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Analysis of a Framework for E-Commerce Consumer Behavior before and During Covid-19

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ABSTRACT

The Covid-19 pandemic has caused changes in the field of business activities. The fear of the pandemic has increased consumer awareness of the economic benefits of e-commerce platforms and the desire of people to absentee shopping, resulting in the growth of e-commerce in the world. Iran is not an exception to this rule. In this article, in order to analyze the behavior of e-commerce consumers, before and during covid-19, Iran's largest online retail site has been studied. In the analysis of consumers' behavior, parameters such as spatial distribution, gender and age range of consumers, product groups, payment method for orders according to the amount of use of information and communication technology in the country before and during covid-19 and the death rate due to corona, were considered. In this research, data mining method has been used to analyze the behavior of e-commerce consumers. In the procedure, first the required data is collected and then in the next step, the data has been refined with the KNIME Analytics platform, and then consumer behavior has been analyzed using k-means and Fuzzy c-means algorithms. The results of the analysis showed that the spread of covid-19 has made the amount of shopping at the country level more uniform, leading older people to shop online and increasing their share of the total e-commerce consumers and the desire to pay for orders online. Also, the examination of product groups showed that the sales growth of health product groups was higher than other groups.

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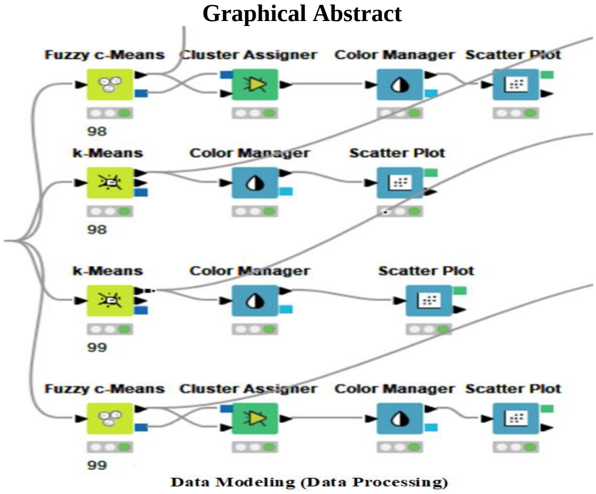
Graphical Abstract



1. INTRODUCTION

The Covid-19 pandemic, which emerged in late Mar 2019 to Feb 2020 in Wuhan, China, brought about various challenges on a global scale, including in the domain of retail. However, this pandemic has expedited the growth of e-commerce (1-3). This paper delves into the analysis of consumer behavior before and during

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Covid-19, focusing on Iran's leading online retail platform, DigiKala. To extract valuable insights from the data, data mining techniques were employed. Data mining is the process of utilizing statistical, mathematical, and machine learning methods on large volumes of data to uncover hidden patterns. Clustering is one of the many data mining techniques, wherein data is categorized into clusters based on their greatest similarities.

In today's world, with the advancements in technology, the proliferation of the internet, and the tools used for it, significant changes have been introduced into the daily lives of people. Offline businesses have gradually evolved with the progress of the internet and its widespread adoption, giving way to e-commerce. The onset of these transformations occurred earlier in some countries and later in others. The spread of the Covid-19 virus has accelerated these changes in all countries, with even more pronounced advancements in countries that have only recently adopted e-commerce in comparison to those that have been utilizing it for years[1].

In Iran, people are relatively familiar with the concept of e-commerce and make use of it, while numerous small and large companies have entered this form of trade. Nevertheless, there is considerable potential for the expansion of e-commerce (4-6).

This paper employs data mining methods, such as the k-means and Fuzzy c-means algorithms, to cluster e-commerce consumers based on their purchasing behavior before and during the Covid-19 pandemic, and subsequently, the results were compared. Furthermore, the process of this paper adheres to the CRISP-DM standard, an analytical standard for the data mining process, which stands for “Cross-Industry Standard Process for Data Mining” (7, 8). In this research, in order to analyze the behavior of e-commerce consumers, before and during covid-19, Iran's largest online retail site has been studied. In the following, the research background is in section 2. In section 3, framework in research is presented, and then in section 4, the research results are given. Finally, in section 5 the discussion and conclusion is presented.

2. RESEARCH BACKGROUND

In the article titled "The Impact of COVID-19 Pandemic on E-commerce Companies: A Data Mining for Indonesian Provinces, " Gunawan (3) focused on the behavior of e-commerce companies rather than consumers, contrary to most research that concentrated on consumer behavior. They collected the data necessary for their study from the official website of the Indonesian National Statistics Agency and gathered COVID-19 data from Google. In this research, they employed data mining techniques, the CRISP-DM standard, and k-means clustering. Their analysis revealed that in densely populated areas with skilled IT residents, the intensity of e-commerce usage is higher (9-11).

Nishat Khan and his colleagues (4) used data mining methods with Python to compare the e-commerce industry before and during COVID-19 in Bangladesh. They used libraries such as NumPy, Pandas software, Label Encoder for converting categorical features into numerical values, and Matplotlib and Seaborn for visualization. They compared various parameters during this time frame, such as working hours, order duration, profit increment, and more. Data for their research were collected through surveys of e-commerce business owners. In conclusion, their study found that although the e-commerce industry had a relatively minor share in Bangladesh's national economy, the pandemic accelerated e-commerce usage across all sectors except for services and jewelry (12, 13).

Atheer and colleagues (5) attempted to estimate the potential number of patients and the likelihood of COVID-19 occurrences in Iraq based on environmental conditions. For this study, they used data mining and k-means clustering in MATLAB software. They also collected their data from samples of patients in Iraq. By comparing the results of their model with confirmed COVID-19 cases, they obtained a strong correlation between their estimated values and real numbers. Furthermore, due to the fluctuating recovery and mortality rates associated with the disease, there is a possibility that 33% of the population will be affected by the pandemic until before December Mar 2020 to Feb 2021 and that it will then decrease (14, 15).

Ghaffari and colleagues (6) examined the impact of the COVID-19 pandemic on the online shopping behavior of customers in Iran. They collected their data through random questionnaires from 484 customers of the DigiKala company, all residing in Tehran. The authors utilized various criteria to classify their research methods. They categorized their descriptive statistics according to the Likert scale spectrum and employed central tendency and dispersion parameters. To this end, they used software such as SPSS 23 and SMARTPLS3. Their research findings indicated that the fear of health and economic well-being had a positive and significant impact on online shopping behavior and the growth of e-commerce in Iran during the COVID-19 pandemic (16-18).

Arabzadeh and colleagues (7) aimed to create a model for the automatic diagnosis of COVID-19. They collected the required data from the Infectious Diseases Clinic of Afsari-Pour Hospital in Kerman and Ali Ibn Abi Talib Hospital in Rafsanjan from March Mar 2019 to Feb 2020 to February Mar 2020 to Feb 2021. The prepared dataset includes 102 records and 12 key features. Data mining

[1] http://gp85.blogfa.com/

techniques and RapidMiner software were used for experiments in this study. The results demonstrated that the diagnosis model, utilizing the SVM data mining technique and 9 key features, achieved the highest accuracy, which is 83.19%. Therefore, this technique proved to be the most suitable method among the seven implemented techniques in this study for diagnosing COVID-19 (19-21).

Javaheri and colleagues (8) examined the effects of the COVID-19 pandemic on household consumption patterns in the Kurdistan Region and compared changes in consumer behavior before and during the COVID-19 pandemic and its impact on household income and expenses. This study was comparative in terms of time and a cross-sectional comparison method was used. The statistical population of this research is the Kurdistan Region of Iraq, and the sample size was determined based on Morgan's table. Data and information were collected through a library research method and field survey using questionnaires with Likert scale 5-point questions for designing the questionnaire. Data analysis was performed using Excel and SPSS 25 software. The overall results of the study showed that the COVID-19 pandemic had a significant impact on changing consumer behavior. Consumer behavior during and before the pandemic underwent significant changes, leading to a reduction in household income and an increase in household expenses (22-24).

Soleimani and colleagues investigated the influence of the emerging risk of COVID-19 on the credibility and inclination toward e-commerce. They collected their data through questionnaires from 98 individuals selected randomly in the Tehran province. Statistical analyses were carried out using SPSS software, and a paired (two-tailed) T-test was utilized to examine the level of e-commerce acceptance and credibility before and after COVID-19. Additionally, a Pearson correlation test was used to assess the relationship between the level of e-commerce acceptance and the necessity for reformation of insurance processes. The overall findings of the research revealed that the COVID-19 pandemic accelerated the adoption and reduced the acceptance time of e-commerce. Given the absence of a natural lifecycle for e-commerce adoption and early adoption despite infrastructure deficiencies and unpreparedness, e-commerce is experiencing premature maturity, which can be considered a potential threat (25-33).

3. METHODOLOGY

The research process is conducted according to the CRISP-DM standard. Furthermore, for clustering, the Analytic Analytics platform is utilized. For the execution of this paper, the KNIME platform has been utilized. Initially, the data was imported into a new workflow page using the "Excel Reader" node, and then the data preprocessing stage was carried out on the data.

Overall, the data had good quality, and extensive data cleaning was not required (Figures 1 and 2).

Selection of an Appropriate Modeling Method: In this article, clustering is employed using the k-means algorithm and the fuzzy c-means algorithm. Additionally, for data processing, the Naim Analytics platform is utilized once again.

k-Means Node: As implied by its name, this node is responsible for clustering using the k-means algorithm. It selects the columns related to the amount of purchases from DigiKala in Mar 2019 to Feb 2020 and the amount of ITC usage in Mar 2019 to Feb 2020. The value of k is determined to initiate the clustering process. This

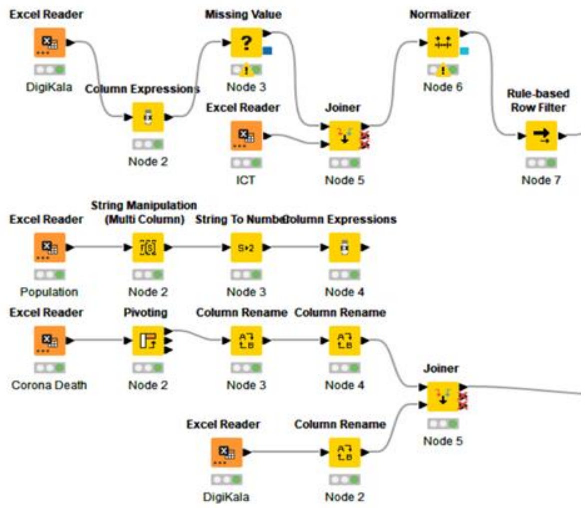

Figure 1. Data Preparation (Preprocessing)

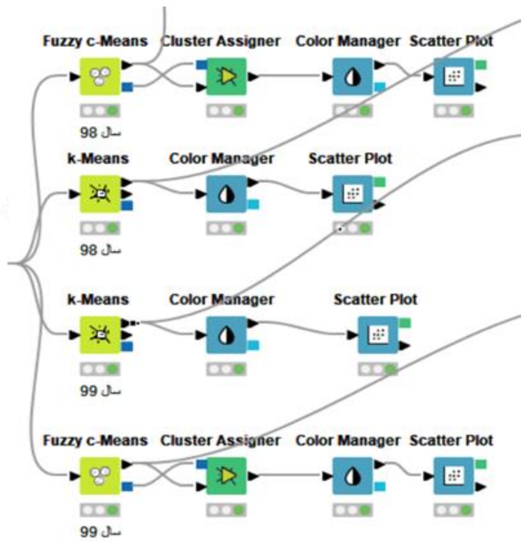

Figure 2. Data Modeling (Data Processing)

operation is repeated for the year Mar 2020 to Feb 2021 with a different k value. (It is worth noting that the methodology for obtaining the optimal k value will be explained in the "Evaluation" section.)

Fuzzy c-Means Node: This node is tasked with fuzzy clustering using the fuzzy c-means algorithm. Similar to the previous node, all operations are repeated.

Color Manager Node: This node is responsible for assigning distinct colors to different clusters to make data clustering distinguishable for users.

Scatter Plot Node: By using this node, clustered data is displayed in a scatter plot. It only requires horizontal and vertical axes and a series of additional settings to display the plot after executing the node.

Result Evaluation: To evaluate the optimal value of k, an external criterion is necessary.
Table Creator Node: This node is used to create a table and insert the required data into it. To find the optimal k value, a table named "k" is created, and values from 2 to 10 are placed inside it.

Table Row to Variable Loop Start Node: To determine the optimal k value, the model must be repeated with the values present in the "k" table. This can be done manually or by creating a loop with this node to iterate the model execution.

Loop End Node: This node signals the end of the loop that was created.

Inject Variables (Data) Node: This node is used to connect the loop start node to the k-Means node.

Silhouette Coefficient Node: With this node, the Silhouette coefficient for different numbers of clusters (k) can be calculated to obtain the optimal value.

In Tables 1 and 2, Silhouette coefficient values for different cluster numbers (k) are provided (Figure 3):

Silhouette Coefficient: The Silhouette coefficient is a measure of how similar an object is to its own cluster (cohesion) compared to other clusters (separation). Its values range from -1 to 1, where a value close to 1 indicates that the object closely matches its own cluster and has the least similarity with other clusters. If most objects have values above a certain threshold, the clustering structure is considered suitable. On the other hand, if many points have low or negative values, the clustering structure may have too many or too few clusters.

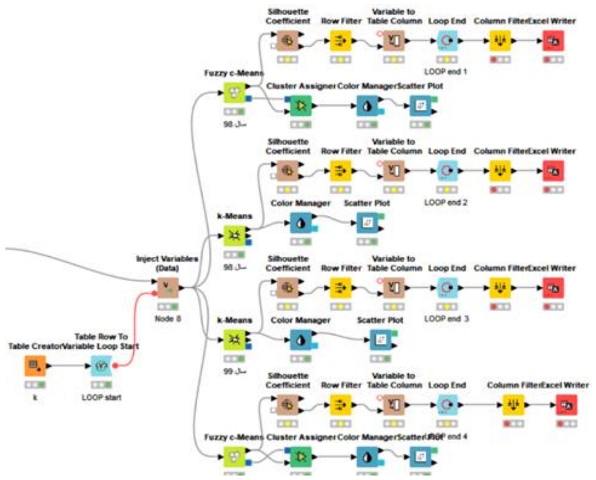

Figure 3. Evaluation

TABLE 1. Silhouette Coefficients for k-Means Clustering for years Mar 2019 to Feb. 2020 and Mar 2020 to Feb. 2021

Number of clusters	Silhouette coefficients for clustering in Mar 2019 to Feb 2020	Silhouette coefficients for clustering in Mar 2020 to Feb 2021
2	0.557	0.577
3	0.566	0.597
4	0.601	90.49
5	0.614	0.589
6	0.552	0.571
7	0.551	0.523
8	0.517	0.501
9	0.562	0.475
10	0.516	0.473

TABLE 2. Silhouette Coefficients for Fuzzy c-Means Clustering for Years Mar 2019 to Feb. 2020 and Mar 2020 to Feb 2021

Number of clusters	Silhouette coefficients for clustering in Mar 2020 to Feb 2021	Silhouette coefficients for clustering in Mar 2020 to Feb 2021
2	0.521	0.577
3	0.614	0.595
4	0.619	0.624
5	0.587	0.572
6	0.640	0.552
7	0.586	0.563
8	0.569	0.613
9	0.551	0.446
10	0.496	0.487

Silhouette can be calculated using any distance metric, such as Euclidean distance or Manhattan distance. As evident from the tables above, the optimal number of clusters for k-Means in Mar 2019 to Feb 2020 was five clusters and in Mar 2020 to Feb 2021 was three clusters. The optimal number of clusters for Fuzzy c-Means in Mar 2019 to Feb 2020 was six clusters, and in Mar 2020 to Feb 2021, it was four clusters .

Variable to Table Column Node: This node collects the Silhouette coefficient values and places them into a table.

Excel Writer Node: The processed data is exported to an Excel file specified as the output using this node.

Based on the results of clustering the country's provinces according to the amount of online purchases from DigiKala and the usage of ITC, it was determined that post-COVID-19, there is more uniformity among the provinces. The number of clusters reduced from 5 to 3 in the k-Means algorithm and from 6 to 4 in Fuzzy c-Means algorithm. Consequently, it is essential for DigiKala to expand its logistics distribution and support centers across different regions of the country to maintain service quality for consumers.

4. RESEARCH RESULTS

Result 1: As seen in Figure 4, the amount of online purchases in all of the country's provinces showed a significant increase in Mar 2020 to Feb 2021 compared to Mar 2019 to Feb 2020. To better understand the growth of online purchases in the country's provinces during two periods before and after the COVID-19 pandemic, the IT usage index in each province was also examined to analyze the impact of COVID-19 on consumer behavior.

Result 2: For a better comparison of the growth rate of online purchases from DigiKala and the growth of ITC usage in the country, data mining with clustering using k-means and fuzzy c-means algorithms was employed to categorize the provinces. The k-means algorithm divided the provinces into 5 clusters based on the amount of online purchases from DigiKala and the level of information technology usage in Mar 2019 to Feb 2020, as depicted in Figure 5. If the same procedure is applied to the year Mar 2020 to Feb 2021, as illustrated in Figure 6, we will observe that the provinces will be divided into 3 clusters. The result obtained from comparing these two charts reveals that during the Covid-19 pandemic, the growth rate of online purchases from DigiKala in provinces with lower ITC usage exceeded that in provinces with higher ITC usage. This has led to a reduction in the number of clusters related to these parameters in Mar 2020 to Feb 2021 compared to Mar 2019 to Feb 2020 and a greater uniformity in terms of the level of online purchases from DigiKala based on the level of ITC usage in the country.

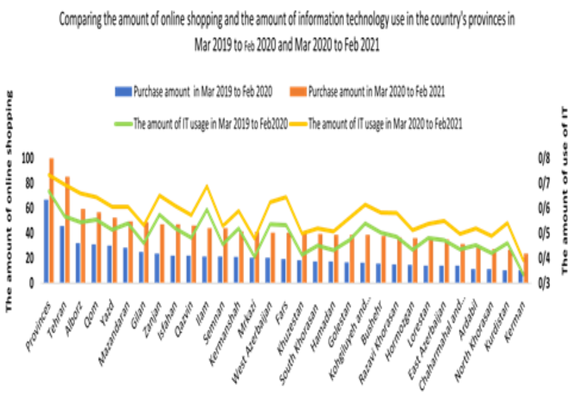

Figure 4. Comparison of Online Purchases from DigiKala and the Usage of ITC in the Country's Provinces in Years Mar 2019 to Feb 2020 and Mar 2020 to Feb 2021

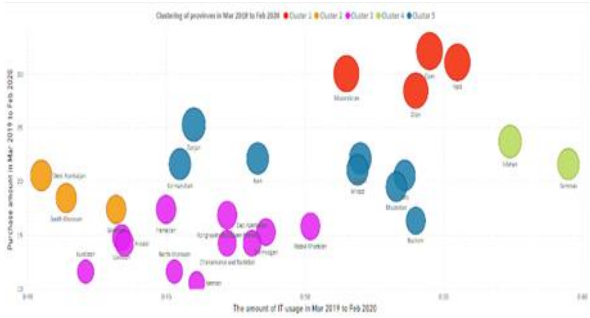

Figure 5. Clustering of Provinces Using K-Means in Mar 2019 to Feb 2020

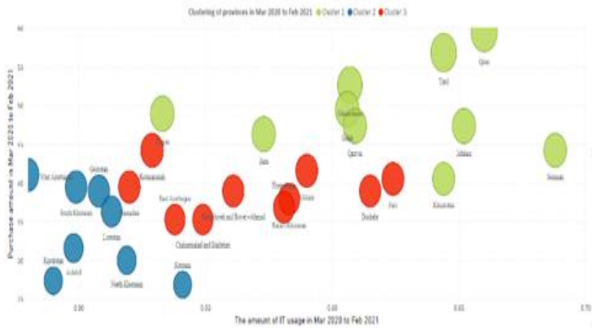

Figure 6. Clustering of Provinces Using K-Means in Mar 2020 to Feb 2021

Result 3: Analysis of statistics related to DigiKala website customers from Mar 2019 to Feb 2020 to 2021 reveals that the prevalence of the coronavirus had no significant impact on the gender distribution of customers. Approximately 70% of DigiKala customers are males, while 30% are females, both before and after the pandemic. For a better understanding of the relationship between gender and online shopping, another parameter, namely, the Covid-19 mortality rate by gender, was also examined. As shown in Figure 7, the statistics indicate that the gender-specific coronavirus fatality rate did not undergo substantial changes from Mar 2019 to Feb 2020 to 2021 and remained relatively constant.

Result 4: Figure 7 displays DigiKala consumers from Mar 2019 to Feb 2020 to 2021, categorized by age groups. Inference from Figure 8 suggests that the Covid-19 pandemic in Mar 2020 to Feb 2021 compelled older individuals, mainly household heads with lower technological literacy compared to the youth, to acquire education and engage in online shopping. As a result, their share in online purchases among all customers increased.

Result 5: The examination of payment method statistics from Mar 2019 to Feb 2020 to 2021, as presented in Figure 9, shows that, as expected, over time, the majority of payments transitioned to online methods, leading to a decrease in payment on delivery. A portion of the growth in online payments can be attributed to increased customer trust in DigiKala and technological advancements. However, a significant part of this shift is also related to the prevalence of the coronavirus.

Result 6: Statistics pertaining to nine product categories in years Mar 2019 to Feb 2020 and Mar 2020 to Feb 2021 are available for the analysis of consumer behavior. Efforts have been made to maximize the utilization of these statistics for analysis. In Figure 10, the sales figures of DigiKala, categorized by primary product groups, in Mar 2019 to Feb 2020 and Mar 2020 to Feb 2021 are depicted. The sales of the "Beauty and Health" product category, which includes all health and hygiene products, experienced a 216% growth in Mar 2020 to Feb 2021 compared to Mar 2019 to Feb 2020, as was anticipated.

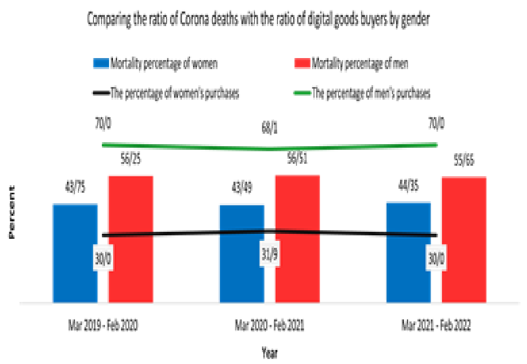

Figure 7. Comparison of Coronavirus Fatality Rate with DigiKala Shoppers by Gender

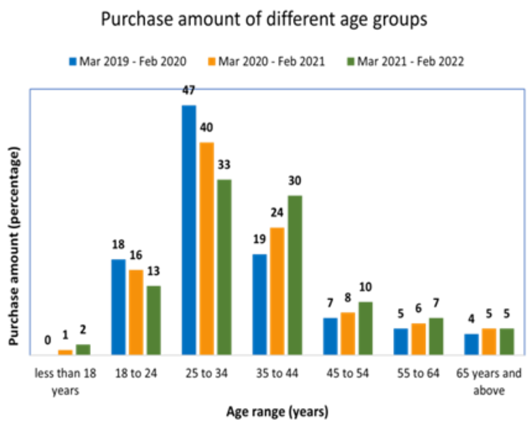

Figure 8. Purchase by Different Age Groups from Mar 2019 to Feb 2020 to 2021

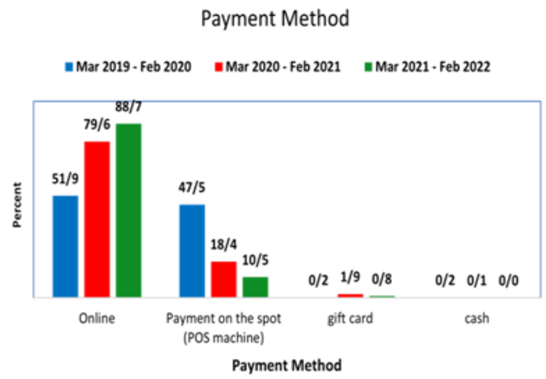

Figure 9. Payment Methods from Mar 2019 to Feb 2020 to 2021

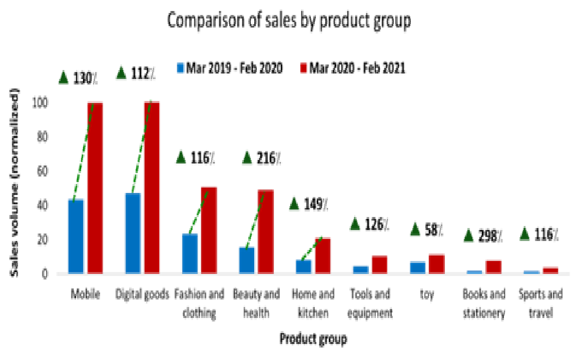

Figure 10. Comparison of Sales by Product Category in Mar 2019 to Feb 2020 and Mar 2020 to Feb 2021

Result 7: In order to examine the impact of Covid-19 mortality on consumer orders in the months of 2021, considering that sales statistics for individual product items by month were available only for the year 2021, this analysis was conducted on 2021 data. As seen in Figure 11, the trend of increasing or decreasing Covid-19 mortality directly affects the level of DigiKala orders.

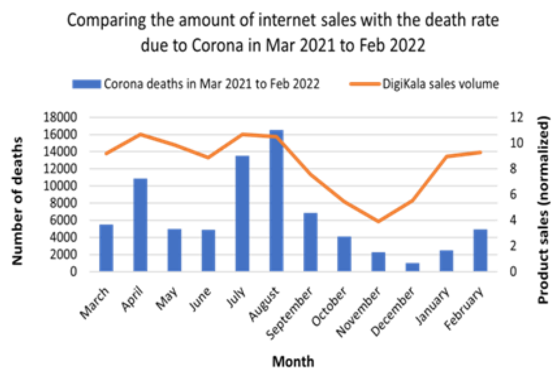

Figure 11. Comparison of DigiKala's Online Sales with Covid-19 Mortality in the Months of 2021

5. CONCLUSION

During the Covid-19 pandemic, the growth of online shopping in provinces with lower online purchasing and less use of ICT (e.g., Kerman, Sistan and Baluchestan, and Kurdistan) was more pronounced than in provinces with higher online shopping participation and greater ICT use (e.g., Tehran, Alborz, and Qom), resulting in a more uniform distribution of online shopping across the country. This transition is evident as the number of clusters in k-means customer shopping behavior analysis decreased from 5 clusters in Mar 2019 to Feb 2020 to 3 clusters in Mar 2020 to Feb 2021, and in fuzzy c-means clustering analysis, it decreased from 6 clusters to 4 clusters.

After the Covid-19 outbreak in Mar 2020 to Feb 2021, older individuals, primarily heads of households with lower technological literacy compared to younger individuals, were compelled to learn and engage in online shopping, leading to an increase in their share of all online shoppers compared to Mar 2019 to Feb 2020.

Based on the conducted analysis, no significant correlation was observed between consumers' gender and the level of online shopping, both before and after Covid-19.

In the years following the Covid-19 pandemic, a substantial portion of online orders transitioned to online payments, reducing the usage of card readers for in-person payments. While some of this growth can be attributed to increased customer trust in DigiKala and technological advancements, a significant portion is also linked to Covid-19, as customers sought to minimize physical contact.

The results of the conducted analyses revealed a significant increase in product sales across all product categories in the post-Covid-19 era. However, the sales growth of the "Beauty and Health" and "Books and Stationery" product categories (related to the months of September and October in Mar 2020 to Feb 2021) surpassed that of other categories, aligning with general expectations.

The examination of the impact of Covid-19 mortality on monthly consumer orders in 2021 demonstrated a direct, significant relationship between these two parameters. As Covid-19 mortality increased or decreased each month, a corresponding increase or decrease in online shopping was observed.

The proposed mechanism for future directions, the following points can be mentioned:

- Using other algorithms to cluster and compare data
- Using the data of the years after the investigation and comparing it with before and during this disease
- Examining the change in consumer behavior by item of product sub-groups
- Clustering of the product group with the highest search and the highest purchase rate
- Use of other statistical analysis

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Persian Abstract

چکیده

همه‌گیری کووید-۱۹ موجب تحولات گسترده‌ای در حوزه فعالیت‌های تجاری شده است. ترس از بیماری همه‌گیر موجب افزایش قابل‌توجه درک مصرف‌کنندگان از مزایای اقتصادی و زیست‌محیطی پلتفرم‌های تجارت الکترونیکی و تمایل مردم سراسر جهان به خرید غیرحضوری و درنتیجه رشد تجارت الکترونیک در جهان شده است. کشور ایران نیز از این قاعده مستثنا نبوده و تعداد مصرف‌کنندگان پلتفرم‌های تجارت الکترونیک در طول کووید-۱۹ رشد قابل‌توجهی داشته است. در این مقاله به‌منظور تحلیل رفتار مصرف‌کنندگان تجارت الکترونیک، قبل و در طول کووید-۱۹، بزرگ‌ترین سایت خرده‌فروشی آنلاین کشور ایران با بیشترین تعداد مصرف‌کننده موردمطالعه قرارگرفته است. در تحلیل رفتار مصرف‌کنندگان پارامترهایی نظیر پراکندگی مکانی(استان‌های کشور)، جنسیت و بازه سنی مصرف‌کنندگان، گروه‌های کالایی موجود در سبد خرید، نحوه پرداخت هزینه سفارش‌ها با توجه به شاخص‌هایی نظیر میزان استفاده از فنّاوری اطلاعات و ارتباطات در کشور قبل و در طول کووید-۱۹ و میزان مرگ‌ومیر ناشی از کرونا، در نظر گرفته‌شده است. در این مقاله از روش داده‌کاوی برای تجزیه‌وتحلیل رفتار مصرف‌کنندگان تجارت الکترونیکی استفاده شده است. درروش انجام، ابتدا داده‌های موردنیاز جمع‌آوری‌شده که در این خصوص لازم به توضیح است، داده‌ها به‌صورت محدود در اختیار بوده است. در گام بعدی با پلتفرم نایم آنالیتیکس داده‌ها پالایش و سپس با استفاده از الگوریتم‌های k-میانگین و c-میانگین فازی رفتار مصرف‌کنندگان تجزیه‌وتحلیل شده است. نتایج تحلیل‌های انجام‌شده نشان داد شیوع کووید-۱۹، موجب یکنواخت‌تر شدن میزان خرید در سطح کشور (کاهش خوشه‌های استان‌ها)، سوق یافتن افراد مسن‌تر به خرید اینترنتی و افزایش سهم آن‌ها از کل مصرف‌کنندگان تجارت الکترونیک و تمایل به پرداخت آنلاین هزینه سفارش‌ها شده است. همچنین بررسی گروه‌های کالایی نشان داد رشد فروش گروه‌های کالایی حوزه سلامت بیشتر از سایر گروه‌ها بوده است.