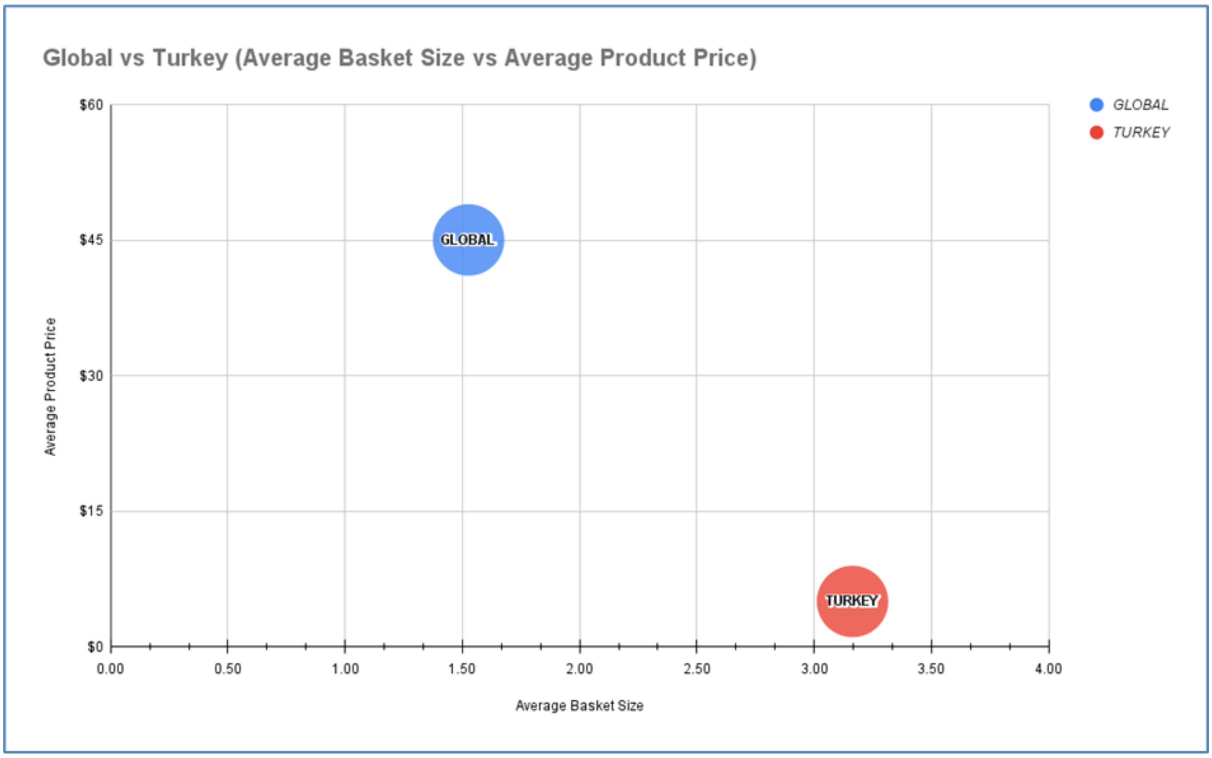

Figure 6: Average Basket Size vs. Average Product Price (Global vs. Turkey)

Interesting and valuable information is available from industry specific data. Supermarket and Hobby & DIY sectors have higher ABS with moderate CTR. Cosmetics & Pharmacy has the lowest CTR whereas Sports & Fashion has the highest CTR. (Fig.7). Note that we grouped the following industries in section other: Food, Lingerie, Luxury Goods, Books / Music / Art, Pet Store, Baby & Kids, Auto Parts, Alcoholic Beverages / Spirits, Accessories, Marketplace, Industrial Equipment, Arts & Entertainment, Apparel & Fashion.

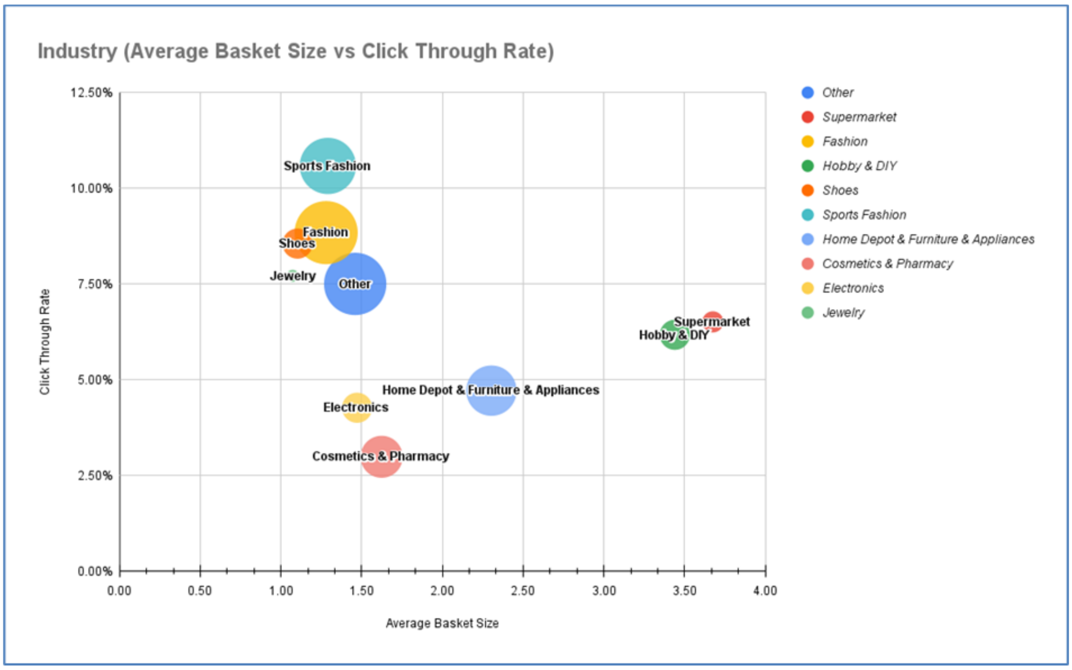

Figure 7: Average Basket Size vs. Click Through Rate According to Industries

It is obvious from the following Figure 8 that Electronics has the highest Average price though CTRs are low.

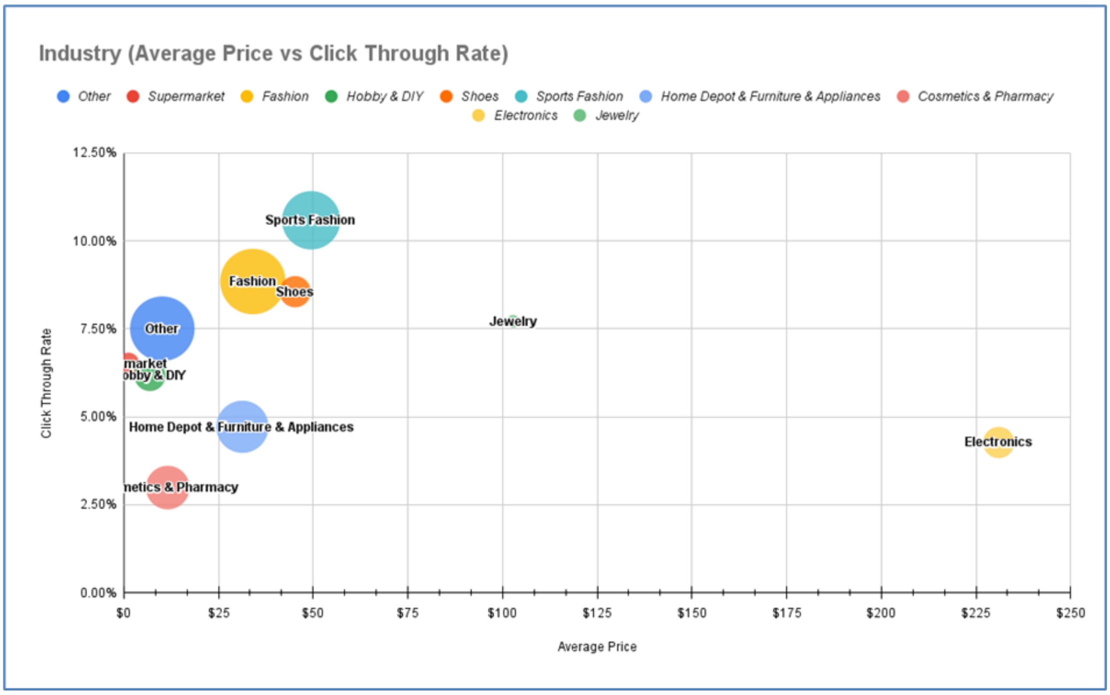

Figure 8: Average Price vs. CTR According to Industries

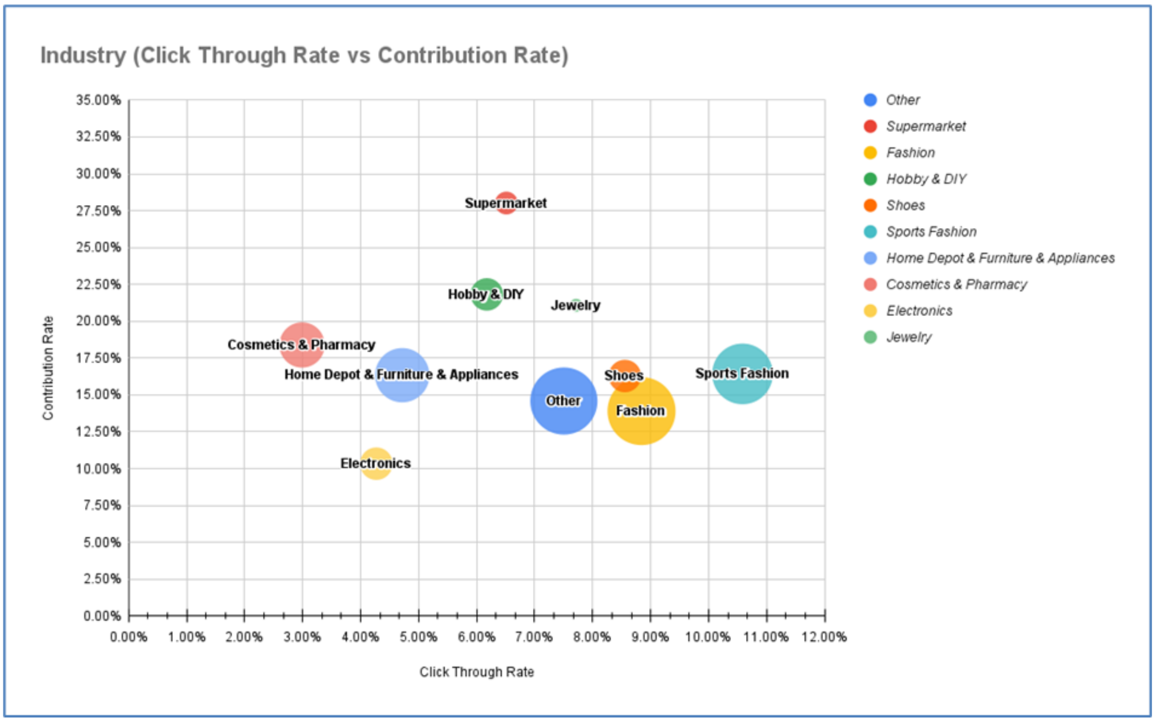

Figure 9: CTR vs. CR According to Industries

The highest CTR is in supermarkets with moderate CTR as can be seen in Figure 9.

The product price rate for the Hobby & DIY sector is approximately twice that of the others with a moderate Basket Rate as shown in Figure 10.

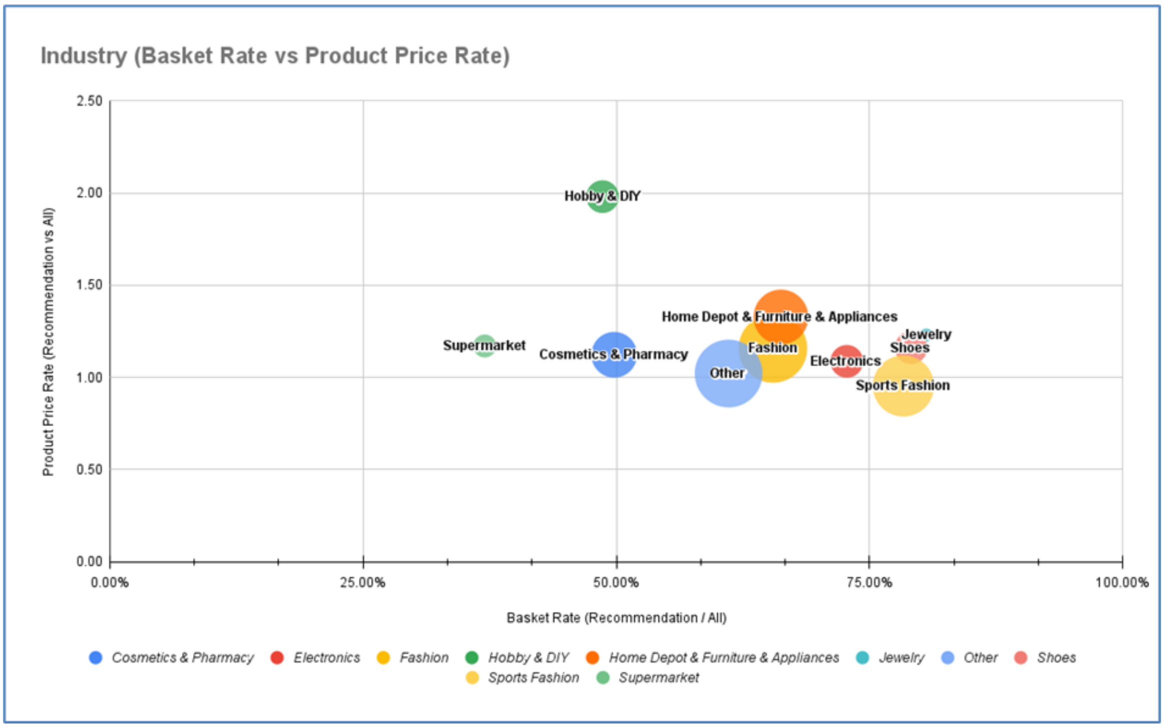

Figure 10: Basket Rate vs. Product Price Rate According to Industries

5. Conclusion

In this study, the big data provided by a recommender system SaaS provider was used to see the impacts of recommender systems in e-commerce web sites. Although there exists a lot of research which competes for better recommendation algorithms in the literature, there is no empirical analysis which evaluates the companies' e-commerce web sites around the world to investigate the effects of RSs from business perspective.

Recommender systems stand out as a primary success story in the practical application of artificial intelligence and machine learning, delivering substantial benefits to businesses. Despite their achievements, numerous avenues for future research persist, often constrained by prevalent research approaches in academia. A promising resolution to many lingering challenges may lie in fostering collaborative industry-academia partnerships, offering a real-world context for refining and advancing recommender system technologies.

Analysis showed that there is no significant difference between tier, region, and localization of companies for contribution rates resulting from usage of RSs whereas the industries are significant. Therefore, company policy makers and recommender system providers should be industry specific to develop more effective recommendation algorithms.

These factors were also investigated from different perspectives which can be seen in detail in Section 4.5.

In conclusion, in this study important insights were obtained from the big data which will be valuable for e-commerce companies and researchers. **This is the first study in literature that uses and analyzes empirical data in this scale from different e-commerce websites globally**.

Acknowledgements

This work was supported by Segmentify Yazılım A.Ş. Research and Development HQ (orchid: 0009-0003-3025-2444).

References

[1] Tüsiad – Deloitte Digital. (2022). E-ticaretin Öne Çıkan Başarısı, Tüketici Davranışlarında Değişim ve Dijitalleşme. https://www.eticaretraporu.org/wp-content/uploads/2022/02/dd-tusiad-e-ticaretin-one-cikan-basarisi-tuketici-davranislarinda-degisim-ve-dijitallesme.pdf [Accessed: 9 May 2023].

[2] Cramer-Flood E. Insiderintelligence- eMarketer. (2023). Global Retail Ecommerce Forecast 2023 Welcome to the Slower-Growth New Normal. https://www.insiderintelligence.com/content/global-retail-ecommerce-forecast-2023 [Accessed: 15 May 2023].

[3] Baluch A. 38 E-Commerce Statistics Of 2023. (2023). https://www.forbes.com/advisor/business/ecommerce-statistics/ [Accessed: 2 May 2023].

[4] Adomavicius, G., Bockstedt, J. C., Curley, S. P., & Zhang, J. (2018). Effects of online recommendations on consumers' willingness to pay. *Information Systems Research*, 29(1), 84-102.

[5] Gomez-Uribe, C. A., & Hunt, N. (2015). The netflix recommender system: Algorithms, business value, and innovation. *ACM Transactions on Management Information Systems (TMIS)*, 6(4), 1-19.

[6] Jannach, D., & Jugovac, M. (2019). Measuring the business value of recommender systems. *ACM Transactions on Management Information Systems (TMIS)*, 10(4), 1-23.

[7] Lee, D., & Hosanagar, K. (2019). How do recommender systems affect sales diversity? A cross-category investigation via randomized field experiment. *Information Systems Research*, 30(1), 239-259.

[8] Adomavicius, G., Bockstedt, J. C., Curley, S. P., & Zhang, J. (2018). Effects of online recommendations on consumers' willingness to pay. *Information Systems Research*, 29(1), 84-102.

[9] Adomavicius G, Tuzhilin A (2005) Toward the next generation of recommendation system: A survey of the state-of-the-art and possible extensions. *IEEE Trans. Knowledge Data Engrg*. 17(6): 734–749.

[10] Pathak, B., Garfinkel, R., Gopal, R. D., Venkatesan, R., & Yin, F. (2010). Empirical analysis of the impact of recommender systems on sales. *Journal of Management Information Systems*, 27(2), 159-188.

[11] Fleder, D. M., & Hosanagar, K. (2007). Recommender systems and their impact on sales diversity. *In Proceedings of the 8th ACM conference on Electronic commerce*,192-199.

[12] Rafeh, R. (2017). Recommender systems in ecommerce.

[13] Schafer, J. B., Konstan, J., & Riedl, J. (1999). Recommender systems in e-commerce. *In Proceedings of the 1st ACM conference on Electronic commerce*,158-166.

[14] Li, S. S., & Karahanna, E. (2015). Online recommendation systems in a B2C E-commerce context: a review and future directions. *Journal of the association for information systems*, 16(2), 2.

[15] Bhavik Pathak , Robert Garfinkel , Ram D. Gopal , Rajkumar Venkatesan & Fang Yin (2010) Empirical Analysis of the Impact of Recommender Systems on Sales, *Journal of Management Information Systems*, 27:2, 159-188.

[16] Senecal, S. and J. Nantel: 2004, 'The influence of online product recommendations on consumers online choices'. *Journal of Retailing* 80(2), 159–169.

[17] Cooke, A. D., H. Sujan, M. Sujan, and B. A. Weitz: 2002, 'Marketing the unfamiliar: the role of context and item-specific information in electronic agent recommendations'. *Journal of marketing research* 39(4), 488–497.

[18] De, P., Y. Hu, and M. S. Rahman: 2010, 'Technology Usage and Online Sales: An Empirical Study'. *Management Science* 56(11), 1930–1945.

[19] Hinz, O. and J. Eckert: 2010, 'The Impact of Search and Recommendation Systems on Sales in Electronic Commerce'. *Bise* 2(2), 67–77.

[20] Amatriain, X. and J. Basilico. 2012. Netflix Recommendations: Beyond the 5 stars. Retrieved from https:// medium.com/netflix-techblog/netflix-recommendations-beyond-the-5-stars-part-1.

[21] Davidson, J., Liebald, B., Liu, J., Nandy, P., Van Vleet, T., Gargi, U., ... & Sampath, D. (2010, September). The YouTube video recommendation system. *In Proceedings of the fourth ACM conference on Recommender systems* (pp. 293-296).

[22] Carlos A. Gomez-Uribe and Neil Hunt. 2015. The Netflix recommender system: Algorithms, business

value, and innovation. *Trans. Manage. Info. Syst*. 6, 4 (2015), 13:1–13:19.

[23] J. Katukuri, T. Könik, R. Mukherjee, and S. Kolay. 2014. Recommending similar items in large-scale online marketplaces. *In Proceedings of the IEEE International Conference on Big Data 2014*. 868–876.

[24] J . Katukuri, T. Konik, R. Mukherjee, and S. Kolay. 2015. Post-purchase recommendations in large-scale online marketplaces. *In Proceedings of the IEEE International Conference on Big Data (BigData'15)*. 1299–1305.

[25] Dias, M. B., Locher, D., Li, M., El-Deredy, W., & Lisboa, P. J. (2008, October). The value of personalised recommender systems to e-business: a case study. *In Proceedings of the 2008 ACM conference on Recommender systems* (pp. 291-294).

[26] Chen, Y., & Canny, J. F. (2011, July). Recommending ephemeral items at web scale. *In Proceedings of the 34th international ACM SIGIR conference on Research and development in Information Retrieval* (pp. 1013-1022).

[27] Jannach, D., & Jugovac, M. (2019). Measuring the business value of recommender systems. *ACM Transactions on Management Information Systems (TMIS)*, 10(4), 1-23.

[28] Pathak, B., Garfinkel, R., Gopal, R. D., Venkatesan, R., & Yin, F. (2010). Empirical analysis of the impact of recommender systems on sales. *Journal of Management Information Systems*, 27(2), 159-188.

[29] Yang, Y, and Padmanabhan. (2005). B. Evaluation of online personalization systems: A survey of evaluation schemes and a knowledge-based approach. *Journal of Electronic Commerce Research*, 6, 2, 112-122.

[30] Kumar, N, and Benbasat, I. (2006). The influence of recommendations and consumer reviews on evaluations of Websites. *Information Systems Research*, 17, 4 425-439.

[31] Vaidya, N., & Khachane, A. R. (2017). Recommender systems-the need of the ecommerce ERA. *International Conference on Computing Methodologies and Communication (ICCMC)* 100-104. IEEE.

[32] Sivapalan, S., Sadeghian, A., Rahnama, H., & Madni, A. M. (2014). Recommender systems in e-commerce. *In 2014 World Automation Congress (WAC)* 179-184. IEEE.