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Social Networks Marketing and Consumer Purchase Behavior: Combination of ISM, AHP and machine learning algorithms

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1. INTRODUCTION AND OBJECTIVES

1.1. Research background and problem statement

Traditional marketing involves promoting products and services through conventional advertising techniques such as brochures, flyers, billboards, radio, and TV ads, among others. The goal of traditional marketing is to reach out to a broader audience and persuade them to buy the product or service.

On the other hand, artificial intelligence (AI) technologies are increasingly being used in marketing to improve customer experience, gain consumer insights, and increase the return on investment (ROI) of marketing campaigns (HALL, 2019). A branch of artificial intelligence called machine learning (ML) is used to automate customer targeting, make content recommendations, find the most profitable ad prices, and communicate with customers. Machine learning is a field of information science that focuses on building a computer system that can improve itself using experience (JORDAN & MITCHELL, 2015).

From another angle, social networks offer new ways to communicate with businesses and consumers. Businesses have been able to overcome the geographical constraints of consumers by creating a public space on the Internet - where users can interact - (WU, 2020). Also, researchers consider social media as a set of communications and interactions between members of a group that often mediate the dissemination of information, opinions, and influence on people. These communities, formed with the aim of sharing information and not just for business reasons, have the highest impact on members' opinions and purchase intentions (CHEUNG ET AL. 2021). These media have become the fastest and most powerful networks and communication and marketing tools. Owing to the change in the type of communication through the use of these communication tools, new challenges and opportunities have been created for companies and brands. Thus, in this competitive environment, ignoring how these sites affect and interactions created between users when using this technology, leaves the organizations in the virtual space alone and negatively affects their popularity for their customers (URBONAVICIUS ET AL. 2021). Given what was stated above, ignoring the share of marketing in the media and its impacts on consumer behavior can have unfavorable consequences for businesses.

AI or Artificial Intelligence marketing is a modern marketing approach that uses innovative technologies such as machine learning and data analytics to perform tasks that are typically done by humans, such as analyzing data, predicting customer preferences, and planning campaigns. AI marketing is highly targeted, using complex algorithms to personalize communication and offer tailored recommendations. For this reason, AI became an integral element of the marketing field. in particular it has become necessary for brands to participate in this technological transformation in order to be competitive in a dynamic market (HAJJAR ER AL. 2020). In summary, AI marketing is a data-driven, personalized marketing approach that uses machines to analyze data and predict customer behavior.

Given the literature and the necessity of research considering the important role of social networks in shaping consumers' purchase habits and behaviors, at first, via examining the literature of the field under study and the experts' opinions, this study attempts to (a)identify strategic factors related to consumer purchase behavior, (b) Prioritizing factors with pay attention to importance and weights based on MCDM methods, (c) test the accuracy of model based on machine learning algorithms. This research will use an interpretive structural modeling (ISM) approach to level portioning and find strategic factors. Then use of Analytic hierarchy process (AHP) for prioritizing of factors. Finally, machine learning algorithms (ML) approaches will be used to determine the accuracy of the model based on experts' opinions.

1.2. Research questions

1. What are the strategic factors of consumer purchase behavior regarding social networks marketing?
2. How effective factors on consumer purchase behavior can be prioritized regarding to social networks marketing?
3. How supervised machine learning algorithms can predict consumer purchase behavior in online social platforms?
4. How accuracy of model can be confirmed based on unsupervised machine learning algorithms in online social platforms?

2. MATERIAL AND METHOD

2.1. Sampling and data collection

The study's statistical population within the domains of ISM and AHP comprises experts possessing experience in microeconomics, social network marketing, and consumer purchase behavior. The ISM and AHP section's sample size comprises 22 experts. To ensure measurement tool validity, content validity was employed, employing a VOXA questionnaire distributed to experts to affirm the precision of ISM section questions. The purposive sampling method in the ISM section is a purposeful judgmental sampling approach, with 22 experts providing responses. This limited sample comprises individuals possessing the requisite knowledge to answer the study's questions. The respondents, totaling 22, are social media experts in Iran with a minimum of 10 years of professional experience in social network marketing and consumer purchase behavior research.

In this particular case study one, the investigation focused on Iranian individuals who actively participated in online social platforms and had completed at least one online purchase. The survey instrument and an online questionnaire were distributed across various platforms, namely Instagram, Facebook, Telegram, YouTube, and WhatsApp. The questionnaire sought to gather demographic data (including Gender, Age, Education, and time spent on online social platforms) from participants. A total of 376 respondents successfully completed the entire survey, resulting in a commendable response rate of 94%. Additionally, a pilot study with a sample size of 30 was executed to ensure the content validity and reliability of the survey instrument.

In case study two, the statistical population consisted of users from Iran and Hungary who had engaged in at least one online purchase through grocery apps. A demographic questionnaire was employed to collect information on participants' sex, education, age, experience with online purchases, and familiarity with grocery apps. The demographic questionnaire for this research was formulated using Google Forms as an online link, presented in both Hungarian and Persian languages through separate links. In Iran, the questionnaire link was disseminated through widely-used online social media platforms such as Instagram and WhatsApp, resulting in the receipt of 349 completed questionnaires via the Google Forms panel. In Hungary, the questionnaire was shared on the Facebook platform and posted in various Facebook groups, garnering 366 completed responses. The choice of these platforms was motivated by their popularity and effectiveness.

The primary data for case study tree, were collected from Instagram, specifically focusing on renowned Iranian food pages. Originally, the plan was to utilize automated tools such as Selenium and Beautiful Soup for data extraction. However, due to unforeseen permission and legal concerns, a decision was made to resort to manual data collection from diverse comments within the identified food pages. To structure the dataset, a CSV (Comma-Separated Values) file was employed, organizing the data into comments and corresponding labels. The labels assigned were categorized as "positive" and "negative" to facilitate sentiment analysis. This manual annotation allowed for a nuanced understanding of the sentiment expressed within the comments. The training dataset was carefully curated to encompass a representative sample of 5000 comments, ensuring diversity in sentiments and opinions expressed. Additionally, a smaller dataset comprising 1000 comments was reserved for testing the accuracy of the models developed.

2.2. Delphi technique

A group of experts in social networks marketing will be formed to define the key factors in modeling consumer purchase behavior (ISM part). Based on the previous literature review and consultation of the group based on the Delphi technique, factors will be determined. Following steps of the Delphi technique based on previous studies (KAMBLE & RAUT, 2019; SALAMZADEH ET AL. 2021) were:

- Identifying the group of experts.
- Determining the willingness of individuals to serve on the group.
- Gathering individual inputs on a specific issue and then compiling them into basic statements.
- Analyzing data from the group.
- Compiling information on a new questionnaire and sending it to each panel member for review.
- Analyzing the new input and returning to the panel members the distribution of the responses.
- Asking each member to study the data and evaluate his/her position based on the responses from the group.
- Analyzing the input and sharing the minority supporting statements with the panel. Coefficient of variation (COV) Changes will be applied to study the indicator's stability to ensure the Delphi technique consensus in this study (WONG ET AL. 2020).

2.3 Interpretive structural modeling (ISM)

Interpretive structural modelling (ISM), proposed by WARFIELD (1974), is used to make a complex system into a visualized hierarchical structure. It is a method of analyzing and solving complex problems to manage decision-making. The management of a manufacturing system consists of a large number of factors associated with physical elements and/or decision-making. The presence of directly or indirectly related factors complicates the structure of the system, which may or may not be articulated in a clear manner. It becomes difficult to deal with such a system in which structure is not clearly defined. Hence, this necessitates the development of a methodology that aids in identifying an inter-relationship structure within a system. As a systematic approach, it can analyze interrelationship properties by exploring various factors from a complex system. In addition, some studies use ISM to explore the effects of one entity on other closely related entity (EBRAHIMI ET AL. 2020). Different steps involved in the ISM technique include: (SINGH & KANT, 2008): (1). Identifying elements that are relevant to the problem or issues. This could be done by survey. (2). Establishing a contextual relationship between elements concerning which pairs of elements would be evaluated. (3). Developing a structural self-interaction matrix (SSIM) of elements that indicates a pair-wise relationship between the system elements. (4). Developing a reachability matrix from the SSIM, and examining it for transitivity – transitivity of the contextual relation is a basic assumption in ISM that states that if element A is related to B and B is related to C, then A is related to C. (5). Partitioning of the reachability matrix into different levels. (6). Drawing a directed graph (digraph) and removing the transitive links, based on the above relationships in the reachability matrix. (7). Converting the resultant digraph into an ISM-based model by replacing element nodes with the statements; and (8). Reviewing the model to investigate conceptual inconsistency and make necessary modifications.

2.4 Analytic hierarchy process (AHP)

Introduced by SAATY (2014), the AHP method is applied broadly as a multi-criteria, decision-making method in various decisions and applications (IMPROTA ET AL. 2019). This method is advantageous as it is easy to use and capable of integrating the comments of many experts and decision-makers. The theoretical basis of quantification in AHP can further substantiate whether there is bias in an agreement achieved by assessment experts. The AHP method is considered both qualitatively and quantitatively, which can usefully evaluate the alternates of multifaceted manifold criteria comprising biased judging and is a specifically symmetrical means capable of transforming intricate problems into the facile hierarchic structure, including project screening. The use of AHP involves major stages, namely (1) development of a hierarchy model, (2) preparation of a pairwise comparison matrix, (3) calculation of priority and eigenvalue and (4) verification of the consistency of the pairwise comparison (SALAMZADEH ET AL. 2021).

2.5 Application of Machine learning (ML)

In machine learning process, data are processed from the past for inducing the correspondence between one or more input variables and an output or the target variable, which is usually discrete and is two or more values. The input variables may be discrete or continuous. As an immense and swiftly developing area, machine learning encompasses wide-ranging approaches to address various tasks. Conventionally, a certain data set is processed in a machine learning algorithm for a specific purpose, and the algorithm has no contribution to data attainment. This paradigm includes two main task classes, viz. supervised (such as K-Nearest Neighbors, Decision Tree, Artificial Neural Network, etc.) and unsupervised learning (Hierarchical, DBSCAN, PCA, SVD, etc.) (MA & SUN, 2020). The following are the various stages of the present investigation included in the machine learning approach: (1). Import the data. (2). Clean the data. (3). Split the data into training and test sets. (4). Create a model. (5). Train the model. (6). Model prediction. (7). Evaluate the accuracy of the model and improve (EBRAHIMI ET AL. 2022a).

2.6 Supervised Machine learning approach

Supervised learning is a type of machine learning in which input and output are specified. In this method, an observer component provides information to the learner. The main purpose of the system is to learn the function or mapping from input to output. In supervised learning, the system tries to learn from previously received examples. The supervised learning process begins with importing data sets, including training and target attributes. The supervised learning algorithm extracts the specific relationship between the training examples and the corresponding target variables and uses the learned relationship to classify new data (EBRAHIMI ET AL. 2022b).

2.7 Unsupervised machine learning approach

Machine learning is a component of artificial intelligence although it endeavors to solve problems based on hidden patterns and data mining to classify and predict. Unsupervised learning algorithms are useful for make the labels in the data that are incessantly used to implement supervised learning tasks. That is, unsupervised clustering algorithms identify inherent groupings within the unlabeled data and label to each data value. It means that, unsupervised association mining algorithms tend to identify rules that accurately represent relationships between features (EBRAHIMI ET AL. 2022c). Table 3 shows all unsupervised algorithms, methods and metric used. The main advantage of ML and algorithms are: (1) Simple and efficient tools for predictive data analysis, (2) Accessible to everybody, and reusable in various contexts, (3) Built on NumPy, SciPy, and matplotlib and (4)Open source, commercially usable - BSD license.

2.8 Sentiment Analysis

Sentiment analysis, a fundamental task in natural language processing, involves the determination of opinions, emotions, or sentiments expressed in textual data. In the context of this study, sentiment analysis was employed to discern the polarity of comments on Iranian food pages on Instagram, categorizing them as "positive" or "negative."

3. RESULTS AND DISCUSSION

3.1 ISM calculations

3.1.1 Building adjacency matrix or SSIM

The 12 factors' contextual associations were established through an Adjacency Matrix, drawing upon insights from 22 experts. To employ the ISM technique effectively, it is imperative to formulate the contextual links between these factors based on recommendations from expert judgments, as emphasized by SADEH and GARKAZ in 2018. Our approach involved discerning the contextual relationships among the 12 factors through structured interviews with experts, a method known for its reduced bias. Notably, significant direct-effect relationships were identified, with F10 (Value co-creation) displaying the most connections to other factors. Conversely, F6 (Perceived risk), F8 (Perceived information quality), and F9 (Social support) exhibited the fewest direct-effect relationships with other factors.

Table 1. Structural self-interaction matrix

	F12	F11	F10	F9	F8	F7	F6	F5	F4	F3	F2	F1
F1	A	A	A	O	O	A	O	O	O	A	A	
F2	O	O	V	O	A	O	O	O	A	O		
F3	V	V	O	O	O	V	O	O	O			
F4	O	O	X	X	O	O	O	V				
F5	A	A	A	O	O	A	O					
F6	O	O	A	O	A	O						
F7	O	A	A	O	O							
F8	O	X	V	O								
F9	O	A	O									
F10	A	A										
F11	X											
F12												

NOTE: F1= Trust, F2=Consumer engagement, F3=Social media WOM, F4=Social influence, F5=Consumer’s value perception, F6=Perceived risk, F7=Perceived usefulness, F8=Perceived information quality, F9=Social support, F10=Value co-creation,F11=Knowledge sharing, F12=Service innovation.

Source: Author’s own work based on MATLAB results

3.1.2 Initial reachability matrix

During this stage, the SSIM underwent a transformation into a binary matrix termed the initial reachability matrix (Table 2). This conversion involved substituting V, A, X, and O with 1 and 0 based on their respective positions. Various authors, including AZVEDO ET AL. (2019), and EBRAHIMI ET AL. (2020), have highlighted the necessity of constructing the reachability matrix in accordance with the SSIM. This entails adapting the SSIM format into that of a reachability matrix by representing symbols as binary digits (either ones or zeros), as specified by Sadeh and Garkaz in 2018. It's worth noting that the SSIM is devised by assigning codes to denote the established relationship between each set of variables "i and j".

Four types of relationships that could exist between any two variables (i and j) are denoted by using the following 4 symbols:

- If the (i, j) entry in the SSIM is V then the (i, j) entry in the initial reachability matrix becomes 1 and the (j, i) entry becomes 0.
- If the (i, j) entry in the SSIM is A, then the (i, j) entry in the initial reachability matrix becomes 0 and the (j, i) entry becomes 1.
- If the (i, j) entry in the SSIM is X then the (i, j) entry in the initial reachability matrix becomes 1 and the (j, i) entry becomes 1.
- If the (i, j) entry in the SSIM is O, then the (i, j) entry in the initial reachability matrix becomes 0 and the (j, i) entry also becomes 0.

Table 2. Initial reachability matrix

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12
F1	0	0	0	0	0	0	0	0	0	0	0	0
F2	1	0	0	0	0	0	0	0	0	1	0	0
F3	1	0	0	0	0	0	1	0	0	0	1	1
F4	0	1	0	0	1	0	0	0	1	1	0	0
F5	0	0	0	0	0	0	0	0	0	0	0	0
F6	0	0	0	0	0	0	0	0	0	0	0	0
F7	1	0	0	0	1	0	0	0	0	0	0	0
F8	0	1	0	0	0	1	0	0	0	1	1	0
F9	0	0	0	1	0	0	0	0	0	0	0	0
F10	1	0	0	1	1	1	1	0	0	0	0	0
F11	1	0	0	0	1	0	1	1	1	1	0	1
F12	1	0	0	0	1	0	0	0	0	1	1	0

Source: Author's own work based on MATLAB results

3.1.3 Developing a reachability matrix to the final reachability matrix

Using the computational tool MATLAB (Appendix E), power iteration analysis was employed to scrutinize the transitivity rules. During this process, certain cells within the initial reachability matrix were populated through inference. Consequently, the ultimate reachability matrix incorporates entries derived from both pairwise comparisons and inferred values. The application of the transitivity concept played a pivotal role in making these inferences and completing the matrix. An entry of 1* signifies the incorporation of transitivity. The transitivity principle, grounded in the works of WARFIELD (1974), If a variable 'I' is linked to 'j,' and 'j' is linked to 'k,' then transitivity dictates that variable 'I' is linked to 'k.' Following the application of this principle, the final reachability matrix was derived with a power of k=4, as outlined in Table 3. This ultimate reachability matrix facilitates the identification of reachability and antecedent sets for each variable. The driving power of each variable corresponds to the total number of variables (including itself) it may influence, while the dependence of a variable is determined by the total number of variables (including itself) that may impact it. These driving powers and dependencies are subsequently employed in the MICMAC analysis or cross-impact analysis, as noted by AZVEDO ET AL. (2019).

Table 3. Final reachability matrix

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	Driving power
F1	1*	0	0	0	0	0	0	0	0	0	0	0	1
F2	1	1*	0	1*	1*	1*	1*	0	1*	1	0	0	8
F3	1	1*	1*	1*	1*	1*	1	1*	1*	1*	1	1	12
F4	1*	1	0	1*	1	1*	1*	0	1	1	0	0	8
F5	0	0	0	0	1*	0	0	0	0	0	0	0	1
F6	0	0	0	0	0	1*	0	0	0	0	0	0	1
F7	1	0	0	0	1	0	1*	0	0	0	0	0	3
F8	1*	1	0	1*	1*	1	1*	1*	1*	1	1	1*	11
F9	1*	1*	0	1	1*	1*	1*	0	1*	1*	0	0	8
F10	1	1*	0	1	1	1	1	0	1*	1*	0	0	8
F11	1	1*	0	1*	1	1*	1	1	1	1	1*	1	11
F12	1	1*	0	1*	1	1*	1*	1*	1*	1	1	1*	11
Dependence power	10	8	1	8	10	9	9	4	8	8	4	4	

Note: During the checking of transitivity* indicates the values which are changed from ‘‘0’’ to ‘‘1’’ and shown with 1*, power=k=4.

Source: Author’s own work based on MATLAB results

3.1.4 Level partitions

The reachability set comprises the element itself along with other elements it can contribute to achieving, while the antecedent set includes the element itself and other elements that may aid in its accomplishment. Subsequently, the intersection of these sets is computed for all factors. Factors with identical reachability and intersection sets occupy the highest level in the ISM hierarchy, The top-level element in the hierarchy does not contribute to achieving any other element positioned above its own level. Once the top-level element is identified, it is isolated from the other elements, and the same process is iterated to identify elements in the subsequent level. This sequence continues until the level of each element is determined, as illustrated in Table 4. The tables indicate five levels for the ISM model, with F1, F5, and F6 identified as the top-level elements in the ISM model for this research.

Table 4. Level partitioning factors

First iteration

Factors	Reachability set	Antecedent set	Intersection set	Level

F1	1	1,2,3,4,7,8,9,10,11,12	1	1
F2	1,2,4,5,6,7,9,10	2,3,4,8,9,10,11,12	2,4,9,10	
F3	1,2,3,4,5,6,7,8,9,10,11,12	3	3	
F4	1,2,4,5,6,7,9,10	2,3,4,8,9,10,11,12	2,4,9,10	
F5	5	2,3,4,5,7,8,9,10,11,12	5	1
F6	6	2,3,4,6,8,9,10,11,12	6	1
F7	1,5,7	2,3,4,7,8,9,10,11,12	7	
F8	1,2,4,5,6,7,8,9,10,11,12	3,8,11,12	8,11,12	
F9	1,2,4,5,6,7,9,10	2,3,4,8,9,10,11,12	2,4,9,10	
F10	1,2,4,5,6,7,9,10	2,3,4,8,9,10,11,12	2,4,9,10	
F11	1,2,4,5,6,7,8,9,10,11,12	3,8,11,12	8,11,12	
F12	1,2,4,5,6,7,8,9,10,11,12	3,8,11,12	8,11,12	
Second Iteration				
F2	2,4,7,9,10	2,3,4,8,9,10,11,12	2,4,9,10	
F3	2,3,4,7,8,9,10,11,12	3	3	
F4	2,4,7,9,10	2,3,4,8,9,10,11,12	2,4,9,10	
F7	7	2,3,4,7,8,9,10,11,12	7	2
F8	2,4,7,8,9,10,11,12	3,8,11,12	8,11,12	
F9	2,4,7,9,10	2,3,4,8,9,10,11,12	2,4,9,10	
F10	2,4,7,9,10	2,3,4,8,9,10,11,12	2,4,9,10	
F11	2,4,7,8,9,10,11,12	3,8,11,12	8,11,12	
F12	2,4,7,8,9,10,11,12	3,8,11,12	8,11,12	
Third Iteration				
F2	2,4,9,10	2,3,4,8,9,10,11,12	2,4,9,10	3
F3	2,3,4,8,9,10,11,12	3	3	
F4	2,4,9,10	2,3,4,8,9,10,11,12	2,4,9,10	3
F8	2,4,8,9,10,11,12	3,8,11,12	8,11,12	
F9	2,4,9,10	2,3,4,8,9,10,11,12	2,4,9,10	3
F10	2,4,9,10	2,3,4,8,9,10,11,12	2,4,9,10	3
F11	2,4,8,9,10,11,12	3,8,11,12	8,11,12	
F12	2,4,8,9,10,11,12	3,8,11,12	8,11,12	
Fourth Iteration				
F3	3,8,11,12	3	3	
F8	8,11,12	3,8,11,12	8,11,12	4
F11	8,11,12	3,8,11,12	8,11,12	4
F12	8,11,12	3,8,11,12	8,11,12	4
Fifth Iteration				
F3	3	3	3	5

Source: Author's own work based on MATLAB results

3.1.5 ISM model and MICMAC analysis

By employing level partitioning for factors, we construct the diagram representing the final ISM model, as depicted in Figure 1. As evident in Table 4, "Consumer engagement," "Consumer's value perception," and "Perceived risk" are classified at Level I, positioning them at the pinnacle of the ISM model. Figure 1 provides a visual representation of the research variables, their interrelationships, and the hierarchical level to which each variable belongs. Figure 2 further illustrates that the linkage factors reside at the base of our model, signifying their role as primary drivers in achieving the other variables within our study. The Matrices d'Impacts Croises Multiplication Appliqué a un Classement (MICMAC) technique is employed to scrutinize the distribution of impacts "through reaction loops and paths for developing hierarchies for members of a set of elements".

MICMAC analysis serves the purpose of exploring factors' dependence and driving power. Simultaneously, MICMAC aids in comprehending the scope of variables and pinpointing the key strategic variables within the system. All factors have been categorized into four groups based on their dependence and driving powers (refer to Table 7): autonomous factors, dependent factors, linkage factors, and independent factors. Figure 2 highlights that "Trust," "Social influence," "Social support," and "Value co-creation" emerge as the most crucial strategic variables in the research, being the nearest to the strategic line.

- Segment I Autonomous: in this segment factors have less dependence and driving powers. In this study, under this segment, there is no autonomous factor.

- Segment II Dependent: in this segment enablers have a strong dependence on power but a weak driving power. this study has three dependents, which are, Consumer engagement(F1), Consumer's value perception(F5), Perceived risk(F6) and Perceived usefulness (F7).

- Segment III Linkage: in this segment enablers have a strong dependence and driving power. In this segment, this study has four factors that are linked, i.e., F2, F4, F9, and F10.

- Segment IV Driver or independent: enablers in this segment have very little dependence but more driving power. In this segment, under this segment, there are four independent factors i.e., F3, F8, F11 and F12.

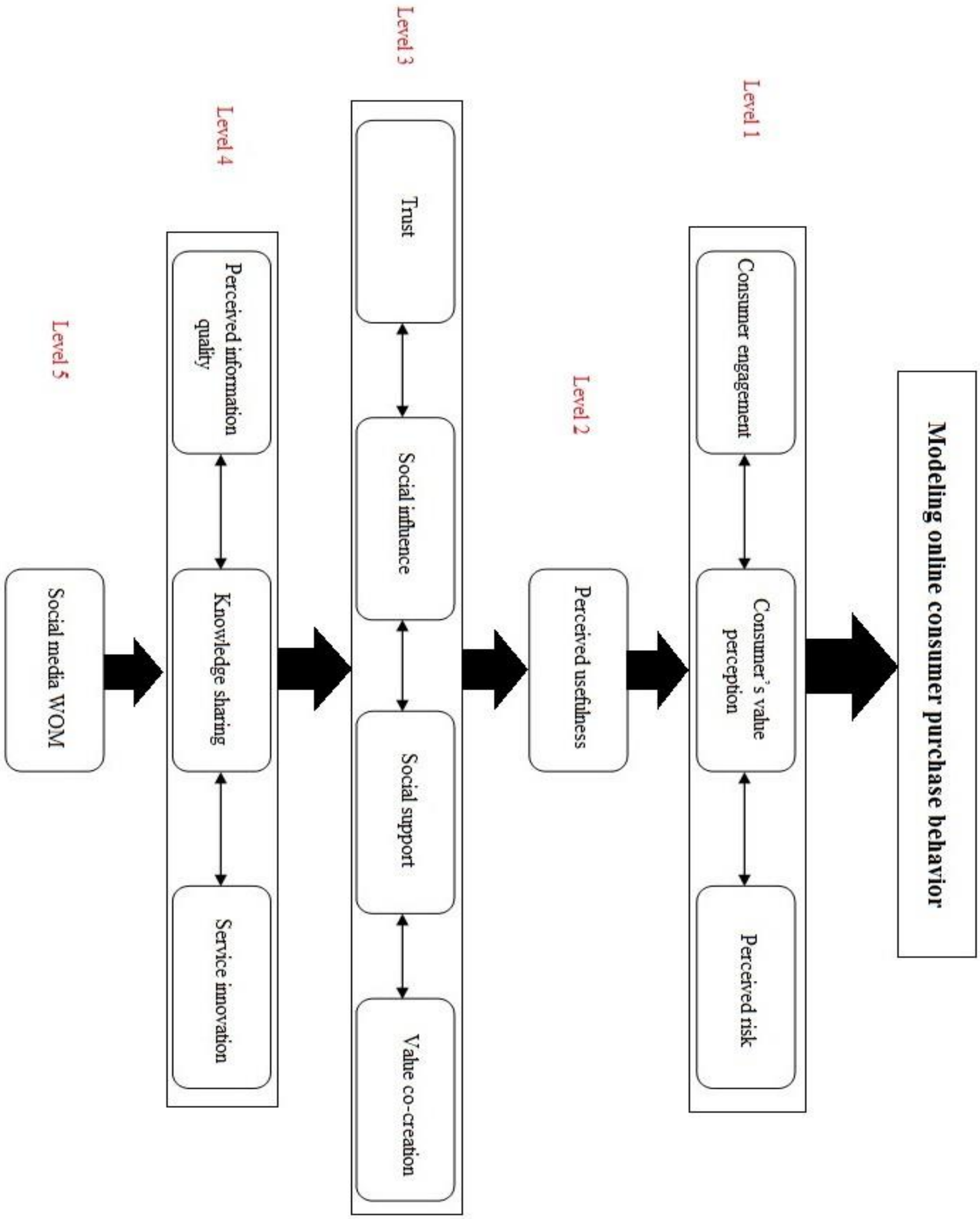

Figure 1. ISM model
(Source: Author's own work based on MATLAB results)

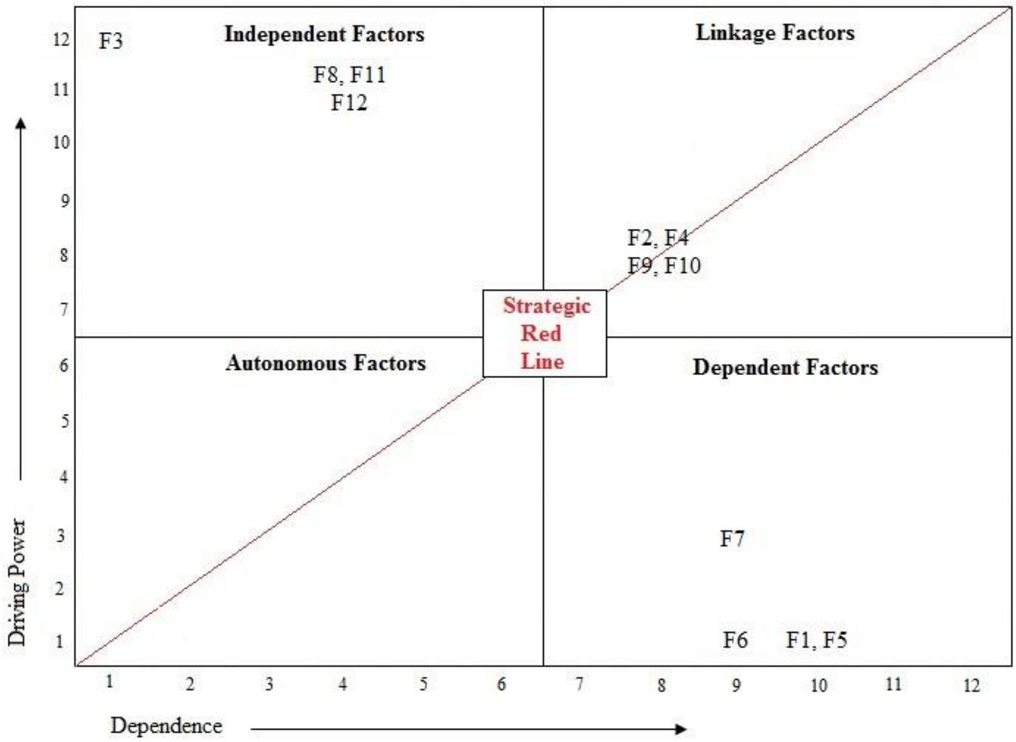

Figure 2. MICMAC analysis
Source: Author's own work based on MATLAB results

3.2 AHP

3.2.1 Development of the hierarchy

After gathering data through the pairwise questionnaire, it is imperative to formulate a conceptual model for addressing a specific decision problem. A hierarchy, as conceptualized by SAATY (1980), represents a distinctive type of system wherein entities are categorizable into distinct groups, and the entities within one group exert influence on those in other groups. In the current context, we are confronted with a decision-making scenario involving 12 criteria outlined in Table 1, and our objective is to deliberate upon 4 alternatives, namely Instagram, Telegram, TikTok, and Facebook, representing popular social media platforms in Iran.

3.2.2 Pairwise comparison matrix and the priority weights within the hierarchy

The generation of a pairwise comparison matrix involves utilizing a scale of relative importance. When comparing an attribute to itself, a value of 1 is invariably assigned, ensuring that all entries along the main diagonal of the matrix are equal to 1. The numerical values 3, 5, 7, and 9 signify moderate importance, strong importance, 'very important,' and 'absolutely important,' respectively, while 2, 4, 6, and 8 denote compromises between the values 3, 5, 7, and 9. This scale, as articulated by SAATY (1980) and further expounded upon by KHANSARI ET AL. 2022, provides a systematic approach to express the relative importance of attributes in the pairwise comparison process.

3.2.3 Consistency index and consistency ratio

Through the computation of criteria or sub-criteria priorities, the AHP facilitates the assessment of comparison consistency employing the Consistency Index (CI), Random Consistency Index (RI), and Consistency Ratio (CR). Perfect consistency is indicated by a CI value of 0, while an accepted level of consistency, denoted by a Consistency Ratio (CR) of less than 10% (CR < 0.1), signifies that the subjective judgments are deemed acceptable. This methodology, as articulated by SALAMZADEH ET AL. (2021), serves as a quantitative measure to ensure the reliability of the subjective assessments in the AHP process.

3.2.4 AHP analysis

Figure 3 presents the total weights of both criteria and alternatives. The respective ranks of criteria weights are as follows: Word of Mouth (WOM) at 18.4%, Social Influence at 14.1%, Value Co-creation at 13.8%, Social Support at 9.2%, Trust at 7.8%, Perceived Usefulness at 6.3%, Consumer's Value Perception at 6%, Service Innovation at 5.8%, Perceived Information Quality at 5.6%, Consumer Engagement at 4.9%, Perceived Risk at 4.5%, and Knowledge Sharing at 3.7%. Notably, WOM and Knowledge Sharing exert the highest and lowest influences, respectively, on the prioritization of factors impacting consumer purchase behavior in social networks. Additionally, the weights of alternative options (Social Networks) are ranked as follows: Instagram at 35.3%, Telegram at 31.6%, TikTok at 20.1%, and Facebook at 13.1%. These results affirm that Instagram is the most influential social network in Iran, significantly impacting consumer behavior, while Facebook exerts the least influence on consumer behavior in the Iranian context.

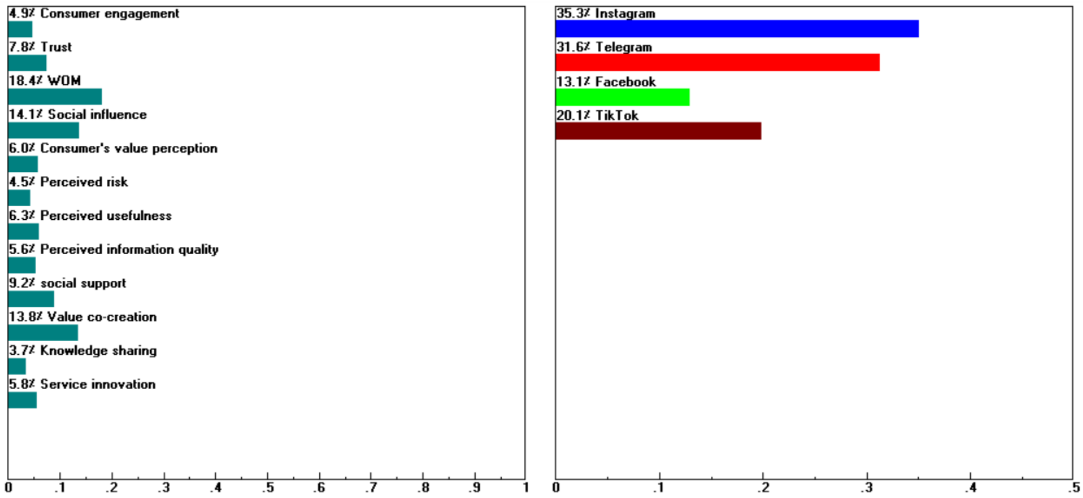

Figure 3. Dynamic sensitivity analysis of criteria and alternatives

Source: Author's own work based on Expert Choice 10.0 software.

We used weighted head-to-head analysis to systematically evaluate all four networks collectively. The findings consistently reveal that Instagram outperforms other social networks, garnering notably higher scores across the specified criteria. In line with the study's objective, it is substantiated that Instagram attains a significantly superior ranking in influencing changes in consumer purchase behavior within the framework of the investigated criteria in Iranian social networks. Following Instagram, Telegram and TikTok emerge as a noteworthy influencer, while Facebook is identified as having the least impact on Iranian consumer behavior.

Concentrating on the analysis of performance sensitivity, Figure 4 additionally illustrates that, within the scope of the study objective, the various criteria exhibit fluctuating trends in their plots contingent upon distinct social networks.

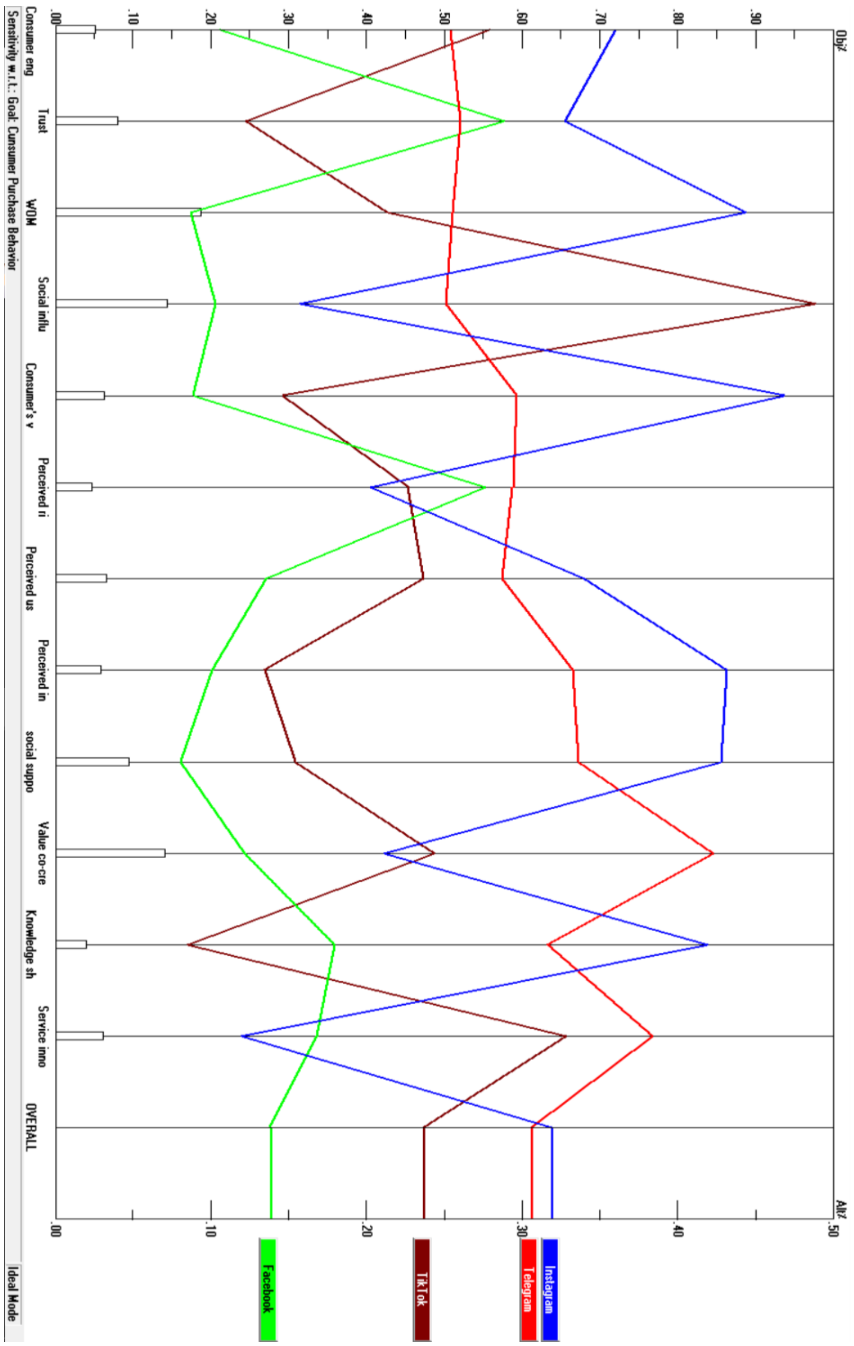

Figure 4. Performance sensitivity analysis

Source: Author’s own work based on Expert Choice 10.0 software.

3.3 Case study one, A decision tree model to predict consumer purchase behavior in Iran

Figure 5 displays a pair plot of demographic data, highlighting Instagram as the most popular online platform across various demographic variables.

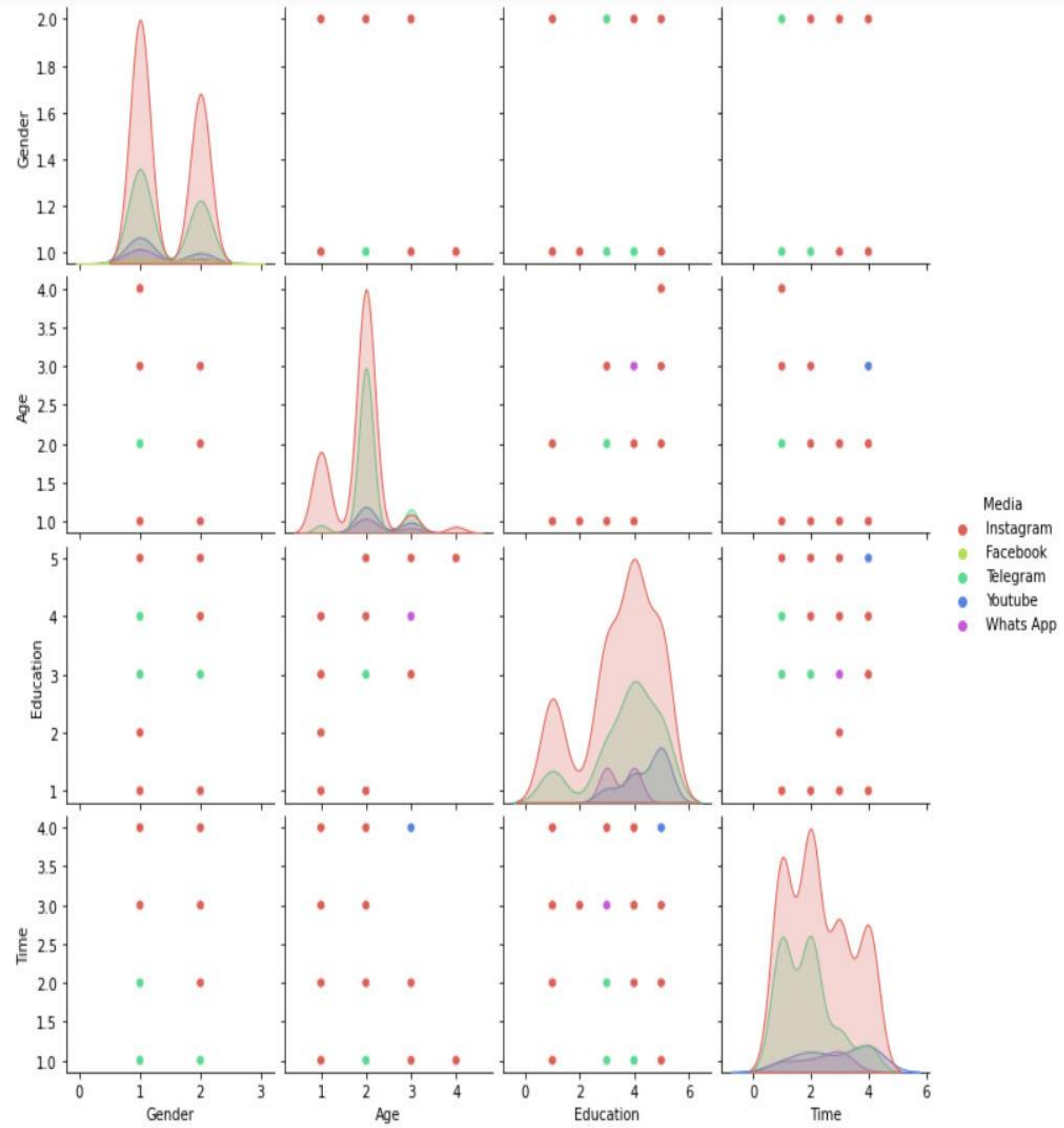

Figure 5. The pair plot of the respondents' demographic data

Figure 5. The pair plot of the respondents' demographic data (Source: authors' calculations based on Python programming/Seaborn package in Jupyter notebook)

Figure 6 illustrates an expansive schematic of online consumer behavior incorporating demographic variables, encompassing a comprehensive array of predictive modes. The codes within this intricate map are tailored to individual consumers, signifying our objective to forecast the online shopping platform choice of each consumer based on gender, age, education, and daily duration spent on online social platforms. Consequently, our model functions as an application with the capability to anticipate consumer behavior utilizing data gleaned from individuals.

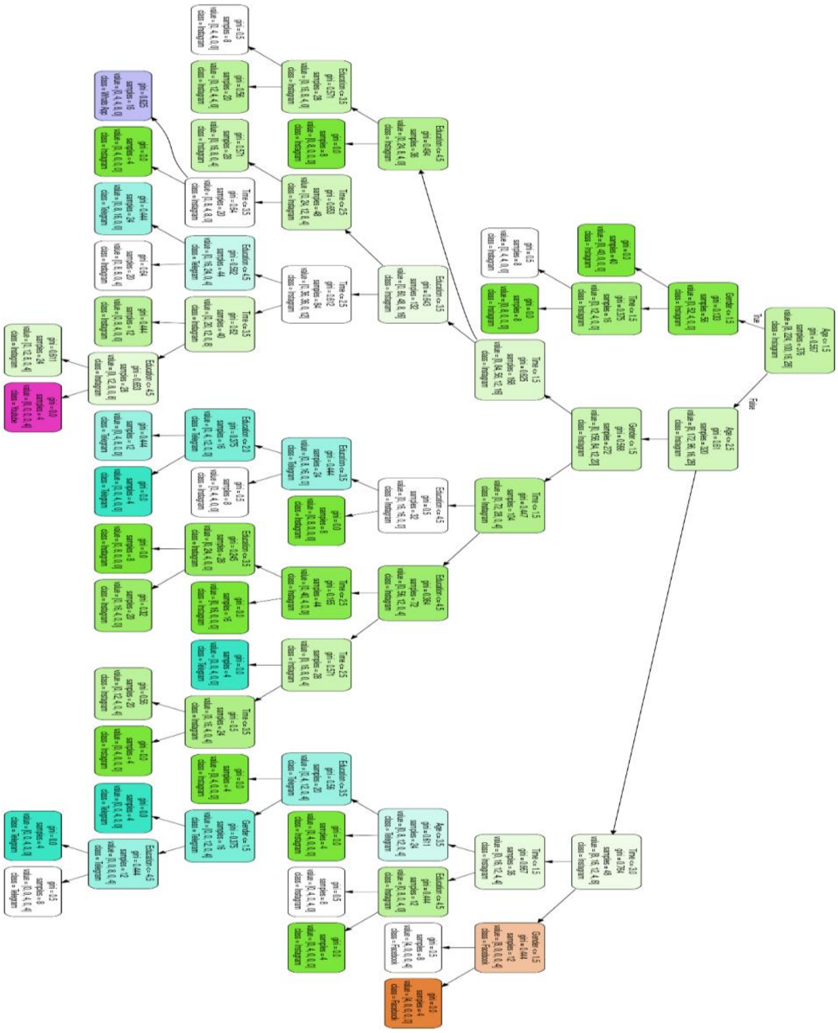

Figure 6. The decision tree model based on map visualization of consumer purchase behavior

(Source: authors' calculations based on Python programming/ Visualization with Visual Studio Code).

To achieve this pivotal objective, program codes have been developed utilizing the decision tree model. In the program, two distinct modes are scrutinized using the format ["Gender", "Age", "Education", "Time"]. Specifically, two codes—[1, 2, 5, 3] and [2, 3, 3, 4]—are selectively integrated into the program. The first code represents a male consumer aged 21-30, possessing a doctoral education and dedicating a minimum of 2-3 hours daily to online social platforms. According to the model's prediction and the associated map (Fig. 6), the likelihood of online shopping and advertisement engagement is highest on the Instagram platform for this consumer. Conversely, the second code characterizes a female consumer aged 31-40, holding a master's degree, and allocating more than 3 hours daily to online social platforms. The model predicts that this consumer is inclined to make purchases and engage with advertisements on the Facebook platform. The assessment of model accuracy, denoted as 0.96, underscores the efficacy of the proposed model. Similarly, individual consumer behavior can be forecasted based on demographic attributes, empowering online businesses to strategize for diverse consumer segments.

3.4 Case study two, Grocery apps and consumer purchase behavior

Figures 7 and 8 present noteworthy insights through pair plots and comparative analyses of demographic data pertaining to Iran and Hungary.

To assess the model's precision, GMM was employed for clustering various grocery applications in both Iran and Hungary. Initial data pre-processing was conducted on the input data for the GMM algorithm, and no issues with missing data values were encountered. Subsequently, the first model was created and fitted with the data. The GMM model offers four covariance types—full, tied, diagonal (diag), and spherical.

Figures 9 and 10 depict the evaluation of model accuracy across these four covariance types. In Figure 9, the analysis reveals that users in Iran are categorized into three distinct groups of app service users, with the full covariance type exhibiting higher accuracy (96%) compared to the other three types.

However, both diag and tied covariance types have yielded accuracy levels exceeding 90%, which are deemed acceptable. Examining Figure 10, it is observed that the apps utilized in Hungary achieved 95% accuracy from the users' perspective, specifically with the diag covariance type, while other covariance types exhibited lower accuracy for Hungarian data. Overall, the classification of apps in both Hungary and Iran demonstrated acceptable accuracy. The findings substantiate the high popularity of the Wolt app in Hungary and the Snapp Food app in Iran with a high degree of accuracy.

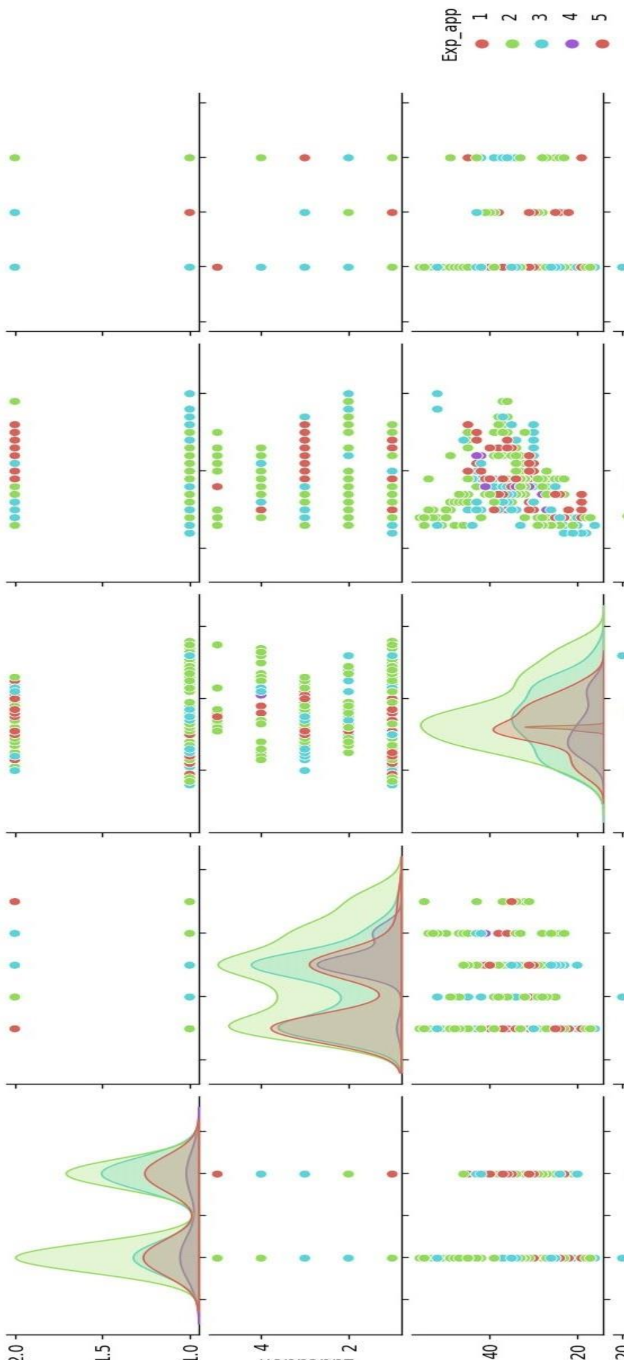

Figure 7. The pair plot of the respondents' demographic data in Iran
(Source: authors' calculations based on Python programming; Seaborn package; VS Code editor)

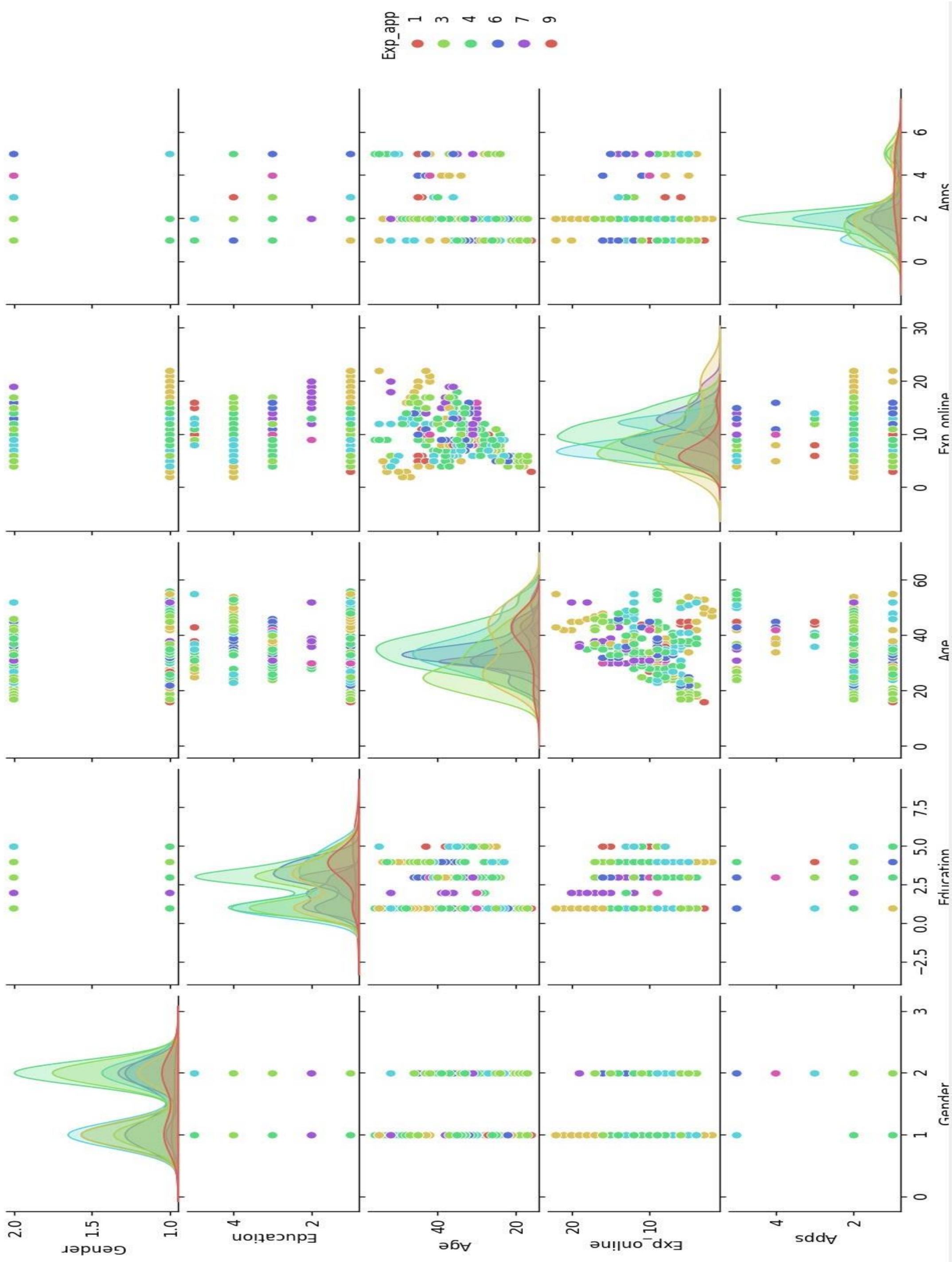

Figure 8. The pair plot of the respondents' demographic data in Hungary
(Source: authors' calculations based on Python programming; Seaborn package; VS Code editor)

The prediction of consumer behavior concerning various grocery apps in Iran and Hungary was executed using the MLP model. The dataset underwent segregation into test and train data, with a focus on incorporating consumer demographic information to enhance predictive accuracy.

To illustrate the model's predictive efficacy, two arbitrary data instances were subjected to testing. In the first case, an individual aged 39 with a bachelor's degree, claiming 5 years of online shopping experience and 3 years utilizing grocery apps, was examined. The algorithm, trained on datasets from both Iran and Hungary, indicated a higher probability of this consumer favoring Snappfood in Iran and Wolt in Hungary over other options. Similarly, for a female consumer aged twenty, possessing two years of online shopping experience and a history of grocery app usage, the model suggested a higher likelihood of selecting Snappfood in Iran and Foodpanda in Hungary.

To gauge overfitting, cross-validation and the mean square error (MSE) criteria were deployed. The MSE value, falling below 0.1 in the MLP algorithm, signifies an acceptable margin of error. Overfitting assessments affirm the model's fitting adequacy, with accuracy values ranging between 0.88 and 0.95 across all evaluations.

Furthermore, The accuracy of the model is more than 80% and this amount is acceptable considering sample size. As observed in the descriptive analysis, Snappfood dominates the market in Iran. In Hungary, Wolt and Foodpanda engage in intense competition, with the research sample favoring Wolt, although it's noteworthy that Foodpanda, despite its shorter presence, has rapidly gained popularity through an extensive advertising campaign. To validate our classification accuracy in the Hungarian context, particularly between Wolt and Foodpanda, we employed evaluation metrics like confusion matrix, accuracy, precision, recall (sensitivity), and F1 score.

Calculations, conducted in Python with 0.3 test data, produced a confusion matrix result of ([70, 1], [2, 21]). High total precision indicates minimal misclassifications of true instances, while high sensitivity reflects accurate identification of various grocery apps. These metrics collectively offer a robust assessment of the model's classification performance.

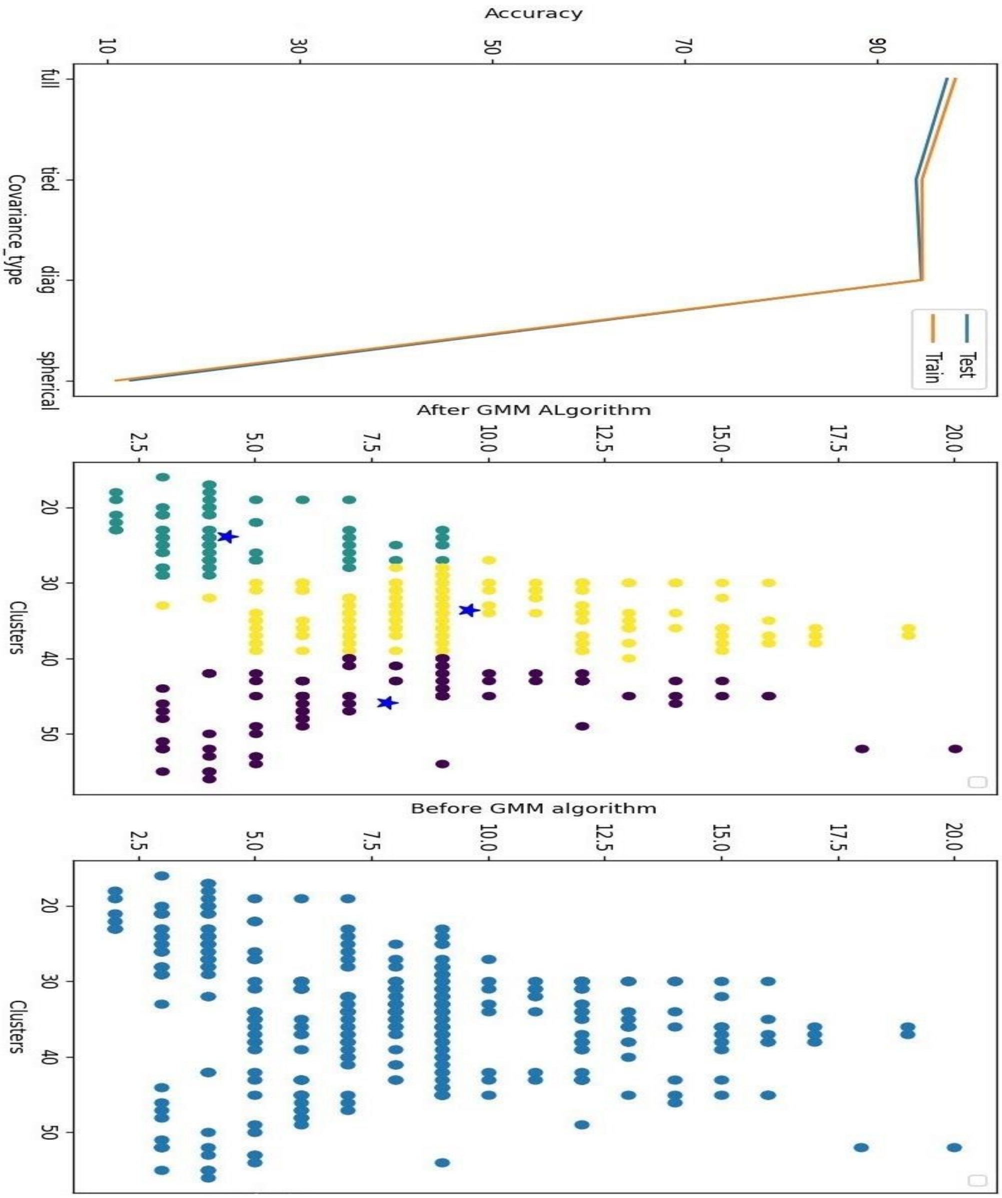

Figure 9. GMM algorithm output based on Iran data
(Source: authors' calculations based on Python programming)

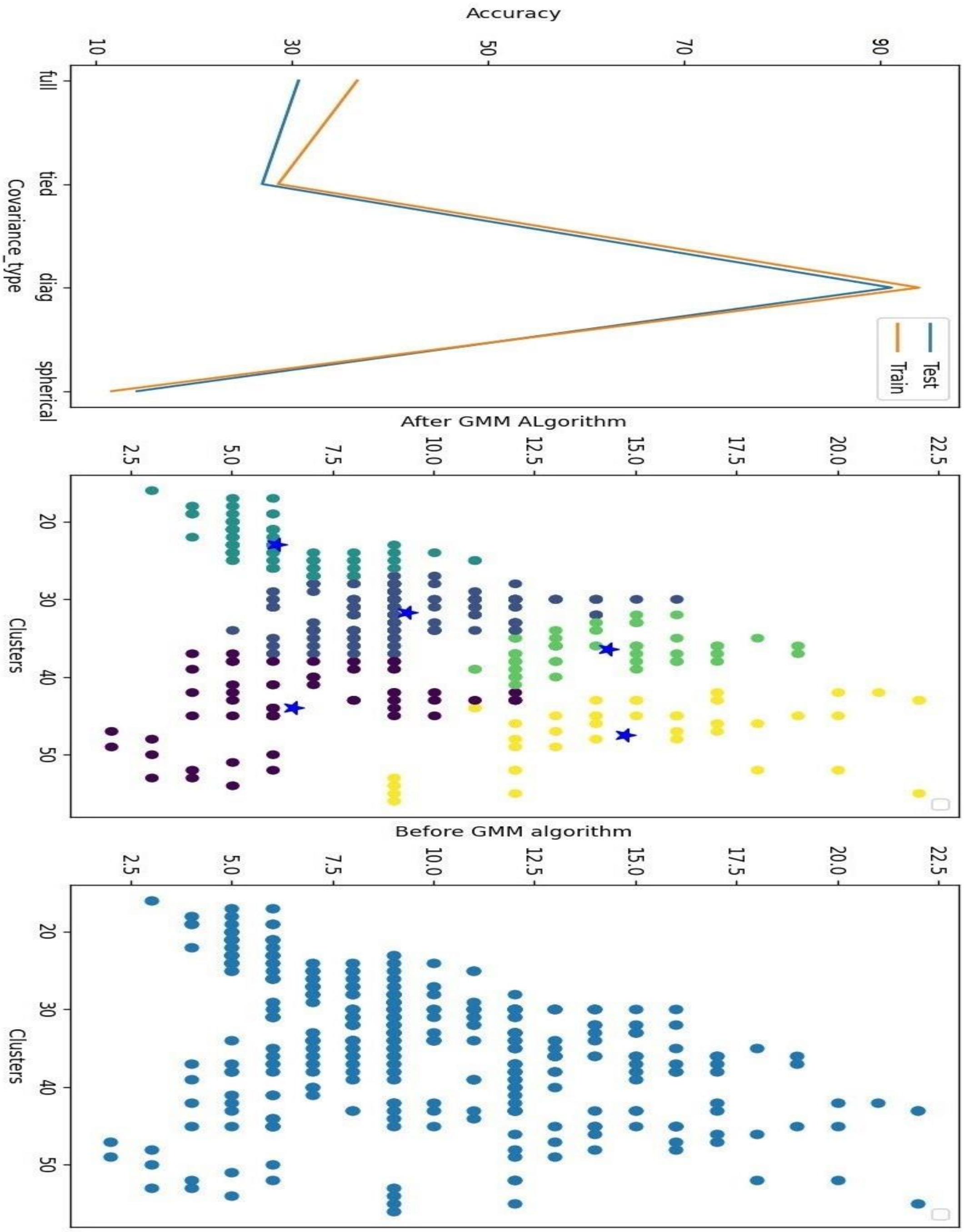

Figure 10. GMM algorithm output based on Hungary data

(Source: authors' calculations based on Python programming)

3.5 Case study three, Sentiment analysis of Instagram comments using NLP

Figures 7 and 8 present noteworthy insights through pair plots and comparative analyses of demographic data pertaining to Iran and Hungary.

To assess the model's precision, GMM was employed for clustering various grocery applications in both Iran and Hungary. Initial data pre-processing was conducted on the input data for the GMM algorithm, and no issues with missing data values were encountered. Subsequently, the first model was created and fitted with the data. The GMM model offers four covariance types—full, tied, diagonal (diag), and spherical.

The analysis of this section was conducted utilizing the TensorFlow framework, implemented within the Google Colab environment. Google Colab's provision of free GPU resources proved instrumental in facilitating efficient deep learning analysis.

To begin the analysis, a critical preprocessing step involved the transformation of textual data into a format suitable for machine learning models. This was achieved through text vectorization, specifically tokenization. Tokenization involves breaking down text into individual units, or tokens, which are then assigned numerical values. This process enables the model to comprehend and operate on textual data, paving the way for subsequent analysis.

Following tokenization, an embedding layer was incorporated into the models. The embedding layer is essential for translating the numerical representations obtained through tokenization into dense vectors. These vectors capture semantic relationships and contextual information within the textual data. The embedding layer enhances the model's ability to recognize patterns and understand the underlying meaning of words in a given context.

All experiments were meticulously documented, employing a systematically defined callback function. To enable a comprehensive comparative analysis of model performances, we established a dedicated evaluation function. The graphical representation in Figure 11 affords an insightful comparison of the eight models, evaluating their efficacy across metrics such as accuracy, precision, F1 criteria, and recall. Notably, the findings in Table 5 underscore the exceptional performance of Model 7—the transfer learning model—with an impressive accuracy rate of 95%. This outcome substantiates its efficacy for fulfilling the research objectives. Moreover, for the sake of transparency and reproducibility, all source codes and datasets associated with these experiments have been made publicly available on our GitHub repository: https://github.com/arad1367/Instagram_NLP_project. Interested readers and fellow researchers are encouraged to explore the repository for a deeper understanding of the experimental design, methodologies, and results.

Table 5. Performance Comparison of Sentiment Analysis Models

Models	Accuracy	Precision	Recall	F1
Baseline	90%	0.91	0.90	0.88
Dense neural network	82.5%	0.68	0.82	0.74
LSTM	90%	0.89	0.90	0.89
GRU	87.5%	0.86	0.87	0.87
BiDirectional	88.7%	0.88	0.88	0.88
Conv1D	87.5%	0.86	0.87	0.86
TF sentence encoder	95%	0.95	0.95	0.95
Small TF sentence encoder	83%	0.86	0.83	0.77

Source: authors' calculations based on Python programming using google colab and TensorFow framework

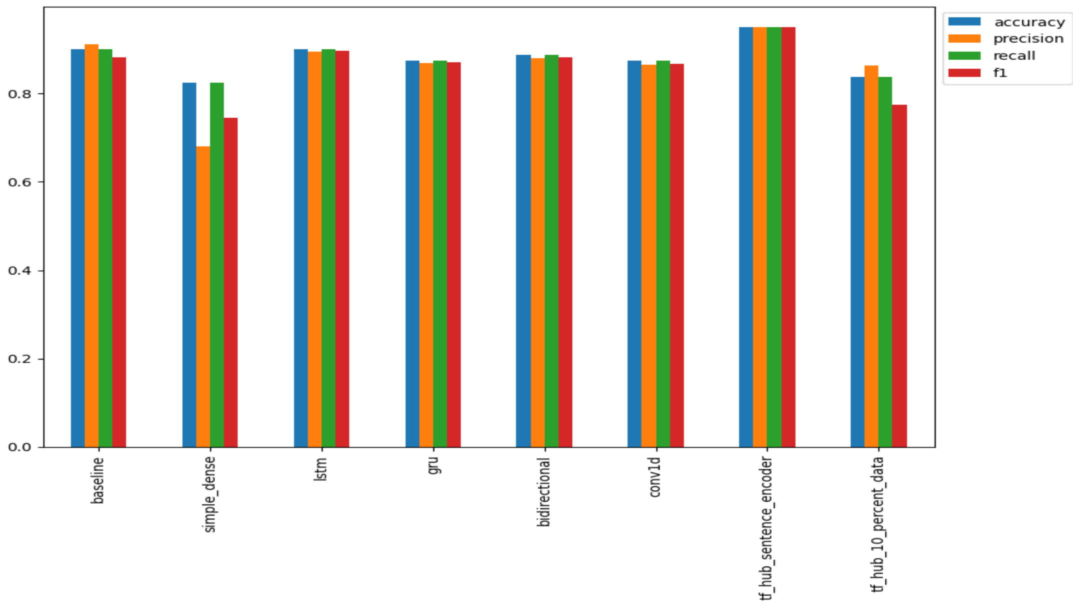

Figure 11. Models accuracy comparison

(Source: authors' calculations based on Matplotlib library using google colab and TensorFow framework)

In the visualization of sentiment analysis metadata, we leveraged the Embedding Projector as a powerful tool to provide a visual representation of the intricate relationships within our dataset. Utilizing a .tsv file, we transformed the textual data into a three-dimensional format, enabling a more intuitive understanding of the distribution of sentiments across various comments.

Figures 12 to 14 serve as illustrative examples of this visualization process, showcasing the effective categorization of comments into distinct positive and negative sentiments. These visual representations offer insights into the spatial arrangement of sentiments within the embedding space, allowing for a nuanced comprehension of the sentiment distribution. During our extensive analysis, we identified a total of 799 unique words within our sampled comments. It is noteworthy that the top five most frequently occurring words include ['', '[UNK]', 'it', 'the', 'i']. The presence of '[UNK]' suggests instances where the model encountered unknown or out-of-vocabulary words. Additionally, the bottom five least common words, namely ['action', 'according', 'abroad', 'abomination', '5'], provide a glimpse into the diversity of vocabulary within the dataset, highlighting less frequently used terms. These visual and lexical analyses contribute to a comprehensive understanding of the sentiment dynamics present in the dataset, enriching the insights derived from the sentiment analysis models.

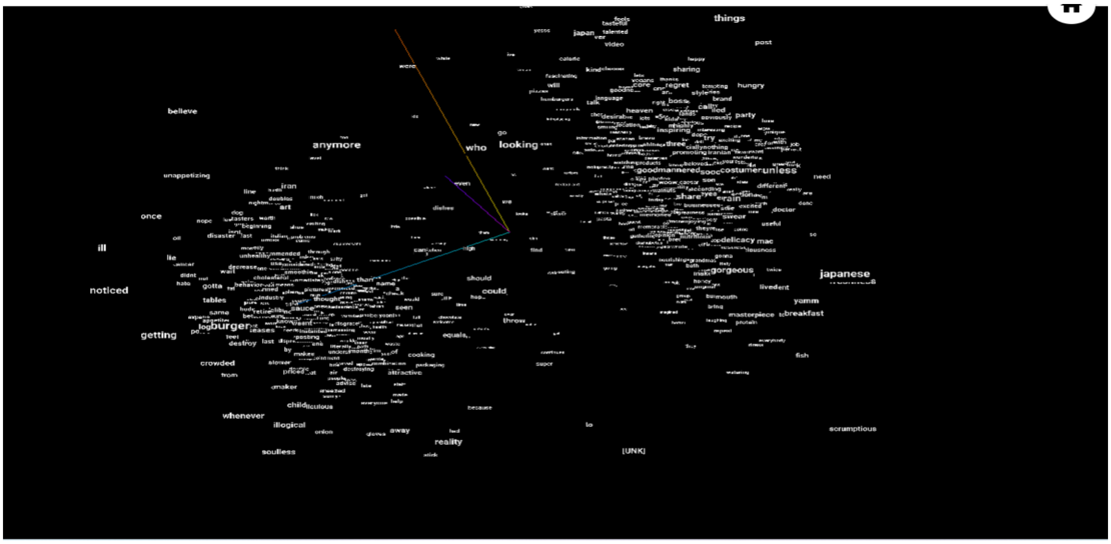

Figure 12. Embedding projector white and black

(Source: authors’ calculations based on metadata in .tsv format)

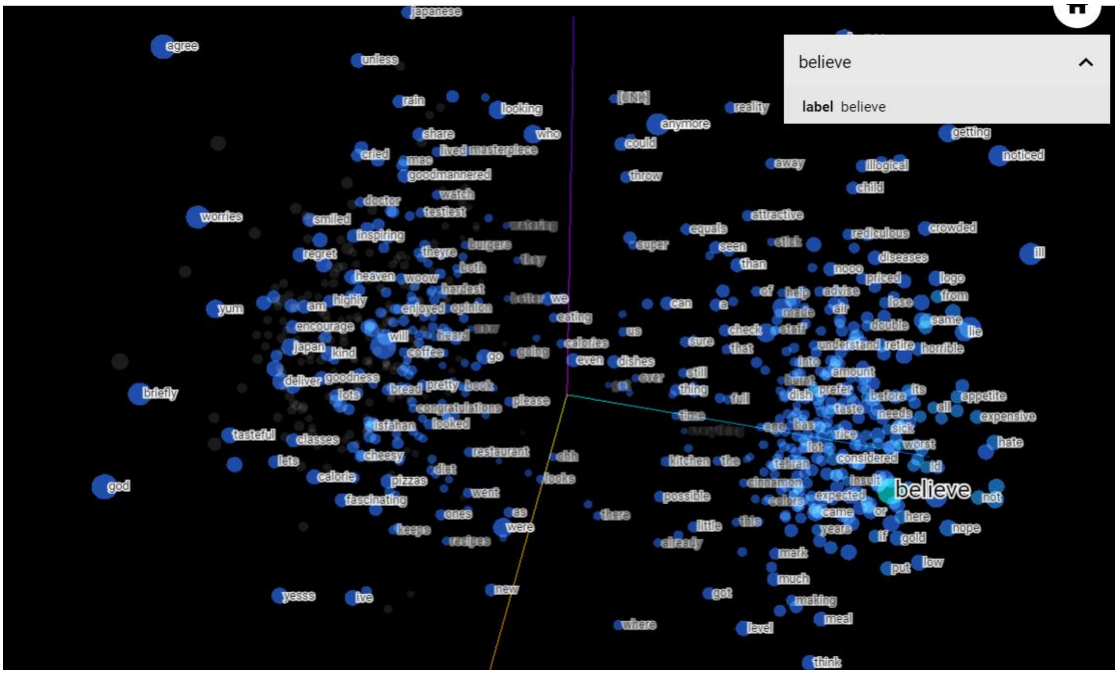

Figure 13. **Embedding projector blue and black**

(Source: authors' calculations based on metadata in .tsv format)

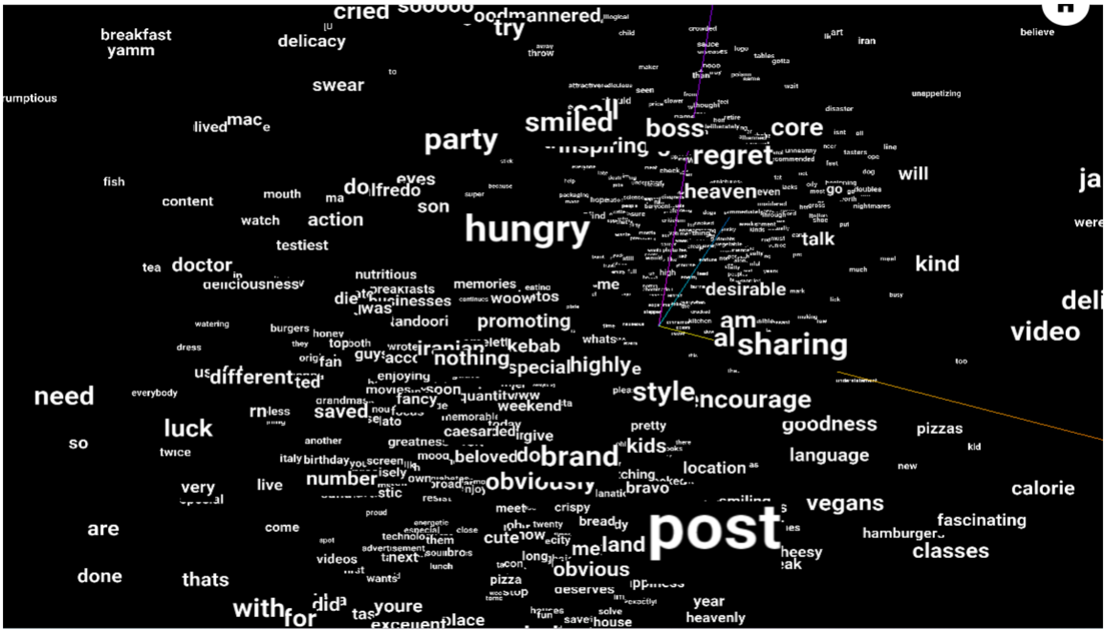

Figure 14. Embedding projector frequency words

(Source: authors' calculations based on metadata in .tsv format)

3.6 Discussion and Findings

3.6.1 Discussion on ISM section

The primary aim of the present investigation was to identify key strategic factors that influence online consumer purchasing behavior on social network platforms. The results emphasize the significance of factors such as "Consumer engagement," "Consumer's value perception," and "Perceived risk" within the ISM model. These factors are deemed crucial for effectively modeling online consumer purchasing behavior.

The study reveals that both positive and negative instances of active consumer engagement significantly impact the behaviors and attitudes of individuals consuming the generated content. Recognizing the considerable marketing implications, companies are increasingly prioritizing efforts related to consumer engagement, given its direct influence on online consumer purchasing behavior (PEZZUTI ET AL. 2020).

3.6.2 Discussion on AHP part

The criteria weights, as determined through the study, reveal a hierarchical influence on consumer purchase behavior. Word of Mouth (WOM) and Knowledge Sharing emerge as the most and least influential criteria, respectively. The substantial weight assigned to WOM underscores the substantial impact of peer recommendations and interpersonal communication on consumer decision-making. Conversely, the lower weight associated with Knowledge Sharing suggests its limited influence in the context of Iranian social networks. The intermediate criteria, including Social Influence, Value Co-creation, and others, contribute variably to the overall prioritization. Social Influence and Value Co-creation, for instance, underscore the importance of societal trends and collaborative value creation in shaping consumer preferences. In evaluating the impact of different social networks, Instagram stands out as the most influential platform, securing the highest weighted score at 35.3%. This signifies its predominant role in affecting consumer behavior within the Iranian social media landscape. The findings align with the study's objective, affirming Instagram's significant superiority in influencing changes in consumer purchase behavior. Following Instagram, Telegram and TikTok emerge as substantial influencers, with weighted scores of 31.6% and 20.1%, respectively. These platforms demonstrate noteworthy impact, contributing to the overall dynamics of consumer decision-making in Iranian social networks. Conversely, Facebook, with a comparatively lower weighted score of 13.1%, emerges as the least influential social network. The findings suggest that, within the Iranian context, Facebook has a diminished effect on consumer behavior compared to other platforms.

3.6.3. Discussion on Machine learning section

Based on case study 1, The map visualization, implemented through a flexible and dynamic program utilizing the decision tree algorithm in Python, offers a practical tool with commendable predictive accuracy. An examination of previous research in the marketing domain highlights a gap in practical models, a deficiency addressed by the current research. The literature review approach, commonly employed in exploring the application of machine learning in marketing, has been adopted in numerous studies. Notably, the model developed in this research contributes a practical perspective specifically beneficial for marketing managers, particularly those involved in online businesses.

The findings from case study 2 underscore Wolt's popularity in Hungary and Snappfood's dominance in Iran, indicating successful business models for grocery apps in their respective markets. Consequently, other grocery apps could enhance their models by drawing inspiration from the strategies employed by Wolt and Snappfood. While prior research lacked a specific focus on global grocery app popularity, the positive reception of grocery apps by South Korean consumers, as highlighted in KIM ET AL. (2021) study, aligns with our observations. Additionally, previous research by CHAKRABORTY ET AL. (2022) affirms the impact of various factors, including attitude, perceived behavioral control, perceived usefulness, perceived ease of use, perceived enjoyment, facilitating conditions, relative advantage, real-time search & evaluation, and subjective norms, on the inclination to use grocery apps.

Based on case study 3, The prevalence of positive sentiments in comments on Iranian food pages on Instagram holds valuable practical implications for businesses and marketers. Leveraging this positive sentiment can lead to enhanced brand perception, refined content strategies, strengthened customer relationships, strategic partnerships, and targeted marketing campaigns. Recognizing the overwhelmingly positive tone provides an opportunity for businesses to strategically align practices, fostering a more vibrant and engaged online community while continually focusing on quality improvement efforts.

4. CONCLUSIONS AND RECOMMENDATIONS

4.1 Conclusion

This study highlights the significance of social support as one of the most crucial strategic variables. Subsequently, all linkage variables are identified as strategic variables based on MicMac analysis. In this context, "strategic" signifies the variables' significance and potential for future investment, as determined through cross-impact analysis. These results reinforce the importance of expert-confirmed variable selection in the field. Termed as linkage factors, the recognized strategic variables exhibit equal driving power and dependence power, contributing significantly to the explanation of online consumer purchase behavior within the modeling framework. Level Partitioning analysis reveals that these linkage variables exert a substantial impact on dependent factors and, consequently, on online consumer purchase behavior. Notably, four dependent variables exhibit the highest dependence power and lowest driving power, signifying their role as goal variables that decisively determine online consumer purchase behavior.

The comprehensive analysis of criteria weights and social network influences has provided profound insights into the dynamics of consumer purchase behavior within Iranian social networks. WOM standing out as the paramount factor, while Knowledge Sharing holds the least impact. This hierarchy underscores the pivotal role of interpersonal communication and the limited influence of knowledge dissemination in the Iranian social media landscape. Notably, the weighted head-to-head analysis elucidated that Instagram reigns supreme as the most influential social network, significantly impacting consumer behavior with a substantial weighted score of 35.3%. This finding aligns seamlessly with the study's overarching objective, reinforcing the notion that Instagram is a dominant force in shaping consumer decisions within the Iranian context.

An essential objective of the map visualization is to achieve "Customization" for customers, particularly in the context of advertising environmentally and eco-friendly products. Tailoring advertisements based on the demographic characteristics of each customer is crucial. The decision tree model, informed by past purchase records, enables the provision of personalized suggestions for future purchases. This research model facilitates the identification of the optimal medium for targeted advertising. In the case of Iran, Instagram emerges as a promising platform for advertising visibility. Businesses can strategically allocate a greater share of their advertising efforts, promoting various products and services, or fostering a culture of environmentally conscious consumption, specifically on this online social platform.

Consumer preferences for grocery apps in Hungary and Iran are shaped by demographic variables such as gender, age, education, and online shopping experience. The segmentation of consumers based on these variables enables marketers to strategically target specific market segments. By tailoring products and services to align with the characteristics of their target audience, grocery app marketers can enhance their effectiveness in reaching and appealing to the right consumers.

Finally, the comprehensive analysis of sentiment within comments on Iranian food pages on Instagram has illuminated a predominantly positive online environment. This pervasive positivity presents practical opportunities for businesses and marketers to strategically enhance their brand image, refine content strategies, strengthen customer relationships, explore strategic partnerships, and design targeted marketing campaigns. The findings underscore the potential for fostering a vibrant and engaged online community. Moreover, the identification of specific words and sentiments further allows for nuanced insights that can guide quality improvement efforts. As we navigate the dynamic landscape of online interactions, understanding and leveraging the prevailing positive sentiments provide a foundation for informed decision-making and strategic actions in the realm of digital marketing and brand management.

4.2. Recommendations and Managerial Implications

The ISM model of the present study showed how online consumer behavior in e-commerce can change under the influence of strategic variables. However, the present model has been formed qualitatively and in the opinion of field experts, and the need for quantitative model testing and case studies is felt. In fact, the present model provides a theoretical view of online consumer purchase behavior that can be the basis for practical development in the future.
The research model can be implemented in the field of online businesses. A quantitative research and model simulation using a machine learning dataset can be performed base on the model. Certainly, quantitative implementation of the model in the future can complement the current research and better show the effect of variables such as perceived risk.

AHP findings collectively contribute to a nuanced understanding of the factors shaping consumer purchase behavior in Iranian social networks. The prominence of Word of Mouth, coupled with Instagram's preeminent influence, emphasizes the significance of interpersonal communication and the role of specific social networks in shaping consumer preferences. The outcomes offer practical implications for marketers and businesses aiming to leverage social media in targeting the Iranian consumer market. The nuanced understanding of influential criteria and social network dynamics can guide strategic decisions, optimizing efforts and resources for effective consumer engagement.

Within the expansive realm of e-commerce and e-business, the model's capabilities and capacities are poised to yield significant benefits in terms of state-of-the-art methods such as map visualization. Informed investments and accurate predictions of consumer behavior are critical components that can positively impact online businesses. In the context of the highly competitive landscape of online businesses in Iran, precise forecasts of consumer behavior can confer a distinct competitive advantage. The significance of the proposed algorithm becomes particularly pronounced when online businesses are consistently striving to customize offerings for each individual customer or consumer. Future researchers can examine user perceptions and attitudes towards personalized marketing with different ML algorithms and stimulations in a practical way. Understand how consumers perceive the customization of advertisements and the ethical implications associated with data-driven marketing practices.

Marketing managers can leverage machine learning algorithms to devise distinct plans and strategies tailored to specific demographic groups such as age, gender, or education. A key revelation from the research underscores the significance of customization in consumer behavior. In the contemporary landscape, the information gleaned from consumers holds substantial value, shaping the future strategies and plans of grocery apps, startups, and online sellers. This emphasizes the pivotal role of personalized approaches in responding to consumer needs and preferences.

Subsequent studies are advised to refine the model by introducing additional demographic characteristics of consumers. The research model's predictive capability for grocery app preferences can be further enhanced by incorporating new variables. Researchers are also encouraged to explore alternative supervised or unsupervised machine learning algorithms in future investigations. Moreover, it is recommended that future researchers extend the application of the current MLP model to various countries for comparative assessments. The consumer behavior prediction model stands as a valuable tool for obtaining insightful comparative results, offering a nuanced understanding of divergent consumer preferences across different nations.

The predominant positive sentiment observed in comments on Iranian food pages on Instagram carries significant managerial implications for businesses and marketing professionals. Recognizing the overwhelmingly positive tone offers an opportunity for managers to capitalize on the favorable online environment, shaping marketing strategies that align with the optimistic sentiments expressed by users. Strategic decisions, such as emphasizing positive customer experiences, cultivating a positive brand image, and fostering community engagement, can contribute to sustained success. Additionally, the insights gained from sentiment analysis enable managers to make informed choices regarding partnerships, content creation, and customer relationship management, all geared towards maximizing positive interactions and solidifying the brand's online presence. The managerial implications underscore the importance of aligning business strategies with the prevailing sentiments to create a positive and resonant impact within the dynamic landscape of social media marketing.

For future researchers delving into sentiment analysis on social media platforms, it is recommended to consider a multimodal approach that integrates both textual and visual data. While this study primarily focused on textual comments, incorporating visual elements such as images or emojis from Instagram posts could enrich the analysis by capturing nuanced expressions that may not be fully conveyed through text alone. Additionally, researchers might explore the use of advanced deep learning models, particularly those designed for multimodal analysis, to harness the synergies between textual and visual information. Furthermore, as social media platforms evolve, staying abreast of emerging technologies and tools for sentiment analysis, and adapting methodologies accordingly, will be essential for a comprehensive understanding of user sentiments in the ever-changing digital landscape. Lastly, collaboration between researchers from diverse backgrounds, including linguistics, computer science, and social sciences, could lead to more robust methodologies and holistic insights into the complex dynamics of sentiment on social media.

4.3. Research Limitations

The present study is subject to certain limitations that merit acknowledgment. Notably, data collection transpired amidst the COVID-19 crisis in Iran, which constitutes a significant constraint, particularly evident in the context of case studies 1 and 2. In the case of case study 1, where generalization of results is sought, it is essential to recognize that respondents responded to demographic inquiries based on their experiences with diverse online social platforms within the Iranian context. It is imperative to recognize the potential for divergent outcomes or experiences in alternate countries and cultures. Furthermore, the study exclusively considered five online social platforms prevalent in Iran, and this selection may introduce bias. The accessibility of certain platforms is hindered in Iran due to content filtering, underscoring the necessity for caution when extrapolating the research findings.

It is crucial to note that the participants in this study responded to demographic inquiries based on their experiences with various grocery apps in Iran and Hungary. Diverse outcomes and experiences may be encountered in different countries or cultures, highlighting the contextual nature of consumer behavior and preferences.

One notable limitation of this research lies in the exclusive focus on sentiment analysis derived from textual comments on Instagram food pages. While the textual data provided valuable insights into user sentiments, it overlooks potential contextual cues and emotions conveyed through visual content such as images or videos accompanying the posts. As Instagram is a visual-centric platform, the absence of multimodal analysis limits the depth of our understanding regarding the interplay between text and visual elements in influencing sentiment. Future research should consider incorporating visual data to present a more comprehensive and nuanced analysis of sentiment dynamics on social media platforms like Instagram.

5. NEW SCIENTIFIC RESULTS

1. Identification of Key Strategic Factors: The study identifies and emphasizes the significance of factors such as "Consumer engagement," "Consumer's value perception," and "Perceived risk" within the ISM model, crucial for modeling online consumer purchasing behavior. Study highlighted "Trust," "Social influence," "Social support," and "Value co-creation" emerge as the most crucial strategic variables.

2. Hierarchical Influence of Criteria Weights: Word of Mouth (WOM) emerges as the most influential criterion, highlighting the substantial impact of peer recommendations on consumer decision-making. Conversely, Knowledge Sharing exhibits limited influence, particularly within Iranian social networks.

3. Influence of Social Networks on Consumer Behavior: Instagram is identified as the most influential platform, followed by Telegram and TikTok, within the Iranian social media landscape. This underscores Instagram's significant superiority in affecting consumer purchase behavior.

4. Leveraging Positive Sentiments: The prevalence of positive sentiments in comments on Iranian food pages on Instagram presents valuable opportunities for businesses and marketers to enhance brand perception, refine content strategies, strengthen customer relationships, and design targeted marketing campaigns.

5. Role of Sentiment Analysis and AI models: Sentiment analysis and embedded projector provide insights into consumer behavior and can help bridge gaps in the fields of business and marketing, particularly in understanding online sentiment and its impact on brand perception and can be follow by large language models and fast deployment for real-time analysis.

6. LIST OF PUBLICATIONS

PUBLICATIONS IN FOREIG LANGUAGE

Scientific journal articles in English

SALAMZADEH, A., DANA, L-P., **EBRAHIMI, P**., HADIZADEH, M., MORTAZAVI, S. (2024). Technological barriers to creating regional resilience in digital platform-based firms: Compound of performance sensitivity analysis and BIRCH algorithm. *Thunderbird International Business Review*. https://doi.org/10.1002/tie.22371 (**Scopus Q1 & WOS**)

EBRAHIMI, P., DUSTMOHAMMADLOO, H., KABIRI, H., BOUZARI, P., & FEKETE-FARKAS, M. (2023). Transformational Entrepreneurship and Digital Platforms: A Combination of ISM-MICMAC and Unsupervised Machine Learning Algorithms. *Big Data and Cognitive Computing*, *7*, 118. https://doi.org/10.3390/bdcc7020118 (**Scopus Q2 & WOS**)

EBRAHIMI, P., KHAJEHEIAN, D., SOLEIMANI, M., GHOLAMPOUR, A., & FEKETE-FARKAS, M. (2023). User engagement in social network platforms: what key strategic factors determine online consumer purchase behaviour?. *Economic Research-Ekonomska Istraživanja*, *36*(1), 2656-2687. https://doi.org/10.1080/1331677X.2022.2106264 (**Scopus Q1 & WOS**)

BOUZARI, P., GYENGE, B., **EBRAHIMI, P**., & FEKETE-FARKAS, M. (2023). Problem Solving and Budget Allocation of SMEs: Application of NCA Approach. *Computation*, *11*(3), http://dx.doi.org/10.3390/computation11030048 (**Scopus Q2 & WOS**)

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