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

Doctoral (Ph.D.) dissertation

by

Pejman Ebrahimi

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Hungarian University of Agriculture and Life Sciences

Name of Doctoral School: Doctoral School of Economic and Regional Sciences

Discipline: Management and Business Administration

Head of Doctoral School: Prof. Dr. Bujdosó, Zoltán, Ph.D.

Institute of Rural Development and Sustainable Economy
MATE, Hungary

Supervisor(s): Prof. Dr. Farkasné Fekete, Mária, Ph.D.

Institute of Agricultural and Food Economics, MATE, Hungary

Prof. Dr. Kot, Sebastian, Ph.D.

Faculty of Management, Czestochowa University of Technology, Poland

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ABBREVIATIONS

ICTs	Information and Communication Technologies
WOM	Word Of Mouth
MCDM	Multiple-criteria decision analysis
ISM	Interpretive structural modeling
AHP	Analytic hierarchy process
ML	Machine Learning
ICC	Intraclass correlation coefficient
B2B	Business to business
B2C	Business to customer
PV	Perceived value
HV	Hedonic value
UV	Utilitarian value
GDP	Gross domestic product
CMB	Common Method Bias
CSV	Comma-Separated Values
NLP	Natural Language Processing
SSIM	Structural Self-Interaction Matrix
MLP	Multi-Layer Perceptron
GMM	Gaussian Mixture Model
LSTM	Long Short-Term Memory
GRU	Gated Recurrent Unit

RNN	Recurrent Neural Network
ANNs	Artificial Neural Networks
CR	Consistency Ratio
CI	Consistency Index
RC	Random Consistency
MSE	Mean Square Error

I. INTRODUCTION

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 (SIAU & YANG, 2017). Machine learning is a field of information science that focuses on building a computer system that can improve itself using experience (JORDAN & MITCHELL, 2015).

In machine learning, instead of manually programming behaviors by predicting desired behaviors from all possible inputs, developers train the system by showing examples of desired behaviors. This power is particularly useful for tasks where it is difficult to plan all possible items and responses, such as image recognition (ie, recognizing a picture of a dog) (THONTIRAWONG & CHINCHANACHOKCHAI, 2021).

In marketing, the same learning method can be used to create a personalized experience for customers through product or service recommendations (using recommendation algorithms) (KOLATHAVIL, 2019). ML models can be used to identify patterns from data and recommend strategic marketing actions. In the digital age where data is abundant, running a marketing campaign means relying on humans to use automation and algorithms (HALL, 2019).

The primary function of the marketing department is to understand and satisfy the needs, wants and preferences of the consumer. Consumer purchase behavior includes all aspects of purchasing, using and disposing of products and services (ZHU ET AL. 2020). In the past, sellers used their daily experiences, which resulted from the direct sale of goods to customers, to obtain the necessary information and knowledge about consumer behavior. With the gradual growth of companies and markets, many marketing decision-makers have lost their contact with customers and have mostly turned to research and study on consumer behavior (PALALIC ET AL. 2021). A company that is aware of how consumer behavior reacts to different characteristics of product, prices and promotions has a special advantage over its competitors. Nowadays, predicting consumer behavior indicates the consumer's tendency to purchase a product or receive a special service in the future (VITHAYATHIL ET AL. 2020). In other words, developing consumer purchase behavior means increasing the likelihood of purchasing. The physical, mental, and sensory actions people take while choosing, purchasing, and using products and services to fulfill their requirements are referred to as the behavior of consumers. During and after these acts, decision-making is one of these activities (MUHAMMAD ET AL. 2021). Predicting and understanding consumer behavior to influence their behavior has attracted the attention of marketers. To be successful, marketers must overtake various factors affecting purchasers and seek to understand the consumers' purchase intention (FU ET AL. 2020).

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.

1.1. Research flow chart

Figure 1 presents a flowchart which is related to research process in different steps. The process is started with introduction and then focus on problem statement. Literature review is an important part to identify variables related to consumer purchase behavior. We used a combination of three different methods to answer research questions. Finally, research findings, managerial implications and conclusion will be illustrated and we will mention suggestion for future research.

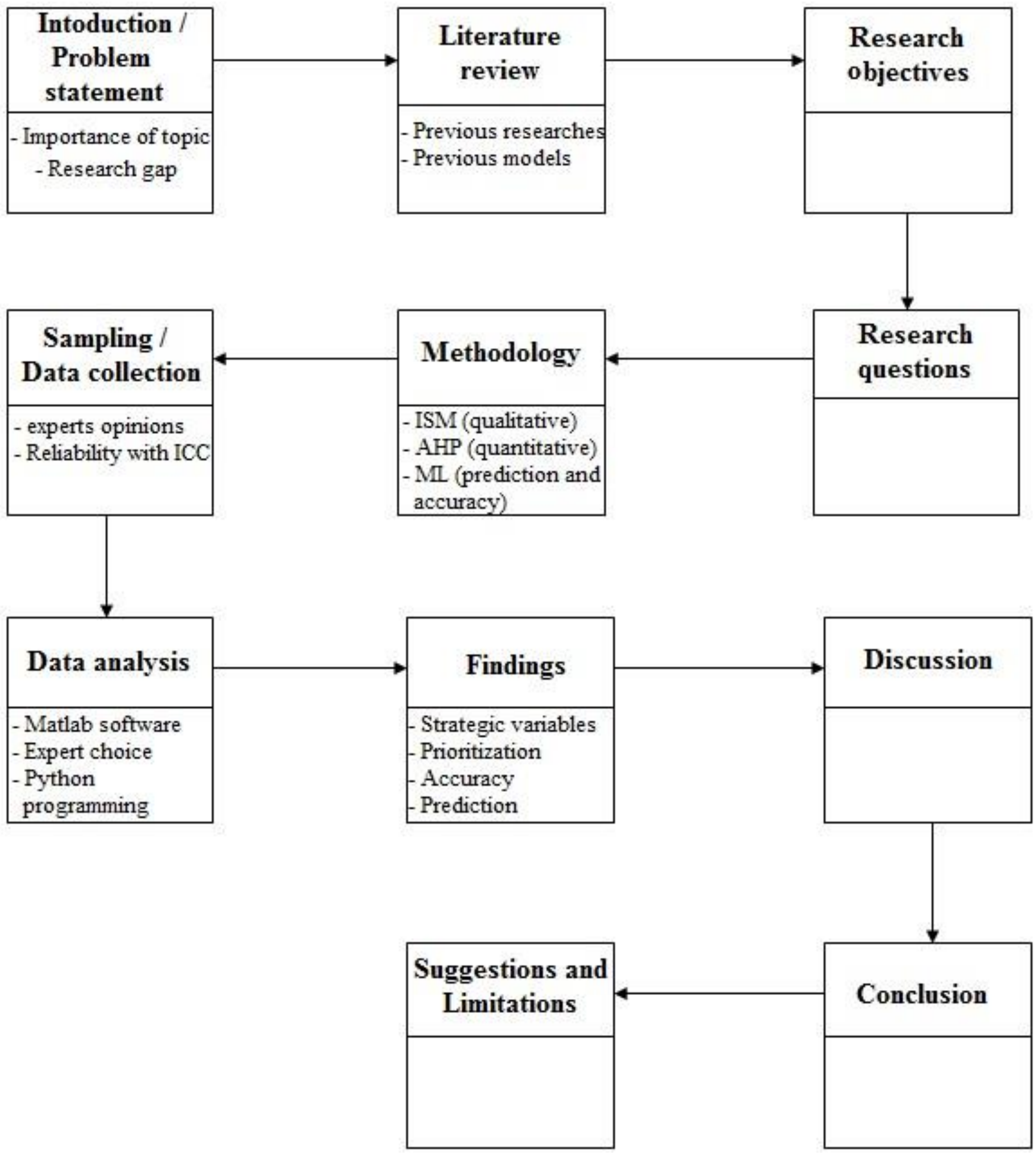

Figure 1. Research flow chart

(Source: Author's own construction)

1.2. 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. It is typically a one-way communication that relies on mass marketing techniques (SUMITHA, 2022). On the other hand, 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 (FERRELL & FERRELL, 2020). 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. In contrast, traditional marketing uses conventional advertising techniques to promote products and services to a broader audience. The rapid advance of AI generates fresh possibilities to mod ify the way we learn, work, and live. The effectiveness and efficiencies of AI have been widely recognized, particularly its ability to extract data that are valuable for assessing human behaviors and patterns (DAENPORT & RONANKI, 2018). So, World in the current script is going through a surge in digitalisation; the husbandry are evolving going from the point and mortar to the structure of click and bricks. This modernisation is affecting each aspect of the ultramodern life; and business, being dynamic, has not been left untouched by this metamorphosis(SUMITHA, 2022).

Social media and digital platforms have provided various businesses with the opportunity to afford different services and entrepreneurship (ARBATANI ET AL. 2019; KAUFFMAN ET AL. 2020). Given the inclusiveness and reputation among people especially young people, this fact is especially important regarding social networks (LIU ET AL. 2019). In fact, social networks have provided the perfect opportunity for marketing in line with various businesses to spread a message, opinion or campaign (BHATTACHARYA ET AL. 2019). One may argue that several organizations now have a competitive advantage due to the introduction of new information and communication technologies (ICTs), particularly social networks and the Internet (ALVES ET AL. 2016; ANDRONICEANU ET AL. 2020).

The present research emphasizes the importance of social networks. In fact, this research seeks to strategic factors for proper marketing in social networks and increase the market share of various businesses. For example, to better understand this, we need to know that 2018 statistics show that around 700 million people worldwide have used Instagram online at least once a month, which is projected to increase by 30% in 2021 (EMARKETER, 2018). So, given the increasing popularity of such media, different businesses need to adopt the right marketing methods regarding consumer purchase behavior to maintain or increase their market share in competitive market conditions (ANDRONICEANU ET AL. 2020).

Additionally, accounts and sites today have over 2.6 billion active monthly users. Additionally, the corporation presently controls four of the largest social media networks: Instagram, Facebook Messenger, WhatsApp, and Facebook (the core platform), each of which has over one billion monthly active users. In the second quarter of 2020 (Fig. 2), Facebook reported over 3.1 billion monthly core Family product users 947869. The most popular social networks (Fig. 3) allow users to interact with friends and individuals beyond political, economic, and geographic boundaries and are often available in numerous languages. Social networking sites are predicted to have 3.6 billion members as of right now. These numbers are likely to rise as mobile device usage and mobile social networks gain popularity in previously neglected regions (STATISTA 2020). Social media usage is one of the most popular online activities. In 2022, over 4.59 billion people were using social media worldwide, a number projected to increase to almost six billion in 2027(STATISTA, 2023).

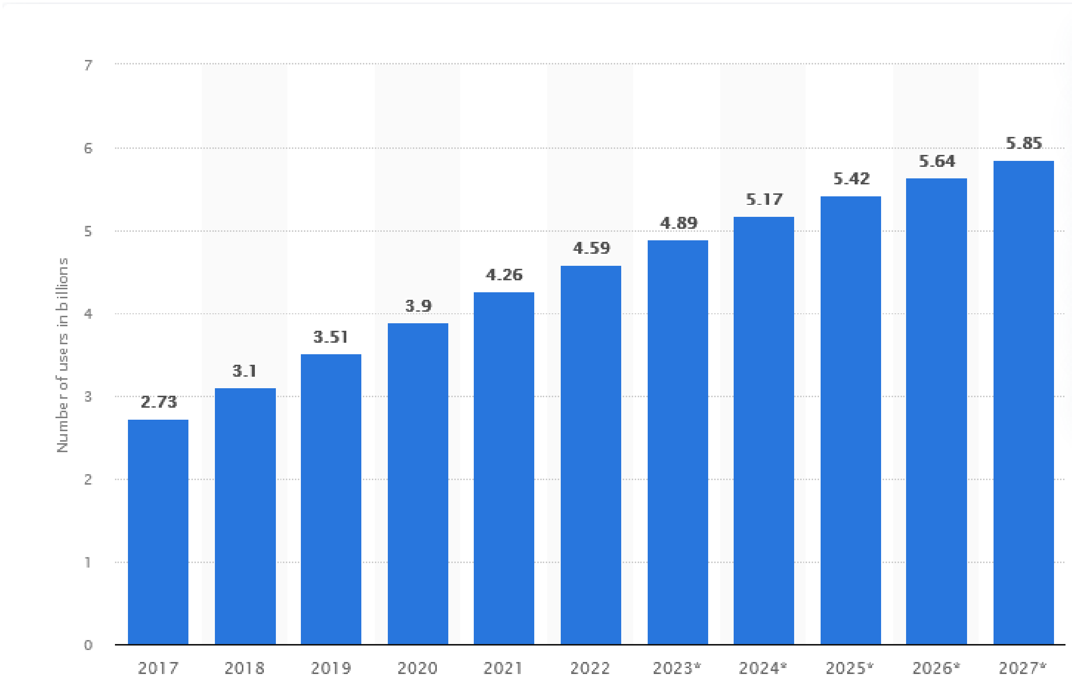

Figure 2 Number of social media users worldwide from 2017 to 2027 (in billions)

Social networks offer many benefits to end-users through quick access to information on different goods and services as well as sharing consumers' views (KANG, 2018; DEDEOGLU ET AL. 2020). On the other hand, social networks have changed consumers' purchase habits through new marketing techniques, information sharing, different evaluations, and the ability to choose different goods and services (ALBORS ET AL. 2008). Thus, these social networks have created a widespread evolution in the structure and access to information for consumers and have played a significant role in the diversity of market investments (EBRAHIMI ET AL. 2020; KHAJEHEIAN & EBRAHIMI, 2021).

One of the most important aspects of social networks is paying attention to the customers' comments and remarks who have purchased the products. In fact, consumers are influenced other consumers by sharing information and expressing negative or positive points about the experience of purchasing a product, and this can change consumers' purchase intentions and behavior (DE KEYZER ET AL. 2017; NAM & DAN, 2018; CHANG ET AL. 2019). This doubles the importance of social networks marketing according to consumer opinion.

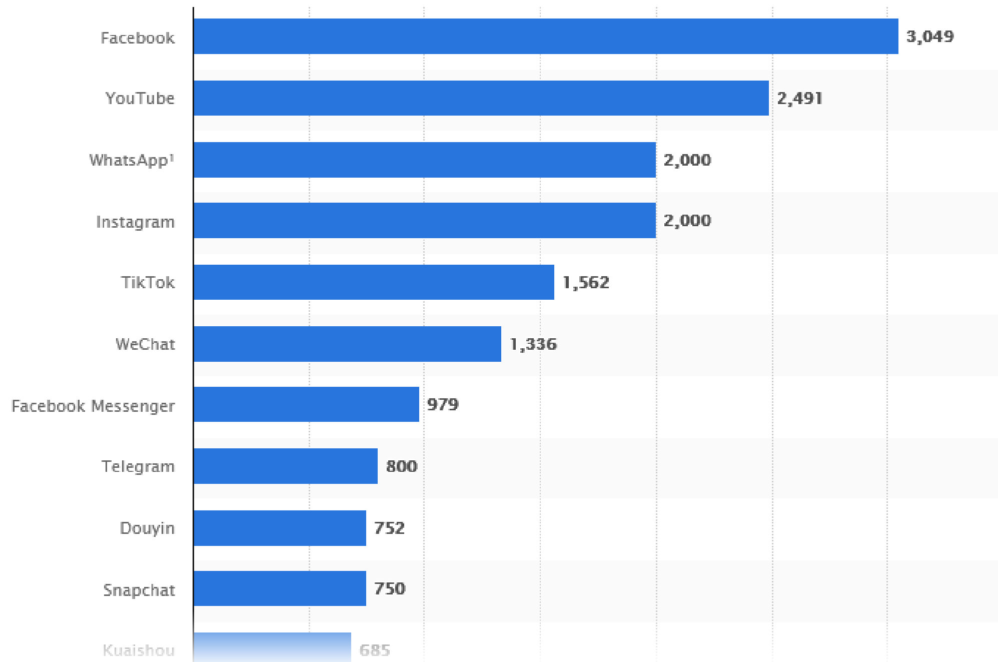

Figure 3. Most popular social networks worldwide as of January 2024, ranked by number of monthly active users (in millions)

Market leader Facebook was the first social network to surpass one billion registered accounts and currently sits at more than three billion monthly active users. Meta Platforms owns four of the biggest social media platforms, all with one billion monthly active users each: Facebook (core platform), WhatsApp, Facebook Messenger, and Instagram. In the third quarter of 2023, Facebook reported around four billion monthly core Family product users (STATISTA, 2024).

Generating content from users is another important point in social networks (EBRAHIMI ET AL. 2020). In fact, this is achieved through users' social interactions with each other and provides an opportunity for consumers to evaluate different products (HAJILI, 2014; HANAYSHA ET AL. 2018; KHAN ET AL. 2018). Other important factors affecting the prediction of consumer purchase behavior in online purchase can be usefulness, perceived ease of use, users' attitudes, subjective norms, perceived behavioral control, trust, commitment, group behavior (SHAREEF ET AL. 2020), customer relationship (SHAH ET AL. 2019), and consumer purchase intentions (REHMAN ET AL. 2019).

Artifcial intelligence (AI) marketing is a system of using client data to anticipate the client's next move and ameliorate the client trip. AI offers a way to bridge the gap between data gathering and execution, by sifting through and assaying extensive data, which was formerly an invincible process (SUMITHA, 2022). data is the primary asset of AIgrounded marketing approaches. Data for marketing comes from a company's own systems, agencies, thirdparty syndicators, client online actions, and numerous other sources; and clearly comprises 'big data' in the total (KAPONIS & MARAGOUDAKIS, 2022). About 25 per cent of moment's marketing budgets are devoted to digital channels, and nearly 80 per cent of marketing organisations make technology-acquainted capital expenditures – generally hardware and software –according to a recent Gartner check. Easily, some of that capital will be spent on AI. The elaboration of big data and advanced logical results have made it possible for marketers to make a clear picture of their target group (WU & MONFORT, 2023).

Artifcial intelligence can reuse both structured and unshaped data with exponentially more speed and delicacy than any human could. Marketers are using the capability of machine literacy to make connections between data points to gain perspective on their client base (BHARADIVA, 2023). These systems can dissect speech to determine emotion from spoken language, produce visual defnitions to show social media trends, and crunch data to make prognostications. Also, algorithms are able to predict consumer behavior, make the right offers to the right customers, and even evolve along with other new technologies such as blockchain. By adding value insights through data mining techniques, chatbots are now playing a key role in digital sales (DING, 2023).

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. This research can provide a real-time analysis of consumer behavior in the market. This research try to show how application of machine learning can help to predict consumer behavior and how ML can interact with business solutions.

1.3. Theoretical framework

The evolution of artificial intelligence (AI) has drastically changed the dynamics of today's business world. One of the most significant applications of AI is in the field of marketing, which assists in enhancing performance and consumer behavior (BHARADIVA, 2023). Artificial Intelligence (AI) has become integral to modern marketing, revolutionizing strategies, and performance. Through advanced data analytics, AI processes vast datasets swiftly, providing insights into customer behavior and market trends. Machine learning and artificial intelligence (AI) play a crucial role in enhancing and expanding the capabilities of business intelligence (ARCE ET AL. 2023). They enable organizations to extract valuable insights from vast amounts of data, automate processes, and make accurate predictions. Machine learning algorithms, a subset of AI, are designed to automatically learn from data without being explicitly programmed. They can analyze complex patterns, identify correlations, and make predictions or recommendations based on historical data. In the context of business intelligence, machine learning algorithms can be used to uncover hidden patterns in data, perform advanced data analysis, and provide valuable insights for decision-making (MARASABESSY, 2024). Personalization is enhanced as AI tailors' content and advertisements based on individual preferences, fostering improved customer engagement. Chatbots and virtual assistants powered by AI offer instant, automated customer support, aiding in lead generation and conversion. AI-driven content creation optimizes marketing materials, while targeted advertising leverages algorithms to reach specific audiences effectively. Automation streamlines repetitive tasks, allowing marketers to focus on strategic planning. Predictive analytics enables businesses to anticipate trends and shifts, contributing to proactive decision-making. Overall, AI empowers marketers with tools that drive efficiency, enhance personalization, and facilitate data-driven decision-making, ultimately improving marketing performance and return on investment and effect on consumer behavior (GEORGE ET AL. 2024).

At current, paying attention to the needs of customers and meeting them is one of the most crucial principles in business world and competition in the market. Therefore, to make a profit and increase revenue, companies must have a correct understanding of consumer behavior and factors affecting their purchase behavior (SUNDARARAJ & REJEESH, 2021). Customers in today's organizations accompany the organizations in the production of goods and services, knowledge development and competitiveness (XHEMA, 2019). Numerous variables may influence customer engagement and change their decisions. A number of these factors will be mentioned below.

Hence, it can be stated can be that in an interactive and dynamic business setting, customer engagement indicates a strategic need to increase the production efficiency of large companies, include increased sales, a stronger advantage over competitors, and profitability. Customer emotions and behavioral interaction positively affect perceived value. Utilitarian value and hedonic value related to consumer’s value perception have significant positive effects on the continuous purchase intention (BIANCHI & ANDREWS, 2018). Also, cognition and emotions as well as behavioral interaction have a direct impact on the continuous purchase intention. Customer interaction can be defined as the psychological process of the customer that leads to loyalty. Social interactions indicate the strength of relationships and the frequency of communication between members of social media (MAJEED ET AL. 2021).

Social interactions between members in the social media space offer a practical and affordable approach to obtaining a range of information or product attributes. Before making a purchase of a certain good or service, the majority of customers would rather get product information and reviews from other customers in order to lower uncertainty and risk. Consequently, word-of-mouth from one consumer can influence other customers more than any company's marketing (YUSUF ET AL. 2018). Because peers are perceived as similar by customers in social groups, trust is a significant factor in the decision to buy (ERKAN & EVANS, 2016). Frequent and beneficial interactions between members of social media help to create positive feelings towards sellers on e-commerce platforms (MUHAMMAD ET AL. 2021). Also, interaction promotes information sharing and better understanding of the needs of the parties and helps to create value for the customer.

According to companies and organizations, customers are no longer the only consumers of goods and services, but they have become partners of these goods and services (DONG, 2015). Customers can offer suggestions for improving services and goods, introduce the company to their acquaintances, communicate with other customers and support a particular brand, and accordingly companies establish long-term and effective communication with their customers, which will have a positive effect on maintaining and increasing customer loyalty and thus affect customers' purchase and re-purchase intention (CHEUNG ET AL. 2021). Also, customer knowledge sharing is a basic concept for many organizations and bridges the gap between what we think and what the customer really wants. This issue leads to superior customer service and increases an organization's ability to achieve the ultimate goal of customer retention and sales growth (PALALIC ET AL. 2021).

Another important factor affecting customer behavior is perceived risk. Risk is an inevitable element in e-commerce and can be considered as the cause of inverse conclusions of a process or project (LI ET AL. 2020). Risk arises from a lack of confidence that is always present throughout the life of the organization. Risk cannot be completely eliminated, but it can be reduced with foresight or properly managed and directed. Therefore, risk can be measured indefinitely (SEO & JANG. 2021). Risk affects many factors involved in trading, for example, on resources, products, services, customers and other partner organizations. It also affects the community and business environments. Customers tend to decrease the risk of purchasing goods or services they receive (ZHANG ET AL. 2020).

Also, perceived information quality is the customer's mental judgment about how a product or service works. Perceived quality is part of the value of a product. With increasing customer perception of quality, customers more likely prefer that product over other products and brands. Product experience, personal needs and consumption situation can affect people's judgment of quality (FU ET AL. 2020). The perceived information quality is valuable to customers by providing a reason to persuade customers to purchase and to differentiate themselves from other brands. In other words, it can be explained that under equal quality conditions, customers perceive more quality than the products they know more and better (TANG ET AL. 2019). Product awareness affects the formation and power of mental association and thus affects the consumer's mental image of all product dimensions, including quality (MAO ET AL. 2020).

Furthermore, although perceived value is acknowledged as a major factor influencing consumer purchasing behavior, it is a subjective concept that depends on several factors that define the unique qualities of various items (PARK ET AL. 2021). The consumer's total opinion of an item or service is known as perceived value. This evaluation is predicated on the consumer's receipt of a good or service and the amount they paid for it. Perceived value primarily represents people's perceptions regarding quality or overall performance, including pricing, in a variety of sectors and academic fields (ALALWAN, 2018).

The value perceived by customers is divided into two types of benefits related to the functional benefits received and the value resulting from emotions. In chasing emotional value, customers focus more on enjoyment than on doing something; thus, their values reflect the amusement and emotions of consuming experiences (LIN ET AL. 2020). Social media are one of the latest advances in information technology as well as a new approach to marketing. Also, unlimited user communication in these media leads to interactions with users. Social media has shifted power away from companies and toward people and communities—that is, innovative users (BIANCHI & ANDREWS, 2018). With the spread of new technologies in the area of electronics in the last decade and the expansion of the use of Web 2 technology, facilities such as social networks have been brought that have caused many changes in life.

Many consumers use new facilities to create, edit, or share content, discuss, and use it to purchase products and services. This paradigm shift has affected the type of communication and the type of business, methods of obtaining information, the ways of making purchasing decisions, etc., and many time and space restrictions have been eliminated in light of social media (PALALIC ET AL. 2021). Researchers think that social media platforms are similar to cyber "coffee shops" in that they allow users to connect and chat with individuals who share their interests. Thus, these platforms make it easier for people to share their knowledge and experiences, the collection of product information, the acquisition of information about consumption activities, and the establishment of social interactions with other members (KIM ET AL. 2019).

Higher user engagement and participation in knowledge sharing through online communities can result in more purchase behaviors. Consumers often share their opinions about products, services, brands, manufacturers and even retailers. As a result, one can consult with these communities for recommendations and advice on options and best prices, and even finding the causes of product failure (GHAHTARANI ET AL. 2019). In general, it can be stated that many factors can affect the customers' purchase intention, and undoubtedly, various dimensions of social media marketing are one of the most prominent of these factors. Each of these dimensions can change a customer's decision to purchase or receive a service.

1.4. Glasser's choice theory

The choice theory was first proposed by William Glasser, the founder of reality therapy and the inspiration for the great thinkers of the 21st century. He showed to all researchers, writers, researchers and advocates that not only do we need to understand why people behave, but we also need to understand how people can learn to control their lives for whatever they want to hold on (EASTERBROOKS & MILLERr, 1997). The choice theory explains that human behavior is based on his or her intrinsic motivations. In his book entitled “Choice Theory”, Glasser states that all of our behaviors are chosen as we continually strive to meet one or more of our five basic needs that are part of our genetic structure (ONEDERA & GREENWALT, 2007).

Choice theory argues that the behaviors we choose play a fundamental role in our existence. Five genetic needs—survival, love and belonging, freedom, fun, and power—drive our behaviors and decisions. Based on Glasser, all human beings have these five basic needs, and if they are met, they will feel in control of their lives and, so they will be satisfied. All human behaviors aim to meet these 5 basic needs that arise from the genetic structure and programming of the human brain during its evolutionary period (OLAWALE ET AL. 2021). A principle of choice theory states: "You cannot force anyone to do what they do not want to do, the only thing you can do is teach him a better way and encourage him to do it." It implies that each person's behavior at any given moment is their best attempt to satisfy their needs, and if this behavior does not achieve its goal, it is because they do not know more effective and efficient ways (MAUZEY, 1998).

According to Glasser, the reason for choosing any behavior is that the behavior (compared to when the person does not choose it) better meets his needs and unwillingness to a behavior is that he does not see this choice in line with meeting his basic needs. In other words, every behavior is an attempt to control the world around us to meet needs, and these behaviors include every choice. We choose all our behaviors, but we have direct access only to the components of action and thought. We can control the components of emotion and physiology indirectly through our actions and thoughts (DANTZLER, 2015).

II. OBJECTIVES TO ACHIEVE

2.1. Research area

The scope of this study is appertaining to microeconomics field regarding to consumer purchase behavior, social networks marketing, and online social platforms.

2.2. Research questions & research objectives

1. What are the strategic factors of consumer purchase behavior regarding social networks marketing?

2. What is the prioritizing of effective factors on consumer purchase behavior regarding social network 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 and sentiment analysis in online social platforms?

- *Main Objective*: Identify, prioritization and modeling of consumer purchase behavior based on social networks marketing and glasser's choice theory.
- *Practical Objective*: The applied objective of the present study is to provide an appropriate and practical model for social networks marketing regarding consumer purchase behavior to consider future research decisions and policies of online businesses.

III.LITERATURE REVIEW

3.1. Social networks marketing

The swift evolution of technology and the exponential expansion of data have fostered an environment where traditional marketing methods are increasingly supplemented, if not supplanted, by advanced analytical tools. Rooted in predictive analytics and optimization algorithms, these tools offer a nuanced understanding of customer behavior, enabling institutions to tailor their marketing efforts with unprecedented granularity. Digital marketing uses digital technologies and media to achieve marketing goals. With the advent of digital media, digital marketing strategies have gained a lot of importance among marketers to reach their target markets and improve their performance (RANA ET AL. 2022).

Traditional marketing is the process of using advertising and other traditional methods to reach customers. This can include TV, radio, print ads, direct mail, and telemarketing. Traditional marketing is often used by businesses that want to reach a large audience quickly and efficiently (SINGH ET AL. 2022). There are several key differences between social media marketing and traditional marketing. Perhaps the most significant difference is that social media marketing is interactive, whereas traditional marketing is not. With social media marketing, businesses can engage with customers and get direct feedback. This is valuable as it can help businesses improve their products or services. Traditional marketing, on the other hand, is not interactive (SHUYI ET AL. 2024).

This means that businesses cannot engage with customers and get feedback. another key difference is that social media marketing is cost-effective, whereas traditional marketing can be expensive. This is because social media marketing does not require a lot of money to reach a large audience. Traditional marketing, on the other hand, can be expensive as it often relies on paid advertising to reach customers. social media marketing can be more effective than traditional marketing in building relationships with customers. This is because social media marketing allows businesses to interact with customers and get direct feedback. Traditional marketing, on the other hand, does not allow for this interaction (MULCAHY ET AL. 2024).

the concept of implementing Social Media Marketing is used to analyze the implementation of Social Media Marketing, namely Content Creation, Content Sharing, Connecting, and

Community Building (HERAWATI ET AL. 2024). Many firms use social media marketing and implement different message frames as a strategy to persuade consumers, enhance engagement, and to purchase their products. Social media plays a vital role in modern marketing with over 91% of U.S. companies using social media platforms to inform, shape, engage, and influence consumer behavior (DENCHEVA, 2023). With an annual growth rate of 9.4 %, and expenditure on social media marketing projected to reach US$3.9 billion by 2027 (STATISTA, 2023), firms are understandably looking for ways to improve the return on their social media marketing investments and to unlock better organizational outcomes (BAEK & YOON, 2022).

Social networks are essential as a means of sharing ideas and information among their users. Social networks become important in the e-commerce, since many users want to know other people's opinions about their product before purchasing or study the experiences of others while using the product (PARSONS & LEPKOWSKA-WHITE, 2018). Virtual space has increased the depth and breadth of information so that the consumer finds a high power of comparison through observation. Also, satisfaction with the received information affects online behavior. Information satisfaction includes information quality, quality of user interaction, and customer security (KIM ET AL. 2020).

Social media have introduced new tools for marketing to improve the efficiency and effectiveness of marketing communications. Social networks have become an important tool for social marketing and have created new challenges for companies on the ways of attracting customers (XHEMA, 2019). Social networks marketing is increasing website traffic or gaining attention to a topic through social media. In other words, any business and economic activity on social media platforms related to marketing goals is called social networks marketing. These goals can include items like increasing the popularity and reputation of the brand, increasing website traffic, attracting customers and ultimately increasing sales of products and services (ZAHAY, 2021). Additionally, social network marketing involves promoting and selling goods and services using websites and social media platforms. On social media, consumers find, research, follow, and buy brands. According to WU (2020), social network marketing is a type of digital marketing that leverages the influence of well-known social networks to accomplish branding and marketing objectives.

3.1.1. Entertainment

Social networks follow various purposes, such as providing information, entertainment, persuasion, as well as transmitting culture to millions of people. There is a need for entertainment and enjoyment since the audience wants to get rid of their immediate worries and preoccupations and experience different forms of pleasure (TSAI & BUI, 2021). The media provide the resources needed to achieve this pleasure. Entertainment is the result of the feeling of joy and pleasure that comes from the experience of being on social media. From a hedonistic point of view, social media users are people who are looking for pleasure and entertainment experience (CHEN & CHANG, 2018). Several studies have identified entertainment as a strong motivation for using social media. Researchers also consider entertainment as a strong motivator for creating content with the help of consumers and stimulating the presence of people on social networks. Users of these media use content related to their favorite brand for entertainment, peace of mind (mental entertainment), and escape from reality (MAJEED ET AL. 2021).

Social media platforms with content that reaches a wide audience are referred to as "creative outlets." Among these are services that encourage people to share their hobbies, creative endeavors, and enjoyment with one another. Take, for instance, Flickr, Pinterest, Instagram, YouTube, and Foodily, which are all platforms for sharing recipes and videos. Individuals exchange online recipes, funny movies they've prepared, and pictures they've taken using creative media with people who share their interests (BIANCHI & ANDREWS, 2018). On the website, users may search, follow the content of those they find most interesting, and exchange ideas with one another. People are connected by their creative outlets on this kind of social media, which also gives users a purposeful outlet for their creativity and offers visually appealing material and amusement to its followers.

3.1.2. Customization

The majority of social network services are profile-based and comprise personalized messaging. It encompasses mobile apps like Whatsapp and Line as well as media services like Facebook and LinkedIn. These networks function similarly to phone conversations, emails, and family Christmas letters, with individualized greetings for an individual or small group of pals (SCHLAGER ET AL. 2018). The degree to which a service is tailored to an individual's needs and preferences is referred to as the level of customization. By personalizing their sites and channels in virtual networks, companies can receive stronger responses from their users (LEVESQUE & BOECK, 2016).

For example, based on customization of messages, there are two types of posts / messages: customized and extensive. The customized type (such as Facebook posts) targets a specific person or a small audience (for example, leaving a comment for a friend or sending an update to a closed community of friends). An extensive post (e.g. Twitter tweets) contains messages that anyone can be its audience (e.g., Twitter account posts published by The Wall Street Journal, President Obama, or other celebrities) (MADHAVARAM ET AL. 2021).

Customization is a context in which organizations can enable their customers to search for customized information and services through social networks (Kim & Ko, 2012User satisfaction in social network marketing may be attained by aligning the objectives, procedure, and content of the marketing to the demands of consumers when they use social media. It is essential for marketers to recognize and comprehend the demands and motives driving people's use of social media in order to create a marketing strategy and relevant advertising attractions (Zhang et al., 2021). This problem makes it possible for marketers to use social networks to meaningfully and personally interact with their target audience. Customization in the context of social media refers to the target audience for communications that users upload (ANSHARI ET AL. 2019).

3.1.3. Interaction

With the expansion of social media communication, people social interaction has also been extended to virtual space, and virtual communication is a major part of the reasons for users to use this space. Social networks play a major role due to their unique capabilities and abilities such as informing, strengthening the expanding communication between people, mobilizing power in various social, cultural, political and other areas (BIANCHI & ANDREWS, 2018). Accordingly, social network refers to a group of people who communicate with each other as a group and share information such as information, needs, activities and thoughts. Social networks influences the daily life of people in the community. For this reason, people increasingly turn to their virtual communities on social networks to obtain the opinions of others. The Internet and information technology have provided a new opportunity for consumers to share their evaluations of various products online (CHEUNG ET AL. 2021). Social networks are a type of media emerged after mass media and allow interaction between the producer of the message and social networks as the recipient. It means that in these networks, the audience and or the recipient of the message is not passive and interacts dynamically and actively with the sender of the message, and has the ability to make changes in the sent message and republish it to other people, and can republish a message combined with his thoughts and intellectual teachings (ONOFREI ET AL. 2021).

Social networks have provided marketers with new tools to increase the efficacy and efficiency of marketing messages, as well as new strategies for attracting and keeping consumers. Social media is an online platform that individuals use to exchange thoughts, experiences, views, and other information, as well as profiles and comments. As a result, social media makes it easier for people to communicate and engage online in groups (MAJEEED ET AL. 2021). In other words, social media bridge the gaps in the market between customers and businesses, and bring consumers and businesses to the negotiating table for a personal conversation. Social media has moved power away from companies and toward people and communities—that is, innovative users (CAMBRA-FIERRO ET AL. 2021).

With the expansion of electronic communication channels and the increasing number of users of these media, the physical boundaries have disappeared. Social networks are online platforms. They are very easy to use and the audience can be accessed quickly through them. Therefore, they have been widely used in the areas of environment, politics, technology and entertainment (CAMBRA-FIERRO ET AL. 2021). A high percentage of Internet users trust the evaluation of consumers' statements and opinions on social media about corporate products. Hence, companies are no longer the only source of information about brand. Social networks have facilitated consumers' communication with each other (PARAMITA ET AL. 2021). Social networks fundamentally changes the interaction between brands and customers. Customer interaction is an important motivating factor for producing content with the help of users. Social networks can help consumers have a space to discuss and exchange ideas. Social interaction describes users who appear on a brand-related social networks platforms to interact with others and talk about products or brands (CHEUNG ET AL. 2021).

Researchers categorize social media into two groups based on the type of interaction and communication: content-based and profile-based. Individual users are the main focus of profile-based social media. The primary goal is to inspire media consumers to establish a connection with these particular themes, which are relevant to the members. Social media platforms with profiles, including Facebook, Twitter, and WhatsApp, promote communication. Social media platforms that are content-based, including YouTube, Flickr, Instagram, Pinterest, and Pinterest, concentrate on material and comments made on sent content. The main goal for users is to connect with content that has been prepared with a specific profile and according to their interests (ONOFREI ET AL. 2021).

3.1.4. Word of mouth (WOM) and electronic word of mouth (eWOM

Gaining an advantage over competitors with WOM advertising is possible in a setting where trust in organizations and advertisements has decreased. WOM is characterized as an unofficial channel of communication concerning the features of a company or item that is exchanged within a community (YUSUF ET AL. 2018). With regard to knowledge and norms, WOM enables an individual to impact the assessment and purchase intentions of comparable customers. WOM marketing is more valid than other marketing techniques because they know that there is no benefit to them in this approval (CHANG ET AL. 2020).

The effectiveness of WOM comes from three key factors. The first is customer communication that is an important factor in WOM. Many conversations with family or friends lead to their support for certain behaviors. Second, unlike one-way communications, such as commercials, WOM, the customer employs a two-way flow. Third, in WOM, the customer has a vicarious experience. It means that people who talk about products and services have experienced that product or service themselves. Thus, the characteristics of the information source are like being an expert in a field, and on the other hand, its similarity with the recipient of information is important in the level of influencing (ZHAO ET AL. 2020). WOM can be positive or negative. Positive WOM includes good and bad recommendations that people give to others about products, services or brands, but negative WOM is considered as one of the forms of consumer complaints and includes negative recommendations that people give each other about products, services and brands (BASTOS & MOORE, 2021).

WOM is more important in the final stages of the purchasing process, since it reassures the consumer and reduces doubts. Therefore, WOM is recognized as one of the main factors in reducing the risk of purchasing a product (MISHRA ET AL. 2021). Also, the effectiveness of information depends on the compatibility of the sender's mental image with the personal perception of the recipient of the information. This type of communication is also one of the most important sources of personal information for consumers to make decisions. Due to the changing marketing environment, finding alternative ways to create an audible voice is essential, and WOM is a very powerful phenomenon for starting and stopping businesses (SEO & JANG, 2021).

The phenomenon of WOM is a substitute for experience. WOM is the consequence and basis of customer retention, and loyal customers are more willing to create positive verbal communication and act as a proponent of the brand for the company. WOM is also considered the exchange of views, ideas or opinions between two or more consumers, neither of which is a source of marketing (WANG ET AL. 2021). Key factors affecting WOM include: 1. Personal factors: reliable source, credibility, idea leadership, experience, previous perceptions of the institution. 2. Interpersonal factors: power requirements. 3. Message characteristics: message clarity, message delivery power, non-verbal communication. 4. Situational characteristics: low product / position risk, low service complexity / multiple separate resources, lack of information recipient, etc. (LIU ET AL. 2021).

WOM is a face-to-face communication between the receiver and the sender. In this regard, the recipient receives the name and brand of the product or service information from non-commercial channels. The main components of WOM marketing, according to the Global Institute of WOM Marketing Association, are a- Giving the necessary training to people about products and services. B. Identifying people who we think are more likely to share their views with others. C) Providing mechanisms that will facilitate the sharing of information by the public people. D- Necessary investigations of how, where and when people views are shared. F- Listening to the statements of supporters, slanderers and neutral people and providing a proper response to them (SEO & JANG. 2021).

Electronic word-of-mouth (eWOM) refers to the sharing of opinions, experiences, and recommendations about products and services through online platforms. It has emerged as a powerful driver of consumer decision-making. Social network centrality and density significantly influence individuals' engagement in eWOM activities (ANASTASIEI ET AL. 2023). Those with higher centrality are more likely to initiate and participate in eWOM conversations, as their opinions carry more weight within the network. Additionally, the density of a social network enhances the reach and impact of eWOM messages, as information spreads rapidly among densely connected individuals (PARK ET AL. 2021). Moreover, established authors (HUETE-ALCOCER, 2017) found that there is a notable difference between the concepts of WOM and eWOM because WOM is based on the credibility between two participants who know each other a priori, while in the case of eWOM, the interaction takes place between participants who know each other very little or not at all.

Positive e-WOM: Positive electronic word-of-mouth (eWOM) is an increasingly important area of research in marketing, as it plays a crucial role in shaping consumer opinions and behaviors. Positive eWOM refers to positive comments, reviews, recommendations, and other forms of electronic communication that consumers share about products or services through social media platforms, online review sites, forums, and blogs (KHOA, 2022). In the literature, it is considered that eWOM is a very relevant component because the ideas and answers published in online media are the results of rational thoughts and not the result of a passing emotion. Positive e-WOM is a form of online communication where consumers share their positive experiences with a particular product, service, or brand. It is a powerful tool that can significantly influence consumer behavior and drive sales (SHABBIR-HUSAIN & VARSHNEY, 2022; BONIFAZI ET AL. 2023).

However, it is important to note that positive e-WOM is not always genuine. Companies may engage in astroturfing, a practice where they create fake positive reviews to manipulate consumer perception (AHMED ET AL. 2019). This can ultimately backfire and harm the brand's reputation. Therefore, it is important for companies to encourage genuine positive e-WOM through exceptional customer service, high-quality products, and ethical business practices. Companies can also incentivize consumers to share their positive experiences through referral programs or social media campaigns. Positive e-WOM is a powerful tool that can significantly influence consumer behavior and drive sales (WU & QIU, 2023).

Negative e-WOM: Negative e-WOM refers to the online communication of consumers' negative or unpleasant experiences with a particular product, service, or brand. It is a form of negative feedback that can affect a company's reputation and ultimately its sales (HANCOCK ET AL. 2022). There are several reasons why people choose to share their negative experiences online. One of these is the lack of other feedback options. People may want to share their experience with a product or service with others but do not have a direct way to do so (BIGNE ET AL. 2023). In these cases, posting a comment online may be the only option. Posts have a major impact on both merchants and the user community from different fields. Another reason is that people believe that their negative feedback can help other consumers make a better decision (NAM ET AL. 2019). By sharing their negative experience, they hope to prevent other consumers from making the same mistake. However, negative e-WOM can have a negative impact on companies and brands. Some studies showed that an increase in negative feedback can lead to a significant decrease in sales. Negative feedback can affect a company's reputation and lead to a loss of consumer trust in its product or service (ZHANG ET AL. 2019; ANASTASIEI ET AL. 2023).

3.1.5. Trend

The importance of social networks and their pervasiveness is clear anyone. For this reason, marketers and companies are always looking for marketing through these networks. In all virtual networks, including Facebook, Instagram, YouTube and LinkedIn, we face the phenomenon of pervasiveness (YANG ET AL. 2008). Many people who have become famous through this way. In this regard, some even earn money through this way. However, it requires high social intelligence and creativity, since to be pervasive, people's tastes should be identified and at something should be offered that is not easy to find. Timing is also a crucial issue that should be considered.

Paying attention to the trend of the day is crucial in digital marketing strategy, since if attractive and useful content is produced based on it, it will attract many audiences and develop the business (VERCELLI, 2016). Public marketing trends help manufacturers communicate effectively with their audience. Cases such as exclusive social networks, stories, videos, social media sales, user-generated content, messaging, influencer marketing and customer service are some of the trends of the day in the world of social media. During a crisis, marketing trends may help firms stay flexible in their strategic marketing plans and avoid being negatively impacted by emerging and unpredictable paradigms (KIM & KIM, 2020).

3.2.industry revolution in marketing to 0.4

People would always use the technology they had available to help make their lives easier and at the same time try to perfect it and bring it to the next level. This is how the concept of the industrial revolution began. Right now, we are going through the fourth industrial revolution, aka Industry 4.0, where we are witnessing the rise of tech & web design companies (SETYAWATI ET AL. 2023). Steam propelled the original Industrial Revolution; electricity powered the second; preliminary automation and machinery engineered the third; and cyberphysical systems—or intelligent computers—are shaping the Fourth Industrial Revolution. Before 2014, the Google search term “Industry 4.0” was practically nonexistent, but by 2019, 68 percent of respondents to a McKinsey global survey regarded Industry 4.0 as a top strategic priority. Seventy percent said their companies were already piloting or deploying new technology (TAGHAVI ET AL. 2023). Fourth industrial revolution builds on the inventions of the Third Industrial Revolution—or digital revolution—which unfolded from the 1950s and to the early 2000s and brought us computers, other kinds of electronics, the Internet, and much more. Industry 4.0 brings these inventions beyond the previous realm of possibility with four foundational types of disruptive technologies (examples below) that can be applied all along the value chain (RATHORE, 2023, 2022):

- connectivity, data, and computational power: cloud technology, the Internet, blockchain, sensors
- analytics and intelligence: advanced analytics, machine learning, artificial intelligence
- human–machine interaction: virtual reality (VR) and augmented reality (AR), robotics and automation, autonomous guided vehicles
- advanced engineering: additive manufacturing (such as, 3-D printing), renewable energy, nanoparticles

After the product-centric marketing 1.0 and the customer-centric marketing 2.0, the marketing 3.0 is both more human and more digital. It seeks to place values at the center of the brand, notably by developing content marketing to talk about mission, ecology, commitment, CSR… It no longer talks to customers but to men and women. It no longer targets a market but addresses a society that is committed, creative and in search of meaning (SETYAWATI ET AL. 2023).

Marketing 3.0 also prefigures the advent of marketing 4.0: it uses digital technologies to convince the customer in a less intrusive way than with traditional advertising, in particular by implementing a content strategy (inbound marketing). Marketing 4.0 simply goes further, leveraging more data to predict consumer behavior and deliver a more personalized experience (NAYAL ET AL. 2024).

Marketing strategy professor Philippe Kotler has been an authority in the field for over 50 years In his recent textbook “Marketing 4.0 – The Digital Age”, prefaced by Professor Pierre Volle, he describes the many digital innovations that have taken marketing into a new dimension in just a few years. Marketing can be classically defined as a set of sales techniques implemented by a company to market its products and services to a defined market. Any marketing strategy requires studying consumer behaviors to influence their purchases and develop sales. The specificity of marketing 4.0 is that it uses the new technologies of the digital world to better understand consumers’ decisions. It uses tools such as Big Data (processing of voluminous data), CRM (customer relationship management) and marketing automation (automation of marketing campaigns) (CHATTERJEE ET AL. 2022).

Marketing 4.0 takes into account not only the development of technologies but also the evolution of customers’ consumption habits, more informed and more demanding. Today’s consumer is more socially responsible but also more connected. He can use social networks to support a product or to denigrate it (NAYAL ET AL. 2024). The customer’s buying journey is becoming more complex than before: they can now ask questions on blogs and forums, or address the brand directly using social networks. In this context, new generation marketing proposes innovative methods to reach the consumer. It focuses on the customer experience by activating numerous digital levers to seduce them, convince them and anticipate their behavior: local referencing, content marketing, predictive algorithms, e-reputation (NAYAL ET AL. 2023)

The primary characteristics of digitization, such as ubiquity, localization, accessibility, and personalization, have impacted small, medium, and large businesses. These characteristics have changed organizations' distribution, promotion, and marketing research processes (DASH ET AL. 2021). In addition, the increased digitization has disrupted or created many marketing models or platforms. Simultaneously, these characteristics have also influenced consumer behavior. Consequently, consumers are searching and shopping online for products and services. During this transitional phase, a new holistic approach known as Marketing 4.0 has come to the rescue. Marketing 4.0 investigates the digital methods for understanding, reaching, satisfying, and retaining customers by establishing effective relationships. In Marketing 4.0, brands become more flexible and adaptive to emerging technological changes to satisfy their consumers (KOTLER ET AL, 2019; KOTLER ET AL. 2016; DASH ET AL. 2023).

3.3. Some Technology Acceptance Models/Theories Affecting on Customer Behavior

Research community accelerated its interest towards technology acceptance in the private and organisational contexts almost three decades ago. By 2000, technology acceptance research had resulted in a substantial body of evidence on user behaviour related to technology (NG, 2020). Numerous models/theories had been introduced to understand the acceptance of the technology, which cumulatively explained 40% of the variance in technology use intention (ARASU ET AL. 2020). The models had roots in different disciplines, which limited the applications of these theories to certain contexts. For example, the Theory of Planned Behaviour and the Theory of Reasoned Action offer a psychological perspective on human behaviour by examining the variables, such as perceived behavioral control, attitude and subjective norms (AJZEN, 2011). The theories provide generic insights into individuals' attitudinal underpinnings, which make them applicable to a wide range of research contexts, not limited to information system management (LIU ET AL. 2022). In contrast, Diffusion of Innovation Theory focuses on innovation-specific factors that determine users' behaviour when it comes to new technology adoption. In addition, the models had different perspectives, reflecting the type of variables in the model, such as subjective norm, motivational factors, attitudinal factors related to technology performance, social factors, experience and facilitating conditions (HARYANTI & SUBRIADI, 2020). The selection of either of the models constrains research findings to particular scenarios and conditions. Therefore, a unified approach was needed to embrace variables reflecting different perspective and disciplines and increase the applications of the theory to different contexts (VENKATESH ET AL. 2003). To provide a holistic understanding of technology acceptance, Venkatesh et al. set the objective for developing a unified theory of technology acceptance (UTAUT) by integrating key constructs predicting behavioural intention and use (VENKATESH ET AL. 2003).

Given that the theories stem from different disciplines, they cast diverse perspectives on technology acceptance and adoption. The socio-psychological perspective on research on individual behaviour was represented by the Theory of Reasoned Action (TRA), the Theory of Planned Behaviour (TPB) and Social Cognitive Theory (SCT). Based on TRA and TPB, individuals' behaviour is measured by the effect of attitude toward behaviour, subjective norm and perceived behavioural control on behavioural intention (AL-EMRAN, 2023). The theories are used in IS management to explore the role of a perceived difficulty in performing the task, the effect of group norms and attitude on accepting. TRA contributed greatly to IS acceptance theories, by providing a theoretical framework that explained human behavior (COPELAND & ZHAO, 2020). SCT is based on the assumption that behavioural, cognitive and environmental factors (i.e. outcome expectations-performance, outcome expectations-personal, self-efficacy, affect and anxiety) have an interactive effect on individuals' behaviour. The theory has been used to investigate human-computer interaction (LIM ET AL. 2020). The acceptance of technology from the vantage point of IS management was largely explained by Technology Acceptance Model (TAM), combined TAM and TPB model (C-TAM-TPB), Innovation Diffusion Theory (IDT) and the model of PC utilisation (MPCU). While TAM and C-TAM-TPB stress the importance of cognitive response to IS features in predicting behaviour, IDT focuses on system characteristics and properties in determining the adoption of innovation (e.g. relative advantage, complexity, compatibility, image). MPCU has very narrow implications, as the model encompasses the factors underpinning the utilisation of personal computers (i.e. job fit, complexity, long-term consequences, affect towards use, facilitating conditions and social factors), unlike other theories examining IS and innovation adoption. The behavioural psychology perspective on technology acceptance was represented by the Motivational Model (MM), suggesting that technology adoption and use behaviour can be explored through user motivations. Users tend to evaluate the likelihood of engaging in behaviour by the degree to which behaviour stimulates instrumental rewards (extrinsic motives) and/or internal reinforcement, such as enjoyment, satisfaction and fun (intrinsic motives) (ASGHAR ET AL. 2023).

3.3.1. UTAUT(Unified Theory of Acceptance and Use of Technology) Model

UTAUT (Unified Theory of Acceptance and Use of Technology) is a model from business informatics that measures the acceptance of an innovation by users in order to gain access to individual usage behavior. This is done by evaluating four influencing factors: performance expectation, effort expectation, social influences and facilitating circumstances. From this, measures for the development and communication of the innovation can be derived (DONMEZ-TURAN, 2020). the study of Venkatesh ET AL. (2003), designed, invented and proposed a model, called the unified theory of acceptance and use of technology (UTAUT) (Al-QAYSI ET AL. 2018). And it was ultimate model that combines what one knows and offers a base to guide future study. It aims at explaining the users' intention to use an interactive system conventional behavior. UTAUT Model conprising four core determinants of intention and usage (Al-RAHMI ET AL. 2020). The determinants variable are effort expectancy, performance expectancy, social influence and facilitating conditions. UTAUT model also identified another four moderator variables (Gender, Experience, Age, and voluntariness of use. The UTAUT model is illustrated in Figure 4.

The theoretical model of UTAUT suggests that the actual use of technology is determined by behavioural intention. The perceived likelihood of adopting the technology is dependent on the direct effect of four key constructs, namely performance expectancy, effort expectancy, social influence, and facilitating conditions. The effect of predictors is moderated by age, gender, experience and voluntariness of use (VENKATESH ET AL. 2003).

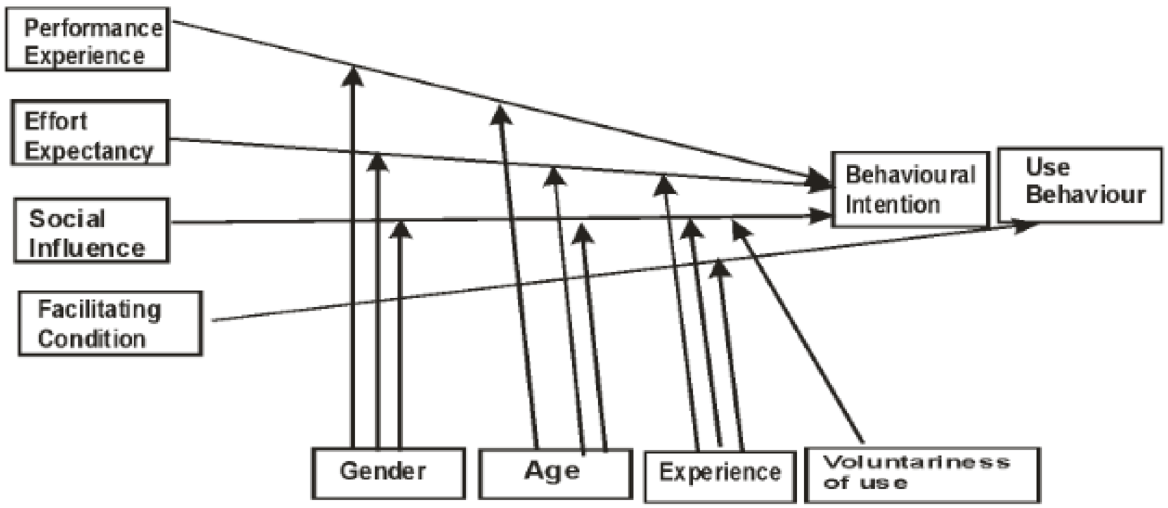

Figure 4. Unified Theory of Acceptance and Use of Technology (UTAUT)

Source: Venkatesh, et al (2003)

at using the system will help him or her to attain gains in job performance" (VENKATESH ET AL. 2003). Performance expectancy is based on the constructs from Technology Acceptance Model (TAM), TAM2, Combined TAM and the Theory of Planned Behaviour (CTAMTPB), Motivational Model (MM), the model of PC utilisation (MPCU), Innovation Diffusion Theory (IDT) and Social Cognitive Theory (SCT) (i.e. perceived usefulness, extrinsic motivation, job-fit, relative advantage and outcome expectations). It is the strongest predictor of use intention and is significant in both voluntary and mandatory settings. Effort expectancy is defined as "the degree of ease associated with the use of the system". Effort Expectancy is constructed from perceived ease of use and complexity driven from TAM, MPCU, IDT, which share a similarity in definitions and scales. The effect of the construct becomes nonsignificant after extended usage of technology (SAMARTHA ET AL. 2022).

Social Influence is defined as "the degree to which an individual perceives that important others believe he or she should use the new system". Social influence is similar to the subjective norms, social factors and image constructs used in TRA, TAM2, TPB, CTAMTPB, MPCU, IDT in the way that they denote that the behaviour of people is adjusted to the perception of others about them. The effect of social influence is significant when the use of technology is mandated In the mandatory context, individuals might use technology due to compliance requirement, but not personal preferences. This might explain the inconsistent effect that the construct demonstrated across further studies validating the model (VENKATESH ET AL. 2003; TANEJA & BHARTI, 2022).

Facilitating conditions is defined as "the degree to which an individual believes that an organisation's and technical infrastructure exists to support the use of the system". The facilitating conditions construct is formed from compatibility, perceived behavioral control and facilitating conditions constructs drawn from TPB, CTAMTPB, MPCU and IDT. Facilitating conditions have a direct positive effect on intention to use, but after initial use, the effect becomes nonsignificant. Therefore, the model proposes that facilitating conditions have a direct significant effect on use behavior. The moderation effects of age, gender, experience and voluntariness of use define the strength of predictors on intention. Age moderates the effect of all four predictors. Gender effects the relationships between effort expectancy, performance expectancy and social influence. Experience moderates the strength of the relationships between effort expectancy, social influence and facilitating conditions (VENKATESH ET AL. 2003; MARIKVAN & PAPAGIANNIDIS, 2023).

Voluntariness of use has a moderating effect only on the relationship between social influence and behavioral intention. UTAUT has made several contributions to the literature. The model provides empirical insight into technology acceptance by comparing prominent technology acceptance theories, which often offer competing or partial perspectives on the subject. UTAUT demonstrates that proposed factors account for 70 percent of the variance in use intention, offering stronger predictive power compared to the rest of the models that examine technology acceptance. The interactive effect of some constructs with personal and demographic factors demonstrates the complexity of the technology acceptance process, which is dependent on individuals' age, gender and experience (VENKATESH ET AL. 2003; MARIKVAN & PAPAGIANNIDIS, 2023).

3.3.2. Ajzen's Theory of Planned Behavior (TPB)

AJZEN (1991), proposed the Theory of Planned Behavior (TPB) wherein the individual's behavior is best predicted by one's intentions; intentions are, in turn, predicted by attitudes about the behavior, the subjective norms (a person's perception of important others' beliefs that he or she should or should not perform the behavior) encasing the execution of the behavior, and the individual's perception of their control over the behavior Ajzen's TPB has been used to predict many different behaviors ranging from gambling behaviors to the use of hormone replacement therapy (CHEN & HUNG, 2016). The Theory of Planned Behavior (TPB) predicts that planned behaviors are determined by behavioral intentions which are largely influenced by an individual's attitude toward a behavior, the subjective norms encasing the execution of the behavior, and the individual's perception of their control over the behavior (RUANGKANJANASES ET AL. 2020). Ajzen's theory has been used to predict an array of behaviors (MARTIN ET AL. 2010; QUINE & RUBIN, 1997; STONE ET AL. 2010). AJZEN's Theory of Planned Behavior was recently applied to social networking. BAKER & WHITE (2010), conducted a study examining the use of the Theory of Planned Behavior to predict adolescents' use of social networking. A questionnaire was given to 160 students that measured the components of Ajzen's theory and then they were asked to return a week later to report their social networking site use in the preceding week. Their study found support for the TPB's components of attitude, perceived behavioral control, and group norms in predicting intentions to use social networking sites. They then found support that intentions predict behavior (CHEN ET AL. 2021).

The TPB (Fig. 5) was developed out of the theory of reasoned action (TRA) (AJZEN 1991), which was originally proposed by FISHBEIN & AJZEN (1975). The TPB, proposed by Ajzen (1991), adapts the TRA by adding perceived behavioral control (PBC) to allow the model to more accurately explain variations in behavior that is not entirely voluntary (SUN & WANG, 2019). An individual develops a positive or negative attitude towards a behavior based on their behavioral beliefs, perceives subjective norms about the behavior based on their normative beliefs and gauges PBC based on their control beliefs (AJZEN 1991, 2006). Attitude, subjective norm and PBC influence behavioral intent (BI). Behavioral intent was used as a predictor of actual behavior, as BI indicates how much effort an individual is willing to put into performing a behavior, and therefore, the stronger the intention to perform the behavior, the more likely the behavior is to be performed (AJZEN 1991, 2006). for example, the TPB states that the more positive the attitude towards Facebook advertising, the more peers are perceived to encourage the behaviour (subjective norms), and the greater the individual's perception that they are free to engage or not with the advertising (perceived behavioral control), the stronger the intent to engage with Facebook advertising (behavioral intent), which will in turn predict the actual performance of the behavior to comment, like or share the advertisement (behavior)

(CHEUNKAMON ET AL. 2020). Since it was developed, the TPB has been used successfully in various contexts to understand and predict human behavior. It has been shown to be generalisable to most contexts. Interestingly, depending on the context the TPB was applied to, attitude, subjective norm and PBC had varying influences on BI, with some being stronger influencers than others (SANNE & WIESE, 2018).

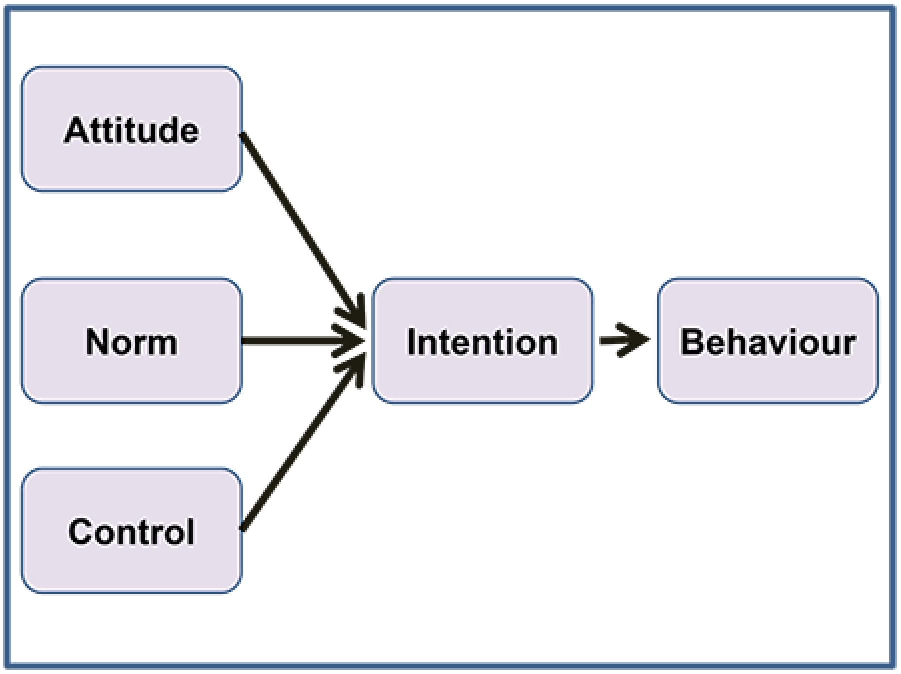

Figure 5. Theory of Planned Behaviour (Ajzen, 1991)

3.3.3 Technology Acceptance Model (TAM) in marketing

The technology acceptance model (TAM) is a theoretical framework developed by Fred Davis in the late 1980s (DAVIS, 1989) that explains why people accept or reject a new technology (NA ET AL. 2022). The TAM's framework profoundly influences researchers and practitioners to understand user behavior for technology acceptance. The TAM has become more comprehensive after including external factors and social-psychological influences in different contexts (VUKOVIC ET AL. 2019). The main goal of technology acceptance theory is, to explore the factors that influence the adoption and diffusion of new technologies throughout a social system. Focused on user-centric technology design, TAM has gained popularity with its diverse applications in software development, online learning platforms, and other virtual environments (ZAINELDEEN ET AL. 2020). It enhances experiences and promotes successful adoption of new technologies. This model describes the cognitive processes forming our technological choices, enabling a pathway to boost wider acceptance of new innovations. The technology acceptance model (TAM) (DAVIS, 1989) consists of three dimensions, i.e., (i) perceived ease of use, (ii) perceived usefulness, and (iii) intentions to use. The TAM model is illustrated in Figure 6.

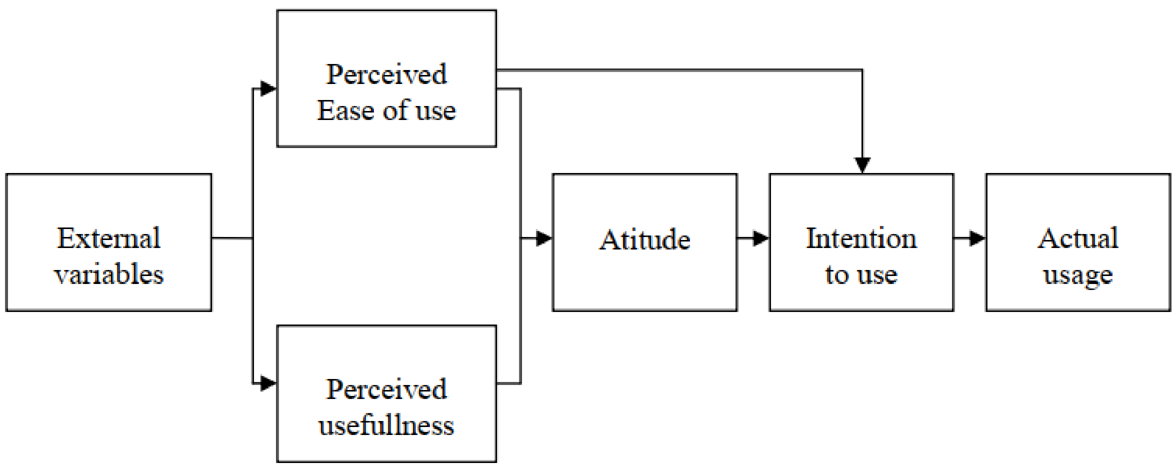

Figure 6. Original Technology Acceptance Model

Perceived ease of use (PEU): PEU indicates the level of comfort associated with utilizing social network platforms (MAGSAMEN-CONRAD ET AL. 2020). The impact of information technology on human life is immense, and its significance in marketing remains indisputable. This trend underscores the role of social media tools in facilitating convenient information access, thereby fostering positive intentions among customers (VUKOVIC ET AL. 2019).

Perceived usefulness (PU): Perceived usefulness defines the level at which scholars believe using social networks will help maintain their activities (JACOB & PATTUSAMY, 2020). In the last few years, social media has spread across the globe. Being a substantial and integral part of today's everyday life, many people, especially on online social networks, have fundamentally changed their communication behavior. Unfortunately, not everybody is integrated into this "new everyday life" yet. This is the reason that customers' perceived usefulness of social media influences their intentions toward social media-based purchase (LIU ET AL., 2022).

Intentions to use (INT) : Intentions involve predicting certain behaviors, such as using social media for purchase (ASGHAR ET AL. 2021). The application and usefulness of social media extend to resource sharing and interaction with others beyond physical boundaries (ASGHAR ET AL. 2022).

3.3.4. diffusion of innovation theory (DoI)

The diffusion of innovation theory (DoI) has been widely used to investigate factors that influence an individual's decision to adopt an innovation or a new technology (HO ET AL. 2020). The DoI model suggests that individuals would only choose to adopt a technology if it presents five characteristics: relative advantage (RA), compatibility (CO), complexity (COM), observability (OB), and trial ability (TR). Given that today the competitive pressure among industries has increased; therefore, competitive pressure may be influenced by some elements such as technological development, globalization and prompt scattering of new technology (MEHRA ET AL. 2020). to affect the industrial structure of the companies, it is useful to accept innovations. This vision, in turn, might alter the way in which competing operates in the industry and gives a competitive advantage to the organization that chooses to take it up (SUN ET AL. 2020). Less time to market, lower costs for products and product development, more creative production ideas and increased product adoption are some of these benefits. Increased market share and higher revenues is, in turn, the outcomes of these improvements for the companies (YUEN ET AL. 2020).

3.3.5. Theory of Reason Action (TRA) in marketing

The Theory of Reasoned Action (Fig. 7) was initiated by Ajzen and Fishbein (1980), this teory was developed to explain how a consumer leads to a certain buying behavior and structured using the basic assumption that humans behave in a conscious way and consider all available information (EVANS ET AL. 2009). The desire is determined by two independent variables, namely their attitude and subjective norms. It can be said that attitudes will affect behavior through a careful and reasoned decision-making process and will have a limited impact on three things (AHMAD, 2014). First, attitudes that are carried out towards behavior are based on attention to the results that occur when the behavior is carried out. Second, the behavior carried out by an individual is not only based on views or perceptions that are considered correct by the individual, but also pays attention to the views or perceptions of others who are close to or related to the individual. Third, attitudes that arise are based on the views and perceptions of individuals, and paying attention to the views or perceptions of others on the behavior, will lead to behavioral intentions that can become behavior (NG, 2020).

Attitudes defined as a feeling that is believed to be a positive or negative expression in relation to the achievement of an objective. If people believe that performing a behavior will lead to mostly positive outcomes then they will hold a favorable attitude (YADAV & PATHAK, 2016). Contarary, a person who believe that performing a behavior will produce mostly negative outcomes, then they will have an unfavorable attitude. For example, if people express their desire to carry out an activity, then that person is more likely to do it than people who don't say what they want (COPELAND & ZHAO, 2020).

Subjective norms are individuals' opinions about how people around them perceive the behaviour to think whether they should or should not perform the behavior. A person who believes that most referents with whom they are motivated more to comply think, that they should perform the behavior will receive social pressure to do so (RANA & PAUL, 2017). It can be concluded, that a person's behavior has something to do with subjective attitudes and norms. The greater support of subjective attitudes and norms, the stronger a person's desire to do something. In addition, a person's beliefs when liking or disliking an action and supported by their perception of the expectations of the people around them for the action can form a person's interest in carrying out the action (KUMAR ET AL. 2023).

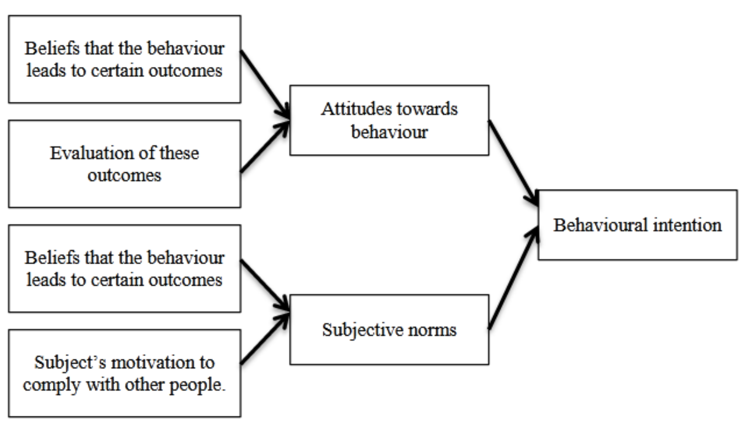

Figure 7. Theory of Reason Action (Fishbein & Ajzen, 1975; Ajzen & Fishbein, 1980)

3.4. Components of consumer behavior affected by social networking

Consumer behavior encompasses the knowledge, feelings, and behaviors people have while making purchases and engaging in other process of consumption. It also encompasses elements of the surroundings that influence behavior, feelings, and knowledge. As previously said, consumer behavior is dynamic since it is subject to continuous changes in information, attitudes, sentiments, and actions on a societal and individual level (ZHU ET AL. 2020). Developing a marketing strategy is challenging due to the ever-changing nature of consumer behavior. To understand consumer behavior, understanding the mental structure of the consumer is crucial, especially when consumers in the market are faced with a wide variety of brands with different prices and qualities. Companies need to know consumers and their purchasing decision processes before developing their marketing policies.

Understanding the factors influencing a consumer purchasing decision and understanding the general processes through which individuals behave, and ultimately understanding the decisions they make, is a key step in creating marketing plans and ultimately gaining a competitive advantage (XHEMA, 2019). Several factors affect consumer intentional behavior, including consumers' attitudes and subjective norms about the product, service, and brand. Hence, it is vital for a company to change and influence the way people think about the brand. Consumer behavior includes interactions between thoughts and feelings and human and environmental behavior (SUNDARARAJ & REJEESH, 2021).

In the field of marketing research, purchase intent and purchase behavior have long been popular. The potentiality, or mental capacity, of a customer to buy a specific product is known as the purchase intention. Merely concentrating on making purchases is insufficient to handle a dynamic market environment given the growth of the Internet economy and the popularity of B2C and B2B platforms (LIM ET AL. 2016). Social media influences the lives of consumers. People are increasingly turning to their communities and social media channels to obtain opinions and feedback before purchasing. An important factor in strategic marketing and advertising situations is the correct understanding of how the consumer makes decisions. Therefore, one of the key responsibilities of marketers is to research and understand customer demands, as well as to analyze and prioritize the elements that influence the behavior of customers. A person's decision to engage in an action is reflected in their mental state, which is known as behavioral intention. Consequently, deeper comprehension of customer behavioral intents helps marketers improve and enhance their communication with their intended target groups (LI ET AL. 2020).

3.4.1. Consumer engagement (CE)

The use of social networks in the area of marketing is growing increasingly, and social networks provide the conditions for socialization of virtual space for consumers by creating the necessary social context. Also, by creating interaction between people, the possibility of purchasing experience in the virtual space for individuals provide a space different from the real world (CHEUNG ET AL. 2021). When consumers buy goods or services, they focus more on what they consider to be worth it, which is established by dealing with vendors (i.e., firms). As a result, improved communication between clients and companies is crucial (WANG & HUANG, 2022).

Customers and companies no longer only have straightforward commercial connections; instead, service-dominant (S-D) and relationship marketing paradigms are evolving, and the idea of "customer engagement" is taken into consideration in this context. Extensive studies have been conducted in the literature to date on the ideas and aspects of customer engagement, most of which are based on theory rather than practical experience. For instance, "establishing in-depth relationships with customers to drive purchase decisions, interaction, and participation" is the definition of customer engagement (RAHMAN ET AL. 2018). Empirical studies on consumer interaction to date have mostly been carried out to identify and validate predecessors and their implications. MARBACH ET AL. (2016) examined how customer participation increases the perception of value. The majority of academics believe the results of consumer engagement might include things like satisfaction, loyalty, trust, attachment, brand relationships, etc. These elements may positively impact consumers' continuous usage behavior, according to a number of studies (PRENTICE ET AL. 2019).

Back in the seventeenth century, the word "engagement" was used to refer to a variety of ideas, such as duty, employment, betrothal, moral or legal responsibility, and/or military conflict. In fields like psychology, sociology, political science, and organizational behavior, the word "engagement" has gained widespread usage throughout the past 20 years (SANTINI ET AL. 2020). Sociologists have researched "civic engagement," psychologists have studied "social engagement," educational psychologists have examined "student engagement," and behavioral and organizational managers have studied "employee engagement" and "stakeholder engagement." APPELBAUM (2011) introduced the term "interaction" and first used it in business discourse. He claimed that both emotional and logical loyalty are essential elements of customer involvement. Since then, the term "engagement" has grown quickly to become a fundamental concept in the marketing field, giving rise to ideas like "customer engagement," "customer engagement behaviors," and "customer branding engagement." (BIANCHI & ANDREWS, 2018).

It combines cognitive, emotional, and behavioral involvement, according to Vivek's description of the aspects of customer engagement. According to the majority of researchers studying the theoretical framework of consumer engagement, it is possible that the outcomes of CE—such as loyalty, trust, attachment, etc.—have a favorable impact on the consumer's intention to make a purchase (YU & ZHENG, 2021). Additionally, some researchers discovered by studying social networking site brand communities that users' active involvement and promotion have created an online community commitment, which has an impact on purchase and word-of-mouth marketing.

Additionally, the expected value determines the customer's motivation. The customer's perceived value is impacted by the engagement's highly interactive and participative nature. Trust is established when both sides feel that they can rely on one another, and interaction comes afterward. When the participation is higher, the customers will be more satisfied in engagement with the company. This fulfillment, which is the gain of perceived worth (utilitarian/hedonistic value), can be material or spiritual (ABBASI ET AL. 2021).

3.4.2. Trust

Trust is one of the most important factors in purchasing through social networks. Trust means the consumer's mental belief about how the seller's obligations to the consumer are fulfilled, which is crucial in purchasing from virtual space. Without trust, relationships between companies and consumers in virtual space will not be possible (Hollebeek & Macky, 2019). Trust reduces behavioral doubts in consumer purchase behavior on the one hand and increases the power of consumer control in transactions on social networks on the other hand, resulting in enhanced purchasing decision (SEIFERT & KWON, 2019).

It should be noted that the virtual environment has a variety of risks. In such an environment, users seek guaranteed security in the transaction as well as privacy. Researchers argue that transaction security is a major limiting factor in purchasing on virtual space, and controlling transaction security and privacy is a major factor affecting consumer trust, and any information penetration has unfavorable consequences for the company, such as financial losses and loss of public trust (WANG et al., 2020). Also, many customers decide to purchase from social networking sites that have a good reputation and appropriate and high-quality information on their site. The company that has these competitive advantages seems to gain more trust among consumers (GIAMPIETRI ET AL. 2018).

Creating a transaction security in virtual space is more difficult than in normal space, since security management in virtual space is more difficult and users have no control over security issues in this space. A number of researchers believe that virtual space users are usually concerned about transaction security in the purchasing process (SEMBADA & KOAY, 2019). They believe that transaction security is a major factor limiting purchasing in virtual space, and controlling transaction security and privacy is an important factor influencing consumer trust. Thus, consumers who feel a higher level of transaction security are likely to have a higher level of trust and will consider social networks as a potential virtual market (CHANG ET AL. 2019).

FUKUYAMA (1995) defines trust as the expectation of regular, correct, and supportive behaviors in a society shaped by the common criteria of a section of that community's members. He believes that technological developments will always highlight the role of trust in understanding business behaviors such as marketing (CARFORA ET AL. 2019). Based on a more accurate definition, brand trust means the customer's willingness to be confident in the brand's capabilities in performing the assigned tasks. Trust can significantly influence customers' purchasing decisions (AL-DEBI ET AL. 2015). The nature of virtual space is such that it is very difficult to trust online purchasing due to the impossibility of seeing and touching the goods or the lack purchaser's face to face communication with the seller of the goods or the service provider on the Internet.

This issues creates high uncertainty in the mind of the purchaser (from various aspects of product / service quality, payment process security, guarantee of personal information provided, timely delivery of goods or services requested, the process of returning goods and refunds in case of dissatisfaction with goods or service received, etc.) to make decision to enter the virtual world and perform the online purchasing process, which can ultimately discourage the purchaser discouraged from purchasing (YU ET AL. 2020). Trust is considered as a basic concept in online purchasing for many reasons. First, online purchasers must enter their personal information when purchasing a product online or when registering on a website. Customers are worried that this information may be shared with third parties for unwanted promotional activities.

Second, the perceived risk level of the customer increases when he enters the details of his bank account and credit card information, etc. in an online website. Purchasers may also be worried about disclosure of their financial information to anonymous entities (IRSHAD ET AL. 2020). Higher levels of trust between the purchaser and the seller will increase the probability of continued relationship. Trust creates a positive feeling in the purchaser and reduces the perceived risk of the customer. Customers with a high level of trust show a positive attitude and positive behavior (LIM, 2015).

3.4.3. Word of mouth (WOM)

One of the factors causing popularity in the online arena is the recommendation of communication channels by others (WOM). People can spread material through WOM thanks to Web 2.0, which facilitates social networks. This has a big impact on how consumers make decisions (YUSUF ET AL. 2018). Customers seek out peer opinions because they consider them to be credible, as seen by the proliferation of review and opinion websites like Epinions and TripAdvisor (EVANS & ERKAN, 2016). A customer searches for a desired topic on a channel that is recommended by many people (more than 5 people) or a channel that is recommended by a trusted person and has the necessary credibility for the customer (NIKITA, 2019). Physical boundaries have disappeared due to the growth of electronic and digital communication channels like social networks, mobile phones, and the Internet, as well as the rise in the number of users of these platforms (WANG ET AL. 2016). Customers can now evaluate products on websites, blogs, newsgroups, chartrooms, and social networking sites, as well as send comments online. People may utilize these media for many purposes, such as finding the information they want and seeking advice from others before making purchases (MEKAWIE & HANY, 2019).

Studies conducted on WOM suggests that WOM communication is more effective than communication through other sources, such as recommendations of important content for newspapers or advertisements, since it had been recognized that information from one person to another provides a valid comparison. Therefore, in today's competitive environment, in addition to customers, managers also need to take advantage of this potential opportunity and use electronic word-of-mouth advertising through customers to realize their purchase intention (SEIFERT & KWON, 2019). WOM on social networks is a significant factor in influencing customers, as was previously established. Customers thus have a tendency to trust the information they learn from those they deal with. This is because these people feel a part of a community and share characteristics with one another, such as comparable beliefs and tastes.

WOM is not created on the company's social page, but on other social networks other than the company's social networks. It makes it possible to spread positive news to other consumers (BASTOS & MOORE, 2021). If we want to introduce a product or service to others by the users themselves, this product or service will have the necessary quality. For example, users may comment on specific company services or products on websites other than the company's own website, such as Internet forums and social networks. In this case, other users search for information about the product or service they want before purchasing and using products and services on the Internet, and these opinions influence their decisions (AL-NSOUR, 2017).

Also, since the customer's perception of advertising affects the choice of product and the purchase intention, it seems that with the expansion of social networks and messengers, the traditional and limited form of advertising has shifted to electronic recommendation and WOM in social (LI & JAHARUDDIN, 2021). As a result, the exchange of positive or negative word-of-mouth messages between customers in networks and cyberspace will lead to positive or negative mental frameworks and thus affect the purchase intention of customers (YUSUF & BUSALIM, 2018). Social media links electronic WOM to online customer interaction about products / brands. Studies suggest that WOM has more credibility and empathy for customers than the sources of information provided by companies (TSAI & BUI, 2021). Researchers can examine the use of electronic WOM on social media from three perspectives: seeking for opinions, presentation of opinions, and transmission of opinions (LIU ET AL. 2021). Consumers who show a high level of opinion-seeking behaviors seek information and recommendations from other consumers when making their purchasing decision. Consumers with a high level of idea-building behavior will have a great influence on consumers' interests and behavior. Finally, online transmission is a special feature of electronic oral advertising that facilitates the flow of information (WANG & HERRANDO, 2019).

3.4.4. Social influence

Researchers define social networks as a chart of relationships and interactions within individuals that often mediate the spread of information and ideas and influence individual. Social influence can affect people to the point where they can even break the rules. The extent to which consumers' attitudes are affected by social influence depends on their ability or preparedness to be affected by these influences. Social influence is the degree to which the consumer believes in the beliefs of others, or in other words, the effect that others have on the individual behavior of the consumer (HU ET AL. 2019).

In other words, social influence means that people change their thoughts, feelings, attitudes or behaviors as a result of interacting with other people. BEARDEN ET AL. (1989) defined social influence as the ability or preparedness of a consumer to be affected by susceptibility to interpersonal influence. Social influence is associated with behaviors such as avoiding negative emotions. Social influence occurs when a person's emotions or beliefs or behaviors are influenced by others. Social influence takes many forms and can be seen in affairs such as adaptation, sociability, peer pressure, obedience, leadership, sales and marketing (CAMBRA-FIERRO ET AL. 2021).

Based on the literature, the two most common dimensions are the ability or preparedness of the consumer to be affected by social influences, the information dimension and the normative dimension. The information element is related to the consumer tendency to seek information about potential purchases by observing or contacting other people or making purchasing decisions through the opinion of experts. This factor is more important when the consumer has little information about the product (KUAN ET AL. 2014). Also, adaptation is the basis of the normative element, as the willingness of individuals to purchase to determine the identity or being approved by others defines this dimension. In other words, to purchase to influence others is manifested in the normative dimension of social influence. Some studies have shown that social influence has a direct effect on behavioral intention (JIMENEZ-CASTILLO & SANCHEZ-FERNANDEZ, 2019).

The social influence of information can occur in two ways: Individuals may seek information or knowledge from others or learn conclusions based on observations of others' behaviors. The social influence of information influences consumer decision-making processes about product evaluation (TANFORD & MONTGOMERY, 2014). People use social media to learn from their early experiences and make judgments about whether or not to buy new products. This phenomenon of social effects on information in an online context may be viewed as a learning process. Information's social impact is correlated with knowledge. Put differently, information and proof have an impact on individuals. Research has demonstrated that social interaction relationships have a good impact on knowledge sharing and exchange (ISHIBASHI ET AL. 2019). Adaptation or recognition are two processes that might result in normative social impact. If one has an incentive to reward or avoid punishment from others, one is expected to be able to influence others. However, this only occurs when one believes that his performance is observable or recognizable by others. In other words, normative social influence indicates that individuals are affected by group equality (FU ET AL. 2020).

3.4.5. Consumer value perception

Since its inception, the notion of "perceived value"(PV) has been the subject of research in many different fields, particularly marketing. PV is "the overall assessment of the effectiveness of a product by consumers through perceived revenue and perceived sacrifice," and it is developed from the study of consumer behavior. Researchers with varying views have diverse definitions of PV based on its definition (PARK ET AL. 2021). To put it briefly, there are two primary perspectives: perceptual and logical. Consumers' perceptual perspective is a mental awareness connected with numerous symbolic and aesthetic principles (i.e., focusing on hedonism), contrary to the logical view, which contends that consumers want to optimize product/service usefulness (i.e., focus on functionality) (ALALWAN, 2018). Research on perceived value concentrates on elements that influence and are measured. One important step is to define the perceived value dimension.

Currently, the majority of studies develop a multi-model of perceived value and agree on the multidimensional theory of perceived value (IRSHAD ET AL. 2020). SHETH ET AL. (1991), for instance, postulated the following five distinct PV components: conditional value, emotional value, cognitive value, social value, and functional value. According to HOLBROOKE (1996), there are eight different categories of PV dimensions: reputation, taste, appearance, morality, convenience, quality, success, and faith. According to BABIN ET AL. (1994), there are two reasons why people want rewards: the first is a conscious desire for useful results, while the other is connected to instantaneous, unconscious sensory reactions. Hedonic value (HV) and utilitarian value (UV) can therefore be used to signify rewards for shopping (WANG ET AL. 2021).

According to the "value-intention" model (HSU & LIN, 2016), DODDS & MONROE (1991) claimed that a person's willingness to engage in a given activity is directly influenced by the perceived value of the behavior's outcome. HIAO ET AL. (2014) provide evidence that customers' continued use of mobile advertising influences their propensity to make frequent purchases based on their perceived value. In order to analyze consumer online purchasing behavior, OVERBY & LEE (2006) split perceived value into two dimensions: hedonistic value and utilitarian value (LIN ET AL. 2020). Prior to making a current buying choice, customers evaluate their past shopping experiences. The buyer won't be willing to buy more unless he is both practically and emotionally satisfied. Value is attached to this satisfaction (SHUKLA ET AL. 2022).

3.4.6. Perceived risk

Talking amongst one another about the company and its goods is the primary source of sales. By sharing positive or negative recommendations for a certain good or service, people prefer to discuss their varied experiences with one another, reduce the risk associated with their purchase, and select the best and most suitable alternative (SEO & JANG, 2021). Perceived risk is defined as a type of uncertainty and outcomes related to a consumer's purchasing actions and can be examined from several aspects including physical risk, financial risk, social risk, time risk, opportunity cost risk and information risk (VENTRE ET AL. 2020). Social risk refers to the possibility of reducing a person's position among friends, family and neighbors by purchasing a product or using a service. Financial risk is the fear of financial loss that the purchase of a product / service can cause now or in the future. Financial risk exists in both subjective and objective forms.

A person with low or variable income, even when purchasing cheap products, experiences high level of subjective risk. In contrast, purchasing a home, even for people with stable financial status, will be associated with high level of objective risk (LI ET AL. 2020). LAROCHE, MCDOUGALL & BERGERON (2005) stated that purchase risk can be defined as a negative and modified effect of the customer's expected outcome of the purchased product (YANG ET AL. 2016). In this regard, KO, JUANG, KIM & SHIM (2004) have defined risk as consumer perception of variable consequences and contrary to the customer's perception of purchasing a product or service. This concept consists of two elements, including uncertainty and consequence. Uncertainty can be identified as the probability of an unfavorable consequence as a lost advantage (CUI ET AL. 2019). Risk perception plays a major role in setting consumer purchasing goals. The perceived risk by the consumer is crucial in determining their evaluation and purchase. Studies in this area have indicated that the perceived risk of the consumer can negatively affect his online purchasing goals (SADIQ ET AL. 2021).

The greater the perceived risk among consumers, the more this perceived risk distracts consumers from their purchasing goals. Consumers who are exposed to higher risk are less likely to purchase products or services online. Thus, perceived risks have a negative impact on consumers' intention to purchase online (KAMALUL ARIFIN ET AL. 2018). The greater the risk that online retailers see, the less likely they are to succeed in driving their customers to purchase from their online retailer or persuade the customers to purchase. Also, researchers refer to the impact of perceived risk on online purchase intentions as time risk, financial risk, information security risk, delivery risk, and product risk. Online marketers need to be aware of the risk perceived by their customers and implement strategies to prevent this risk (LI ET AL. 2020).

3.4.7. Perceived usefulness

In the technology adoption paradigm, perceived usefulness is the second element. In other words, perceived utility is the extent to which an individual feels that utilizing a specific system or technology improves his performance. Perceived usefulness is a perceived comparative advantage that has been created over the past and is directly related to customer attitudes (VENTRE & KOLBE, 2020). The use and willingness to continue using an organization's services or products may depend on cognitive beliefs about perceived usefulness. Perceived usefulness also reinforces online purchaser's intention to continue using a website (AGAG & EL-MASRY, 2016). It can also be said that consumers generally do cost-benefit analysis when purchasing a product. Perceived usefulness is consumer evaluation of the value of products and services. This value is the comparison between the profit that the product brings to the customer versus the cost that the customer spends (BIANCHI & ANDREWS, 2018).

Nowadays, due to the change in consumer purchase behavior and increasing their online purchase intention, the use of applications, websites and media that direct online purchases towards ease and simplicity along with usefulness have been considered. Any software that increases the feeling of usefulness in users causes users to have a more favorable attitude towards that program (FU ET AL. 2018). Although appearance, advertising and social influences may affect the behavior of e-users in the early stages of purchasing, after using the software, the appearance and basic features suddenly decline and the perceived usefulness will have the greatest impact on their attitude (BONN ET AL. 2015). Therefore, it can be stated that in social networks, profitable motivations such as trust and security, the possibility of social exchanges, the breadth of business pages and the ability to quickly compare products and services determine the purchase intention (LIM ET AL. 2016). Since working with the Internet, Internet-based applications and websites has expanded nowadays, and many people have enough experience working with most software in today's world, perceived ease of use is not a prerequisite for e-commerce success, since experienced e-users take it for granted. The emphasis should be put on perceived usefulness in commercial applications and websites, and this should be accompanied by providing an advantage different from competitors. Perceived usefulness is defined as an individual's belief that the use of an information technology provides benefits to its users. This takes a belief in decision making (VENTRE ET AL. 2020).

3.4.8. Perceived information quality

Another important factor that affects people purchasing from social networks is the quality of information on the company's site. Information quality includes the accuracy and completeness of the information provided by the company to the user. Purchasers in virtual space are highly dependent on the information provided by the company, since users in this space have little information about goods and services (MCCLURE & SEOCK, 2020). Thus, consumers tend to trust a site that provides accurate and timely information. In this regard, studies indicate that the quality of information for social media sites is probably more important than other types of e-commerce sites, since the information about the goods and services available on these sites is provided by consumers (FU ET AL. 2020).

Some researchers consider the quality of information to include the consumer's general perception of the completeness and accuracy of the information provided about their services and products and the process of making their purchase transaction. When different social networks have the same information about the product, an individual's perception of the quality of the information provided is the factor that causes the consumer to select a particular social network, since the consumer's perception of the quality of information leads to his trust in that network (KIM ET AL. 2020). The perceived worth of an online shopping site may be enhanced by system quality, which includes security and accessibility; information quality, which includes variety and currency; and service quality, which includes responsiveness and speed (CHENG & HO, 2015).

The quality of customer reviews of a product or service, when combined with relevant, timely, accurate and comprehensive information, can have a positive impact on the customer's evaluation of the product and the purchase intention. The perceived information quality produced in the online community is influenced by the degree of comprehensiveness, personalization, timeliness and structure. The quality of information shared by companies, manufacturers, and service providers on social media platforms influences users' intention to make a purchase as well as their degree of confidence in the platform (MAO ET AL. 2020). Due to the rapid advancement of information technology, user-generated online comment data has become a significant tool for decision-making. Utilizing information is necessary before making a decision. Numerous elements, including the information's quality, might affect how ready someone is to accept and believe what they are told (TANG ET AL. 2019). Familiar information (such as brands) increases consumers' ability to recognize information. As a result, it increases their willingness to accept information.

Customers become more concerned with the accuracy of information when inaccurate and incomplete information is spread, since this has an impact on the acceptability of user-provided information (YIN & ZHANG, 2020). Information quality, which is defined as the fitness of information qualities for users, is a crucial variable for the success of an information system model. Information quality, according to this definition, is defined as users' perceptions of how well information features suit their needs and purposes (ERKAN and EVANS, 2016). Information quality has been defined by studies on online reviews as the informational characteristics of the reviews' content quality. Research has demonstrated that positive ratings significantly influence how websites, products, and purchase predictions are evaluated. Information quality can be examined as a multidimensional structure. Information quality has dimensions such as completeness; in a sense that how information can meet the user's information needs, or the dimension of reliability, which is related to information accuracy. There is also the "timeliness" dimension, which is related to how information is provided (GAO ET AL. 2017).

However, the information quality can also be examined in a single dimension. Based on the information system success model, information quality can be studied in one dimension and there are measurements that guarantee reliability and validity (FILIERI ET AL. 2018). The environment of social media content affects how effective it is at generating user engagement. Consumers, however, focus more on visual material than verbal stuff. Professionals have more online information usefulness and presentation skills (i.e., quality and accuracy) than the general public (YILMAZ FERHATOGLU & KUDSIOGLU, 2020). The degree of solidity between the information that is delivered and the objective facts is referred to as content quality. Good content accurately depicts the state of the goods or services, and consumers gain from knowing the details, which raises their perception of the quality of the information.

Utility quality describes how well information fulfills its purpose on its own. Utility quality measures how helpful information on social business platforms is to consumers or entrepreneurs in helping them select the best products and make the best decisions (ZHAO ET AL. 2020). Users will recognize the high quality of the information if its utility quality is sufficient to facilitate purchases. The degree to which online reviews are thorough and adequate to enable consumers to find relevant information is a measure of the expression quality. The overall evaluation of information quality will rise if people are able to completely comprehend products or services through the use of information (JIANG ET AL. 2021).

3.4.9. Social support

Researchers studying e-commerce have paid close attention to social support. It is an essential sign of participation and positive behavior. The definition of social assistance as "resources provided by another person" is broad. It specifically refers to a person's experiences receiving support, attention, and assistance from members of their social group (HU ET AL. 2019). Peer influence depends on social support since it produces supportive relationships among people.

These strong connections increase the likelihood that one party will influence the attitudes, intentions, and perceptions of the other. Social support comes in various forms and satisfies a person's physical, psychological, and cognitive needs. There are often two aspects of e-commerce: informational and emotional. Informational social support is defined as assistance that comes in the form of advice, comments, ideas, and knowledge that can be beneficial to the individual. The outward manifestation of interior feelings like concern, solicitude, and understanding is known as emotional social support (LIANG ET AL. 2021).

The s-commerce method promotes user involvement and information sharing among users. Additionally, when users require knowledge, they typically turn to the group for assistance (BAI ET AL. 2015). When someone is assisted by others in obtaining knowledge, this is known as informational assistance. Informational impact occurs when the audience embraces this information as a verifiable fact. An individual is more likely to engage in group information exchange activities if they have a greater level of social support (LIU & BAILEY, 2019). Therefore, the prerequisite for informative impact is informational social support. Consequently, a consumer is more likely to exhibit reciprocal action toward informational social support if she perceives this support to be substantial. As a result, his connections with fellow group members are enhanced by their ongoing support of one another, which further highlights the influence of group norms on this particular consumer (HAJLI & SIMS, 2015). Increased consumer adherence to social standards is the outcome. Strong informational support might also increase the recipient's reliance on the organization. As a result, by fitting in, the beneficiary usually manages to maintain a normative connection with the group. Furthermore, a consumer's comprehension of the group improves with increased information from the group. He becomes aware of the group's nature, which makes it easier for him to conform to the group's arbitrary standard (HU ET AL. 2019).

A person who receives emotional support from a social group is shown to be cared for, understood, or empathetic toward. When faced with difficulties, people require not only immediate assistance but also emotional support and gestures of caring that serve to both indirectly and positively remedy the issue (ZHOU, 2017). A group of people's interpersonal ties can be strengthened by this kind of assistance. Mutual trust—the belief that other people's communications, comments, or recommendations are reliable—increases in an e-commerce community where members are closely connected to one another. As a result, users in the focus group are more inclined to [1] accept and implement one another's opinions, counsel, and proposals (LIU & BAILEY, 2019). Emotional support facilitates the expression of emotions by another person. Care recipients typically see the caregiver favorably and experience warmth and encouragement. Customers believe that others are positive about them because of this encouraging atmosphere. They will understand that others look to them to defend their interests. They therefore have a propensity to follow others' norms. As a result, emotional social support within a user community might produce a phenomenon wherein the normative influence that one individual has on others is reinforced (LIANG ET AL. 2021).

3.4.10. Value co-creation

Due to high competition between businesses, increasing profitability and market share is essential for the success of organizations. Thus, organizations seek to influence their customers' behavioral decisions so that they can encourage customers to purchase and re-purchase by increasing the perceived value of their services, since customer loyalty and their purchase intention causes reduce the cost of attracting new customers. In recent years, one of the most important research priorities in the area of marketing and education is attention and research on the behavior of value co-creation for customers in creating value for them (SEIFERT & KWON, 2019). Many business units have turned on ways to engage customers in the company's various processes, such as producing, distributing, and developing a new product rather than aimless advertising. By encouraging customers to engage in collaborative behavior to create value from their perspective, organizations and companies can experience increased market share, revenue, profitability, and even innovation more effectively (OH ET AL. 2018).

Customer value co-creation behavior makes customers think of themselves as part of the company. It also increases their loyalty to the products and services of a particular company. As a result, the brand of that business becomes a priority for customers and makes that brand preferable to other brands (KUNJA & ACHARYULU, 2018). In other words, successful businesses increase customer trust by creating a platform for interaction with other customers. Through this platform, they express positive changes in their products and services, and according to the feedback received from customers, they strengthen empathy and build support for their company's brand. Also, by prioritizing their brand for customers over other brands, they have a positive and effective effect on the customer's intention to purchase the products and services (SEE-TO & HO, 2014).

Recent changes in the areas such as consumer habits, needed services, and the state of technological innovation have increasing role of social media in refining their brand-related activities. Social networks play a major role in creating the conditions for the emergence of participatory behavior and citizenship of customers as dimensions of value co-creation behavior for the customer (CHOI ET AL. 2016). Also, social networks such as Instagram, as a free media, have made it easy for companies to advertise their products on it, and by increasing the number of visitors to their page; it has provided the conditions for sharing more information among the audience and receiving feedback from them and has caused the value co-creation behavior in customers (ALGHARABAT, 2018).

Under such conditions, only companies that have benefited from the customers' value co-creation behavior can receive feedback, create a sense of responsibility towards the brand and brand support, and can achieve a positive image of their brand with customers and have a positive effect on customers' preference and intention to repurchase and increase market share and profitability in the existing competitive market (RANJAN & READ, 2016). In fact, customers not only play the role of purchasers and users of goods and services, but also play a significant role in the process of designing and providing services. This participation and engagement of customers in the processes and activities of companies can help create value for them. Value can be positive or negative, subjective or objective (LACOSTE, 2016). Value for the customers suggests that when they receive a product or service, they feel better than before receiving the product or service.

Value is created through interactions. Co-creation systems are made up of different elements. Each element can be a decision maker in the system. In other words, in the co-creation system, the occurrence of a behavior is the result of the internal structures of the elements themselves and the interaction of the elements with each other (TUAN ET AL. 2019). Also, the value co-creation refers to the highest level of customer participation and cooperation in the company's activities and processes, which results in an approach based on continuous interaction and communication between customers and the company. By creating a dynamic environment for customer engagement and participation in the company's processes and activities, customers understand the true value of the received services and products and the created positive experience and it can have an effective effect on increasing their satisfaction and loyalty to the brand and company (CAMBRA-FIERRO ET AL. 2018).

Value co-creation has been highly considered due to its close relationship with taking advantage of opportunities and achieving the success of the services provided by companies. Value co-creation behavior literature suggests that customers not only receive marketing information, but can also respond to information and data as value builders (AHN ET AL. 2019). Value-co-creation is the result of combining the efforts of the company, employees, customers, shareholders and all other factors that somehow contribute to the production of service. Value co-creation is based on the fact that no value proposed by the company is valuable until it is used. Customer-employee interactions create value that is higher and beyond the value that can only be obtained through the consumption of products and services (BU ET AL. 2022).

3.4.11. Knowledge sharing

Customers today have quick and simple ways to communicate with one another about wants, requirements, ideas, and information thanks to the growing usage of social networks (Facebook, Twitter, Instagram, WhatsApp, YouTube, etc.) (XU ET AL. 2020). In an effort to improve coordination, decision-making, and planning, as well as knowledge sharing, organizations are revamping their internal and external ties and establishing knowledge networks. Producing knowledge and using it through innovation is necessary for a business to be competitive in the long run. Since customer knowledge influences every facet of consumer behavior, it is a crucial topic to study and comprehend in the field of marketing (GHAHTARANI ET AL. 2020). "The provision or receipt of task information, know-how, and feedback regarding a product or procedure" is the definition of knowledge sharing. It has been linked to a number of desired managerial outcomes, such as productivity, task completion time, organizational learning, and innovativeness. Sharing customer information is one of the most important resources that a business can use to improve customer interactions and develop a long-lasting competitive advantage (SONMEZ CAKIR & ADIGUZEL, 2020).

In collaborative tasks, the significance of sharing knowledge has been emphasized. Organizational advantages, including increased back-office productivity, closer ties with customers, better strategic planning, adaptability to market changes, better decision-making, and quicker and more adaptable supply chain management procedures, have resulted from increased information sharing. Ineffective communication of information can result in issues with project coordination and, consequently, inadequate collaboration. However, establishing a successful knowledge-sharing process is not without its difficulties, particularly when teams must deal with time zones and geographical and cultural disparities (KIM ET AL. 2019).

Consumer perceptions these days are influenced more by social media information and knowledge sharing, including advertising and user experiences, than by word-of-mouth recommendations from friends and family. This problem has a big impact on their purchasing behaviors. Sharing information entails assisting others or exchanging knowledge (TRAN, 2020). It requires domain-knowledge specificity on the part of the adopter and supplier to concentrate on the particular context of the interaction; these contexts, which include pricing, product conception and design, and new product planning, are examples of how a supplier demonstrates their grasp of market positioning and customer expectations (MAJEED ET AL. 2021). Sharing customer information has a direct positive impact on an organization's human resource performance and creativity. As a result, it produces better goods and services as well as more competent marketing staff. Furthermore, knowledge exchange is essential to the execution of information systems. In other words, internal knowledge sharing signifies people's involvement and engagement with an organization's common knowledge (CHANG ET AL. 2020).

3.4.12. Service innovation

In the context of the global economy, services have grown in importance. The services sector accounts for over 70% of the GDP in many affluent nations. In general, innovation is thought to be an important factor that supports economic progress and refers to a company's efficient use of resources and creative production methods to satisfy market demands (LI, 2021). According to DRUCKER (1985), innovation includes a wide range of new goods and services that are beneficial and raise living standards. Examples of these include new goods and services, new processes, new technology, new raw materials, and new business models (WANG ET AL. 2016). Innovation in goods and services is prevalent throughout many different industries. For instance, new features like multi-room digital video recorders, cloud storage, and faster internet are being offered by ISPs like Dish and DirectTV. Product and service innovation is crucial because newly produced goods and services enhance customer lifestyles and foster commercial and economic expansion (KIM ET AL. 2020). Additionally, brands must invest in innovation if they want to succeed and gain a competitive advantage in a market that is expanding quickly. In reaction to product innovations, consumers take four different kinds of actions.

The first kind of innovation is optional innovation—a choice made on its own to embrace or reject innovation. When a choice is reached by consensus among the social system's participants, it is considered a second kind of collective innovation decision. The choice made by an individual or group with authority is the third sort of innovation decision, known as authority innovation. Contingency decisions are the fourth category. It entails deciding whether to approve or disapprove of an invention that may be implemented following a previous choice (ZAREI ET AL. 2019). BETZ (1987) was the first to develop the notion of service innovation, arguing that it differs from product and technological innovation. A service that involves only a minor, incremental improvement or modification falls within the category of completely new or discontinuous innovation. A new concept, goal, strategy, technique, and pattern of innovation are all incorporated into the unit of service innovation. Service innovation, according to GREMYR ET AL. (2014), is basically a new service that businesses offer to their clients. According to WOO ET AL. (2021), in other words, they saw clients as partners in service innovation.

According to YEAP AI LEEN & RAMAYAH (2011), service providers are transitioning from old business methods to new channels, business models, procedures, and technology due to shifting customer demands, regulatory requirements, and service competition. As a result, service innovation is essential, as services are the engines of development in contemporary economies. Businesses are attempting to introduce innovative services that let clients check out new offerings. They therefore raise the standard of service innovation and focus on client loyalty.

Because innovation influences elements like consumer expectations, perceived value, commitment, and trust/confidence, it has a big effect on customer loyalty. According to YANG ET AL. (2017), online buyers' perceptions of innovation positively influence their propensity to make another purchase. (CHANG & LEE, 2020). Table 1 presented a summary of factors affecting consumer purchase behavior based on literature review.

Table 1. Summary of factors affecting consumer purchase behavior

No	Factors	Key References
F1	Consumer engagement	(WANG & HUANG, 2022) (YU & ZHENG, 2021) (ABBASI ET AL. 2021) (Cheung ET AL. 2021) (SANTINI ET AL. 2020) (PRENTICE ET AL. 2019) (BIANCHI & ANDREWS, 2018) (RAHMAN ET AL. 2018)
F2	Trust	(IRSHAD ET AL. 2020) (YU ET AL. 2020) (WANG ET AL. 2020) (SEMBADA & KOAY, 2019) (SEIFERT, & KWON, 2019) (CARFORA ET AL. 2019) (GIAMPIETRI ET AL. 2018)
F3	Social media WOM	(TSAI & BUI, 2021) (BASTOS & MOORE, 2021) (LI & JAHARUDDIN, 2021) (PARK ET AL. 2021) (MEKAWIE & HANY, 2019) (SEIFERT, & KWON, 2019) (WANG & HERRANDO, 2019) (YUSUF & BUSALIM, 2018) (Al-NSOUR, 2017)
F4	Social influence	(FU ET AL. 2020) (INDRA ET AL. 2020) (HU ET AL. 2019) (JIMENEZ-CASTILLO & SANCHEZ-FERNANDEZ, 2019) (ISHIBASHI ET AL. 2019) (HSU & lIN, 2016) (KUAN ET AL. 2014) (TANFORD & MONTGOMERY, 2014)
F5	Consumer's value perception	(PARK ET AL. 2021) (WANG ET AL. 2021)

		(IRSHAD ET AL. 2020) (LIN ET AL. 2020) (ALALWAN, 2018) (WU ET AL. 2018) (HSU & LIN, 2016)
F6	Perceived risk	(SADIQ ET AL. 2021) (ZHANG ET AL. 2020) (VENTRE ET AL. 2020) (LI ET AL. 2020) (CUI ET AL. 2019) (KAMAUL ARIFFIN ET AL. 2018) (YANG ET AL. 2016)
F7	Perceived usefulness	(VENTRE & KOLBE, 2020) (VENTRE ET AL. 2020) (WU, 2020) (FU ET AL. 2018) (BIANCHI & ANDREWS, 2018) (AGAG & EL-MASRY, 2016) (BONN ET AL. 2015) (LIM ET AL. 2016)
F8	Perceived information quality	(FU ET AL. 2020) (KIM ET AL. 2020) (MCCLURE & SEOCK, 2020) (ZHAO ET AL. 2020) (ZAREI ET AL. 2019) (FILIERI ET AL. 2018) (CHEN & CHANG, 2018) (GAO ET AL. 2017) (ERKAN & EVANS, 2016)
F9	Social support	(LIANG ET AL. 2021) (LIU & BAILEY, 2019) (HU ET AL. 2019) (HU ET AL. 2019) (BAI ET AL. 2015)
F10	Value co-creation	(BU ET AL. 2022) (SEIFERT & KWON, 2019) (KUNJA & ACHARVULU, 2018) (ALGHARABAT, 2018) (CHOI ET AL. 2016) (ChOI ET AL. 2016) (SEE-TO & HO, 2014)
F11	Knowledge sharing	(GHAHTARANI ET AL. 2020) (TRAN, 2020) (XU ET AL. 2020) (MAJEED ET AL. 2021)
F12	Service innovation	(LI, 2021)

		(CHANG & LEE, 2020) (KIM ET AL. 2020) (ZAREI ET AL. 2019) (AGAG & EL-MASRY, 2016)

Source: Author's own work based on literature review

3.5. Summing up the relationship of social network marketing and consumer purchase behavior

In the past decade, Internet technology has developed rapidly around the world. The rapid adoption of the Internet has enabled marketers to acquire and foster effective use of Internet technologies through e-commerce (PARSONS & LEPKOWSKA-WHITE, 2018). Although e-commerce enhanced the comprehensive of products and services, it provided a one-way communication that prevented effective consumer feedback. This limitation was quickly overcome with the advent of social media through Web 2.0. These media enabled the use of a wide range of interactive tools and communication techniques which are user generated (GHANNAM ET AL. 2018).

Social networks has introduced a new set of business and marketing initiatives that influence consumers' purchase intention. Social networks has changed the dynamics of consumer behavior by shortening the consumer purchasing process. The consumer purchasing process is a sequential process that sees consumers in different steps of purchasing. These steps include need recognition, information search, evaluation of alternatives and purchase (MUHAMMAD ET AL. 2021). Several studies have shown that through social networks marketing, the consumer purchase sequence process changes and its steps are reduced, since consumers can go through certain steps and it is likely to lead to purchase behavior in them. At current, the information that consumers are exposed to has become richer in light of social networks. The second step improves the information search. Social networks is a rich highway in which product information can be obtained in a simple text, hyper mark-up text, or in downloadable magazines and pamphlets (PALALIC ET AL. 2021).

Social networks provides access to information everywhere. There are no geographical boundaries for marketing goods and services on social media. In other words, through social networks, a large group of audiences can access a company's marketing communications from an array of background. It increases the consumer's purchase intention by reducing the effort to obtain product information (STEPHEN, 2016). When information is readily accessible, all forms of search costs are reduced, which predicts high levels of purchase intention behavior. The most fundamental element of social networks that influences consumer purchase behavior is the ability of social networking platforms to promote dual forms of user-company communication (URBONAVICIUS ET AL. 2021).

According to Web 2.0, social networks allow users to send information by posting, reviewing, ranking and liking. This information largely serves as feedback to the organization. However, it has a greater impact on other consumers in the social context. User-generated content is more appealing to consumers than company-generated communications. Thus, consumers are motivated to purchase through incentives generated by other consumers on social networks through a dual communication path (FU ET AL. 2020). There is a positive relationship between user-generated content and desirable consumer behavior. The consumers' purchase intention is also influenced by the group on social networks. Accordingly, social networks platforms enable peer and group purchasing, which is synonymous with a group of friends going out for purchasing in offline environments. Therefore, social media directs the consumer's purchase intention through the leadership of the opinion and the influence of the reference group. Since consumers have a natural tendency to belonging, they tend to purchase what other consumers purchase (VITHAYATHIL ET AL. 2020). Table 2 presented a summary of previous studies in the field of consumer behavior.

Table 2. Previous researches in the field of consumer behavior

No	Researchers	year	Topic	Keywords	Variables examined in the model
1	CHEUNG ET AL.	2021	The role of consumer-consumer interaction and consumer-brand interaction in driving consumer-brand engagement and behavioral intentions	Consumer-brand interaction Consumer-consumer interaction Consumer participation Consumer-brand engagement Ongoing search behavior Social media	Consumer-consumer interaction, consumer-brand interaction, cognitive engagement, Emotional engagement, Behavioral engagement, ongoing search behavior, repurchase intention
2	SADIQ ET	2021	Predicting Online	Online travel	Perceived Risk, Trust,

	AL.		Travel Purchase Behavior: The Role of Trust and Perceived Risk	purchase; OTP; subjective norm; perceived risk; trust; attitude–intention gap	Attitude, subjective Norm, Perceived behavioral control, purchase intention, control variables : Age, Gender, Household Income
3	PARK ET AL.	2021	A study of antecedents and outcomes of social media WOM towards luxury brand purchase intention	Luxury product Perceived quality Perceived value Social media WOM Consumer characteristics	Perceived Quality, Perceived Value (social value, personal value, functional value), demographics(: gender, age, education, income), social media WOM, perceived social Status, Purchase Intention.
4	LI & JAHARUDDI N	2021	Influences of background factors on consumers' purchase intention in China's organic food market: Assessing moderating role of word-of-mouth (WOM)	organic food; background factors; purchase intention; purchase decision; WOM (WOM); consumers in China	Background factors(individual, social, information), purchase intention, word-of-Mouth(WOM), Purchase Decision.
5	MAJEED ET AL.	2021	The influence of social media on purchase intention: The mediating role of brand equity	Consumer Psychology; Communication Theory; Information Technology Keywords: Fashion; social media; uses and gratification; purchase intention; brand equity	Surveillance, social Interaction, Information Sharing, Remuneration, Entertainment, Brand Equity, Purchase Intention
6	BASTOS & MOORE	2021	Making word-of-mouth impactful: Why consumers react more to WOM about experiential than material purchases	Experiential purchase Material purchase Word-of-mouth Substantiveness Consumer reaction	WOM Topic[Experiental vs. Material Purchase], Self-Identification, Other-Identification, WOM Substantiveness[Involvement & Meaningfulness], Value-Creating Reactions[Information Acquisition, Purchase

					Intention, Secondary Sharing, Review Writing]
7	WANG ET AL.	2021	The dual concept of consumer value in social media brand community: A trust transfer perspective	Business value Consumer value Trust Social media brand community	Customer Perceived Value(Utilitarian Value, Hedonic Value, Social Value), Customer Trust Development(Trust in social Media Brand Community, Trust in Brand, Trust in Social Media), Customer Generated Value (social media WOM, Purchase Intention)
8	LIANG ET AL.	2021	Social support, source credibility, social influence, and solar photovoltaic panels purchase intention	Solar photovoltaic (P.V.) . Social influence . Social support . Source credibility . Perceived monetary benefits . Environmental concerns	Source Credibility(Expertise of Peers, Trustworthiness of Peers), Social Support(Informational Social Support, Emotional Social Support), Social Influence(Informational Social Influence, Normative Social Influence), Perceived Monetary Benefits, Environmental Concerns, Willingness to Buy Solar PV Panels, Purchase Intention
9	WU	2020	Organizational Acceptance of Social Media Marketing: A Cross-Cultural Perspective	Globalization; cultural convergence theory; cultural divergence theory; Technology Acceptance Model (TAM); social media marketing; digital divide	Types of Organization: (Global Organizations with Headquarters in the U.S. Domestic Organizations in the U.S. Non-U.S. based Global Organizations Non-U.S. based Domestic Organizations), Perceived Ease of Use (PEU), Perceived Usefulness (PU), Subjective Norm (SN), Behavioral Intention(BI).
10	CHANG &	2020	The effect of	Service	Service innovation

	LEE		service innovation on customer behavioral intention in the Taiwanese insurance sector: the role of WOM and corporate social responsibility	innovation, Customer behavioral intention, Corporate social responsibility, WOM, Life insurance	(Service concept Client interface Service delivery system Technology options Behavioral intention) Word-Of–Mouth, Corporate social responsibility (Economic CSR, Legal CSR Ethical CSR, Discretionary CSR), Behavioral intention
11	VENTRE & KOLBE	2020	The Impact of Perceived Usefulness of Online Reviews, Trust and Perceived Risk on Online Purchase Intention in Emerging Markets: A Mexican Perspective	Perceived usefulness of online reviews; trust; perceived risk; purchase intention	Perceived usefulness of online reviews, Trust, Perceived risk, purchase intention
12	ZHAO ET AL.	2020	Electronic word-of-mouth and consumer purchase intentions in social ecommerce	Electronic word-of-mouth Information quality Trust Social psychological distance Purchase intention	Information Quality, Social Psychological distance, Sense of power, Trust, Purchase intention
13	TSAI & BUI	2020	Impact of WOM via social media on consumer intention to purchase cruise travel products	Social media; cruise tourism; travel information search; prospect theory; mental accounting theory; value-based adoption model (VAM); WOM; purchase	Information Reliability, Enjoyment, WOM praise, WOM Activities, Purchase Intention

				intentions	
14	HOLLEBEEK ET AL.	2020	The effects of consumer esports videogame engagement on consumption behaviors	Cognitive engagement, Affective engagement, Behavioral engagement,	Purchase intent, Community engagement, Coproduction, Word-of-mouth, New player recruitment
15	MAKUDZA ET AL.	2020	The Effect of Social Media on Consumer Purchase Behaviour in the Mobile Telephony Industry in Zimbabwe	social media, consumer behaviour, purchase intention, marketing, WOM	Firm generated social media communication, user created social media communication, social media WOM, social media platform, consumer purchase intention
16	INDRA ET AL.	2020	Impact Of Social Influence And Safety On Purchase Decision Of Green Cosmetic	Safety, Social Influence, Purchase decision and Customer Satisfaction.	Social influence, safety, purchase decision, consumer' satisfaction

Source: Author's own work based on literature review and previous researches

IV. MATERIALS AND METHODS

4. General overview of the applied methodology

In this research, we adopt a multi-step approach to comprehensively investigate the factors influencing consumer purchase behavior within social networks. We provide a detailed explanation of each step in this section and the next section. Firstly, we employ the Interpretive Structural Modeling (ISM) approach to identify strategic variables associated with factors affecting consumer purchase behavior in social networks. This method allows us to establish hierarchical relationships among these variables and uncover their interdependencies.

Next, we utilize Multi-Criteria Decision Making (MCDM), specifically the Analytic Hierarchy Process (AHP), to prioritize criteria based on their respective weights. AHP helps us quantitatively assess the relative importance of each criterion, aiding in effective decision-making.

Subsequently, we conduct three distinct case studies leveraging Machine Learning (ML) and deep learning techniques. In the first case study, we provide a visual representation of consumer purchase behavior through map visualization, offering insights into spatial patterns and preferences. In the second case study, we focus on grocery applications in Hungary and Iran, utilizing demographic features of consumers to determine which grocery apps are most suitable for specific user segments. This analysis aids in enhancing user experience and tailoring services to meet diverse consumer needs.

Finally, in the third case study, we employ sentiment analysis on Instagram food comments to predict whether customer feedback is positive or negative in real-time. This involves the application of TensorFlow transfer learning and live deployment techniques to enable dynamic and accurate sentiment prediction. Overall, our methodology integrates qualitative and quantitative approaches, incorporating advanced ML techniques to provide a comprehensive understanding of consumer behavior in social network environments. We delve into each aspect in detail, elucidating the intricacies of our methodology and its implications for research and practice.

4.1. Sampling and data collection (ISM & AHP)

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 (see Appendix B) 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. Within the research sample, 54.5% and 45.5% of respondents were male and female, respectively. The majority (54.5%) fell within the age group of 35-45 years, and 46.4% held master's degrees, indicating a high level of education among respondents. Most respondents owned businesses on Instagram, specializing primarily in marketing. Sampling persisted until reaching the theoretical saturation stage.

To establish the measuring instrument's reliability, the Inter-class Correlation (ICC) coefficient value will be verified for consistency, drawing on prior research (EBRAHIMI ET AL. 2020; BOUZARI ET AL. 2021; EBRAHIMI ET AL. 2021; FEKETE-FARKAS ET AL. 2021; SALAMZADEH ET AL. 2021). Experts were requested to rate the questionnaire based on the 'average measure of every factor,' and these scores were employed to calculate the ICC coefficient. Additionally, the absolute agreement coefficient value will be confirmed within 95% confidence intervals.

In the first step, to interview with experts, by sending a message on social media, some successful and well-known online business owners in Iran asked to specify a time to interview if they were willing to cooperate. Finally, online business owners announced their desire to participate in the interview and fill structured questionnaire. Also, since this research was conducted during the Covid-19 pandemic, all interviews were conducted via skype. The ISM questionnaire is divided into three sections. The first section included the demographic characteristics of the respondents who will ask to introduce themselves at the beginning of the interview and answer descriptive questions. In the second section, the way of filling the questionnaire is explained with an example.

In fact, to avoid any errors and transparency, the work procedure, and the way of filling the questionnaire in the interview will first fully explain to the respondent experts. The third section (ISM part) also included a matrix of relationships between variables. The interviewer asked a question about the pairwise comparison of both factors separately from the interviewee. For example, what is the relationship between F1 and F2? The interviewee will select one of the symbols V, A, X, and O based on the table.

V: F1 variable i leads to F2 variable j

A: F2 variable j leads to F1 variable i

X: Both variables i and j leads to each other

O: Both variables i and j are unrelated

In AHP section a pairwise comparison scale is used, and experts answered pairwise questionnaire based on table 3. Following the collection of pairwise questionnaires in the AHP section, the acquired data underwent analysis using descriptive statistics, specifically employing measures such as frequency, proportion, and percentage, through SPSS 21.0 software. Additionally, Expert Choice 10.0 software was utilized to analyze the data using the Analytic Hierarchy Process (AHP) method. The computed results indicated that all responses to the questionnaire yielded a consistency ratio (CR = CI/RI) of < 0.1, thereby affirming the acceptance of the decision maker's pairwise comparison matrices.

Table 3. AHP pairwise comparison scale

Weight	Definition
1	Equal importance
3	Weak importance of one over other
5	Essential or strong importance
7	Very strong importance
9	Absolute importance
2, 4, 6, 8	Intermediate values between the two adjacent judgments
Reciprocals of previous values	If factor' i' has one of the previously mentioned numbers assigned to it when compared to factor 'j', then j has the reciprocal value when compared to i.

Source: SAATY (1980)

In the machine learning part, we examine three different case studies.

4.2. Sampling and data collection (Machine learning: case study 1)

In this particular case study, the investigation focused on Iranian individuals who actively participated in online social platforms and had completed at least one online purchase. The survey instrument (refer to Appendix C) 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. The findings indicated that 60.6% and 39.4% of respondents were male and female, respectively, with a predominant representation in the 21-30 age group (62.3%). Additionally, 37.2% of participants held a bachelor's degree. Participants were tasked with identifying the online platform they considered most pivotal for shaping their perceptions of advertisements and online stores.

A majority (62.3%) devoted a minimum of 1-2 hours daily on online social platforms to explore diverse commercials or online shops. In the research process, data were acquired through the widely employed convenience sampling method to minimize bias (Alshurideh, Al Kurdi, Salloum, Arpaci, & Al-Emran, 2020).

Furthermore, the study applied the Common Method Bias (CMB) test (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003; Ebrahimi et al., 2022a). 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.

4.3. Sampling and data collection (Machine learning: case study 2)

In this study, 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 (Appendix D) 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.

In Hungary, Facebook was deemed more prevalent than other online platforms, with a superior response rate based on the authors' observations. Conversely, in Iran, Instagram was chosen due to its widespread popularity, enabling swift and high-quality data collection. WhatsApp, another popular platform in Iran, was also utilized. Notably, Facebook is inaccessible in Iran due to government filtering, leading researchers to avoid sharing the questionnaire link on this platform. Additionally, while Telegram is popular in Iran, the filtering of this platform prompted the cessation of questionnaire sharing. Ultimately, all collected data were translated into English, resulting in two distinct files for subsequent analysis.

In the Iranian sample, 50.4% of respondents were male, while 49.6% were female, contrasting with Hungary where the statistics were 44.5% and 55.5%, respectively. Regarding education, 37.5% of Iranian respondents had a bachelor's degree, while in Hungary, a higher percentage (38%) had a diploma or lower. The most frequent age in Iran was 30 years old (9.5% of respondents), and in Hungary, it was 22 years old (11%). In both countries, around 38-40% of respondents were 30 years old or younger. About 45.6% of Iranians had over 2 years of experience with grocery app shopping, while in Hungary, 23.5% had at least 4 years of experience. Snappfood was highly popular in Iran (78.5%), whereas in Hungary, Wolt led with 63.1%, followed by Foodpanda at 22.1%.

4.4. Sampling and data collection (Machine learning: case study 3)

The primary data for this study 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. This separation aimed to evaluate the model's generalizability and performance on unseen data.

Natural Language Processing (NLP) techniques were employed for model training. Various NLP models were utilized to capture the intricate nuances of language and sentiment within the comments. The choice of models and algorithms played a crucial role in achieving meaningful insights from the collected data.

Given the manual nature of data collection, ethical considerations were paramount. Measures were taken to ensure the privacy and consent of individuals whose comments were included in the dataset. Steps were also taken to adhere to ethical standards and comply with legal requirements.

To validate the quality of the manually collected data, a thorough review process was implemented. Inconsistencies or potential biases in labeling were identified and addressed, enhancing the reliability of the dataset. In the following chapter, the outcomes of the model training process and the results obtained from the analysis of the collected data will be presented in detail.

4.5. 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).

4.6. 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; AGRAWAL, 2020; DHIR & DHIR, 2020):

(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.

4.7. 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; ZEKHNINI ET AL. 2020). 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).

4.8. 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).

4.8.1. 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). This algorithm consists of a target/output variable (dependent variable) predicted based on a set of predictors (independent variables). The developed function maps the inputs to the corresponding outputs based on this set of variables. The learning process continues until the model achieves the desired level of accuracy on the training data. Some of the supervised learning algorithms are linear regression algorithm, decision tree, random forest, K-Nearest Neighbors, support vector machine algorithm, logistic regression, naive bayes classifier algorithm, gradient descent. To select an optimal algorithm for the problem, parameters such as accuracy, training time, linearity, number of parameters, and desired specific application must be considered.

4.8.2. 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 4 shows all unsupervised algorithms, methods and metric used. The main advantage of ML and algorithms are:

- Simple and efficient tools for predictive data analysis
- Accessible to everybody, and reusable in various contexts
- Built on NumPy, SciPy, and matplotlib.
- Open source, commercially usable - BSD license

Table 4. Unsupervised ML algorithms

Method name	Parameters	Scalability	Usecase	Geometry (metric used)
K-Means	number of clusters	Very large n_samples, medium n_clusters with MiniBatch code	General-purpose, even cluster size, flat geometry, not too many clusters, inductive	Distances between points
Affinity propagation	damping, sample preference	Not scalable with n_samples	Many clusters, uneven cluster size, non-flat geometry, inductive	Graph distance (e.g. nearest-neighbor graph)
Mean-shift	bandwidth	Not scalable with n_samples	Many clusters, uneven cluster size, non-flat geometry, inductive	Distances between points
Spectral clustering	number of clusters	Medium n_samples, small n_clusters	Few clusters, even cluster size, non-flat geometry, transductive	Graph distance (e.g. nearest-neighbor graph)

Ward hierarchical clustering	number of clusters or distance threshold	Large n_samples and n_clusters	Many clusters, possibly connectivity constraints, transductive	Distances between points
Agglomerative clustering	number of clusters or distance threshold, linkage type, distance	Large n_samples and n_clusters	Many clusters, possibly connectivity constraints, non Euclidean distances, transductive	Any pairwise distance
DBSCAN	neighborhood size	Very large n_samples, medium n_clusters	Non-flat geometry, uneven cluster sizes, outlier removal, transductive	Distances between nearest points
OPTICS	minimum cluster membership	Very large n_samples, large n_clusters	Non-flat geometry, uneven cluster sizes, variable cluster density, outlier removal, transductive	Distances between points
Gaussian mixtures	many	Not scalable	Flat geometry, good for density estimation, inductive	Mahalanobis distances to centers
BIRCH	branching factor, threshold, optional global clusterer.	Large n_clusters and n_samples	Large dataset, outlier removal, data reduction, inductive	Euclidean distance between points

Source: www.scikit-learn.org

4.8.3. Gaussian Mixture Model (GMM)

The Gaussian Mixture Model is a probabilistic framework that characterizes a dataset as a blend of multiple Gaussian distributions. Each Gaussian component captures distinct patterns within the data, making GMM versatile for clustering and density estimation. This model assigns probabilities to data points across different clusters, making it adaptable for applications like image segmentation and pattern recognition (SALAMZADEH ET AL. 2022).

4.8.4. Multi-layer Perceptron (MLP) Algorithm

The Multi-layer Perceptron stands as an artificial neural network specialized in supervised learning. Comprising interconnected nodes organized into layers, including input, hidden, and output layers, MLP employs a feedforward mechanism for information processing. Renowned for modeling intricate relationships, MLP finds widespread application in tasks such as classification and regression. Training involves adjusting weights through backpropagation, a process that optimizes the network to enhance accuracy in predictions (SALAMZADEH ET AL. 2022).

5.8.5. 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."

4.9. Model Comparison considering sentiment analysis

4.9.1. Naive Bayes Model with TF-IDF Encoder (Baseline Model)

- Description: A classic machine learning approach, Naive Bayes with TF-IDF encoding served as a baseline model.
- Strengths: Simplicity, interpretability.
- Considerations: Limited ability to capture complex relationships in sequential data.

4.9.2. Simple Feed-Forward Neural Network

- Description: A basic neural network designed to capture sequential dependencies.
- Strengths: Ability to model non-linear relationships in data.
- Considerations: Limited in handling long-range dependencies.

4.9.3. LSTM Model (Long Short-Term Memory)

- Description: A recurrent neural network architecture with long-term memory capabilities. Strengths: Effective in capturing long-range dependencies.
- Considerations: Increased computational complexity.

4.9.4. GRU Model (Gated Recurrent Unit)

- Description: A variant of LSTM, computationally more efficient.
- Strengths: Efficiency in handling sequential data.
- Considerations: May struggle with long-range dependencies.

4.9.5. BiDirectional RNN Model

- Description Utilizing bidirectional recurrent neural networks to consider context from both past and future inputs.
- Strengths: Enhanced understanding of contextual information.
- Considerations: Increased computational requirements.

4.9.6. Conv1D Model

- Description: A one-dimensional convolutional neural network suitable for capturing local patterns in sequential data.
- Strengths: Effectiveness in identifying local features.
- Considerations: Limited in handling long-range dependencies.

4.9.7. Transfer Learning Pretrained Sentence Encoder

- Description: Leveraging pre-trained models for transfer learning, incorporating external knowledge.
- Strengths: Improved performance and accuracy through knowledge transfer.
- Considerations: Model may need fine-tuning for specific tasks.

4.9.8. Transfer Learning Pretrained Sentence Encoder with Smaller Dataset

- Description: Similar to the above, with the additional exploration of model performance with a smaller dataset.
- Strengths: Evaluating the impact of data size on transfer learning.
- Considerations: Balancing model complexity with available data.

Each model's architecture, training parameters, and performance metrics were meticulously assessed to provide a comprehensive understanding of their effectiveness in sentiment analysis. The subsequent chapter delves into detailed results and implications derived from these models.

V. RESULTS AND DISCUSSION

5.1. ISM

The 12 factors' contextual associations were established through an Adjacency Matrix, drawing upon insights from 22 experts as indicated in Table 5. 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 SADE and GARKAZ in 2018.

5.1.1. ISM calculations, Building adjacency matrix or SSIM

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. The graphical representation of these relationships, utilizing SSIM, is depicted in Figure 8.

Table 5. 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												

Source: Author’s own work based on MATLAB results

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.

5.1.2. Initial reachability matrix

During this stage, the SSIM underwent a transformation into a binary matrix termed the initial reachability matrix (Table 6). This conversion involved substituting V, A, X, and O with 1 and 0 based on their respective positions. Various authors, including FAISAL (2010), CHANG ET AL. (2013), 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" (SINDHU, 2020).

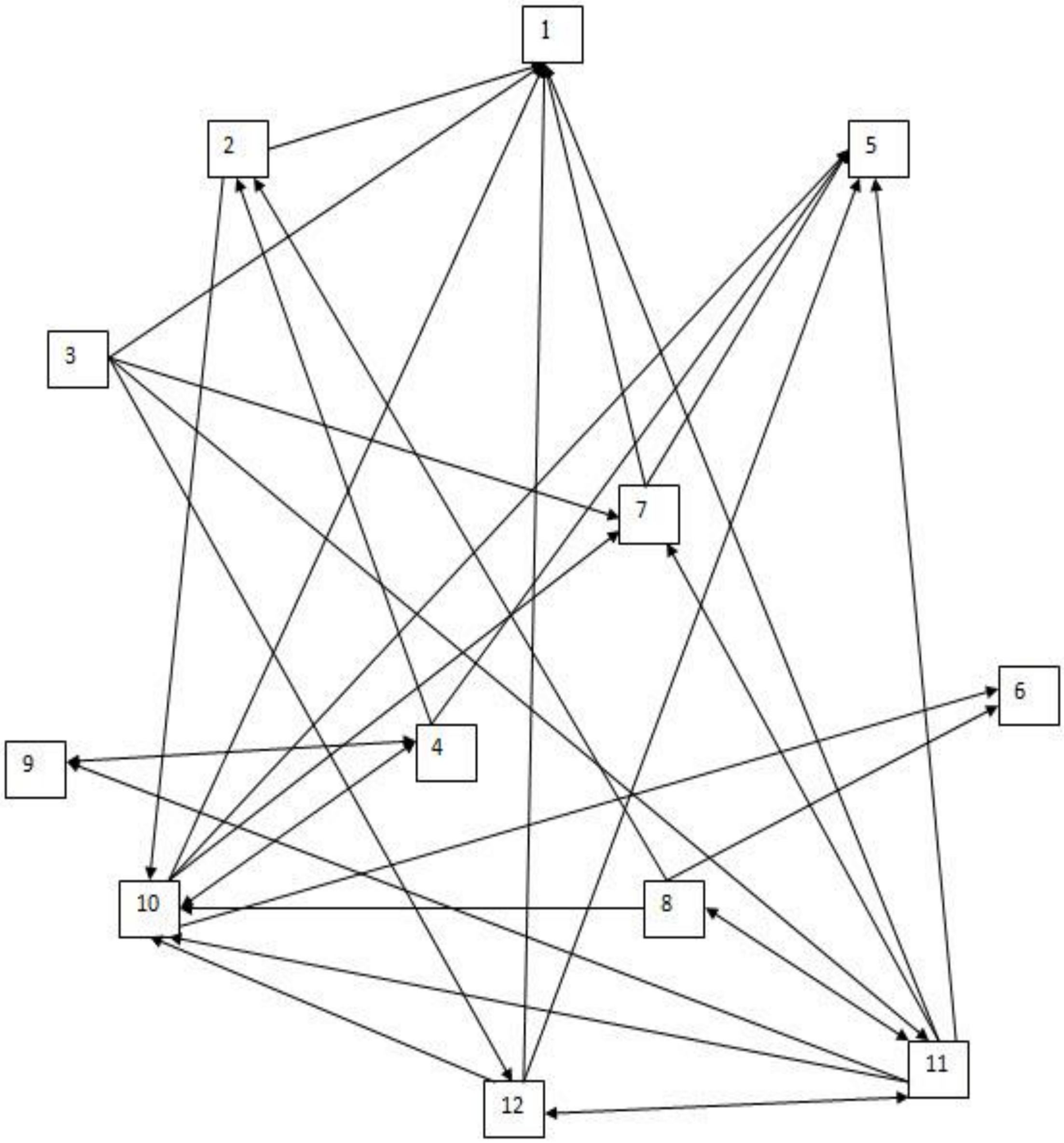

Figure 8. Digraph based on SSIM

Source: Author’s own work based on MATLAB results

.

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 6. 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

5.1.3. 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. As outlined by SHEN ET AL. (2016), the final reachability matrix can be generated through the utilization of the following equation 1:

Equation (1): $R_f = R_i^K = R_j^{K+1}, K > 1$

where R_f is the final Reachability Matrix, and R_i is the initial Reachability Matrix.

The transitivity principle, grounded in the works of WARFIELD (1974), GAN ET AL. (2018), and EBRAHIMI ET AL. (2020), asserts that 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 7. 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 Matrices d'Impacts Croises Multiplication Appliqué a un Classement (MICMAC) analysis or cross-impact analysis, as noted by AZVEDO ET AL. (2019).

Table 7. 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

5.1.4. 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, as demonstrated in Appendix F: Level Partitions Program with MATLAB. The top-level element in the hierarchy does not contribute to achieving any other element positioned above its own level (SINGH & KANT, 2008; DALVI-ESFAHANI, RAMAYAH, & NILASHI, 2017; DIGALWAR, RAUT, YADAV, NARKHEDE, GARDAS, & GOTMARE, 2020).

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 8. 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 8. 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

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.

5.1.5. ISM model and MICMAC analysis

By employing level partitioning for factors, we construct the diagram representing the final ISM model, as depicted in Figure 9. As evident in Table 8, "Consumer engagement," "Consumer's value perception," and "Perceived risk" are classified at Level I, positioning them at the pinnacle of the ISM model.

Figure 9 provides a visual representation of the research variables, their interrelationships, and the hierarchical level to which each variable belongs. Figure 9 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.

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" (WANG

ET AL. 2008; GAN ET AL. 2018). MICMAC analysis serves the purpose of exploring factors' dependence and driving power (WARFIELD, 1974; GAN ET AL. 2018; DHIR & DHIR, 2020). Simultaneously, MICMAC aids in comprehending the scope of variables and pinpointing the key strategic variables within the system (EBRAHIMI ET AL. 2020; KHAN ET AL. 2020).

All factors have been categorized into four groups based on their dependence and driving powers (refer to Table 7 and Figure 10): autonomous factors, dependent factors, linkage factors, and independent factors. Figure 10 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., Consumer engagement (F2), Social influence (F4), Social support (F9), and Value co-creation (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., Social media WOM (F3), Perceived information quality (F8), Knowledge sharing (F11) and Service innovation (F12).

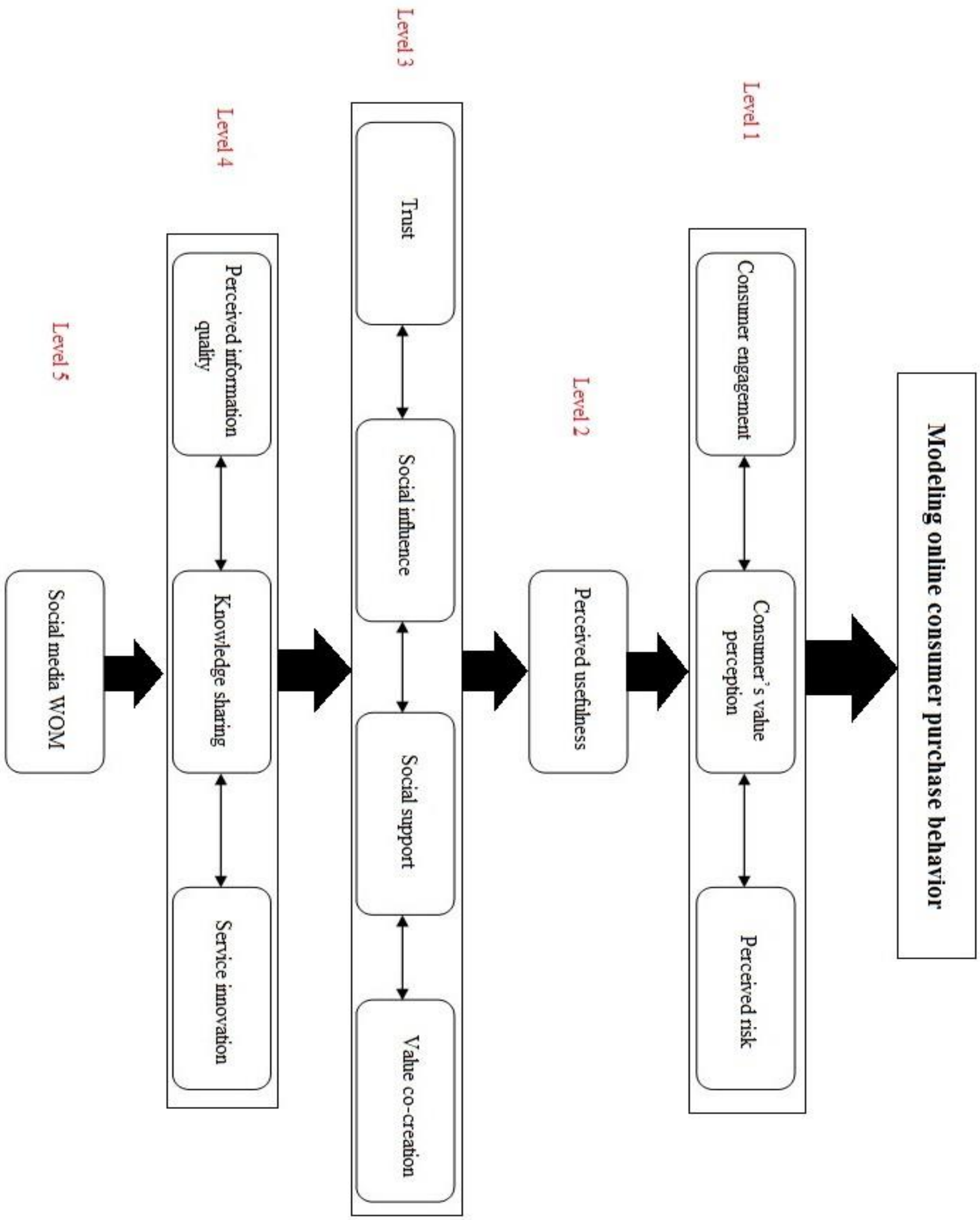

Figure 9. ISM model

(Source: Author’s own work based on MATLAB results)

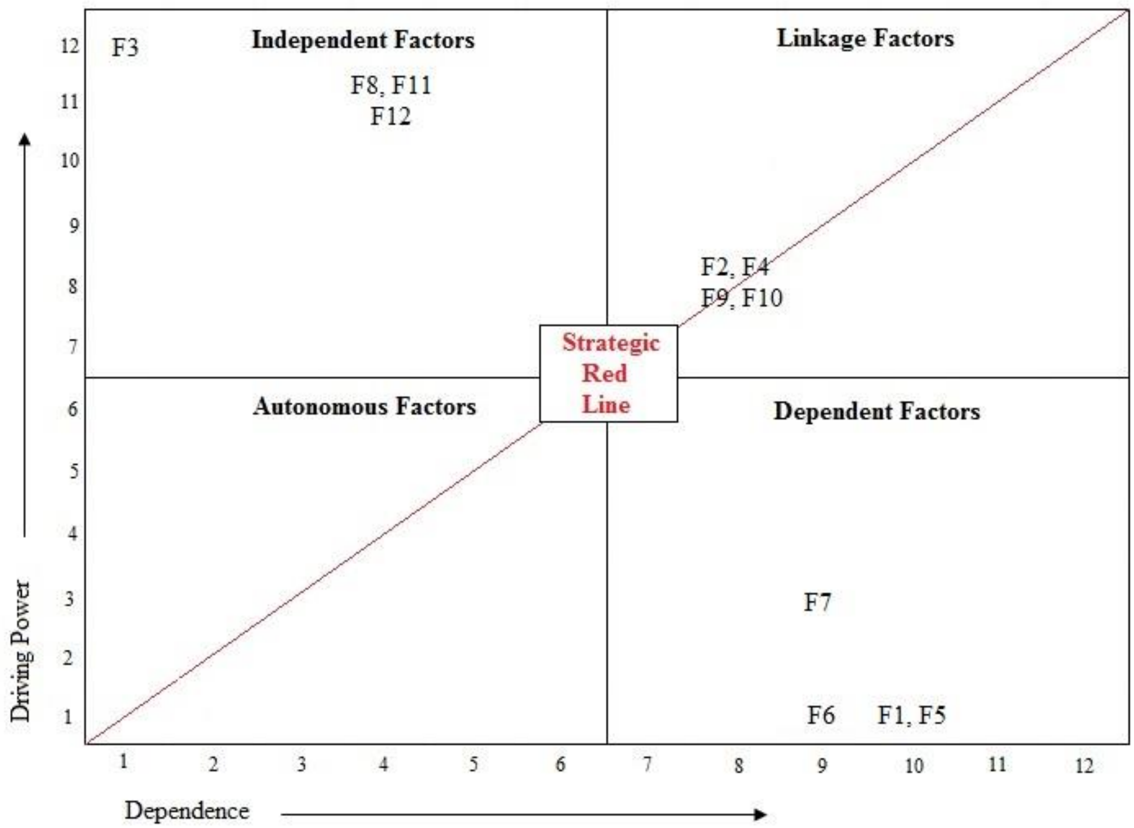

Figure 10. MICMAC analysis

Source: Author's own work based on MATLAB results

5.2. AHP

After gathering data through the pairwise questionnaire (see Appendix G), it is imperative to formulate a conceptual model for addressing a specific decision problem.

5.2.1. AHP calculations, Development of the hierarchy

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.

5.2.2. 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 KHANSARIi ET AL. 2022, provides a systematic approach to express the relative importance of attributes in the pairwise comparison process.

5.2.3. Consistency index and consistency ratio

Through the computation of criteria or sub-criteria priorities, the Analytic Hierarchy Process (AHP) facilitates the assessment of comparison consistency employing the Consistency Index (CI), Random Consistency Index (RI), and Consistency Ratio (CR), as defined by Equations (1) and (2). 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.

$$CI = (\lambda max - n)/(n-1) \quad (1)$$

where

CI is the consistency index;

λmax is the maximum eigenvalue;

n is the size of the measured matrix.

$$CR = CI/RI \quad (2)$$

where

CR is the consistency ratio;

CI is the consistency index;

RI is the random consistency index.

5.2.4. AHP analysis

Figure 11 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.

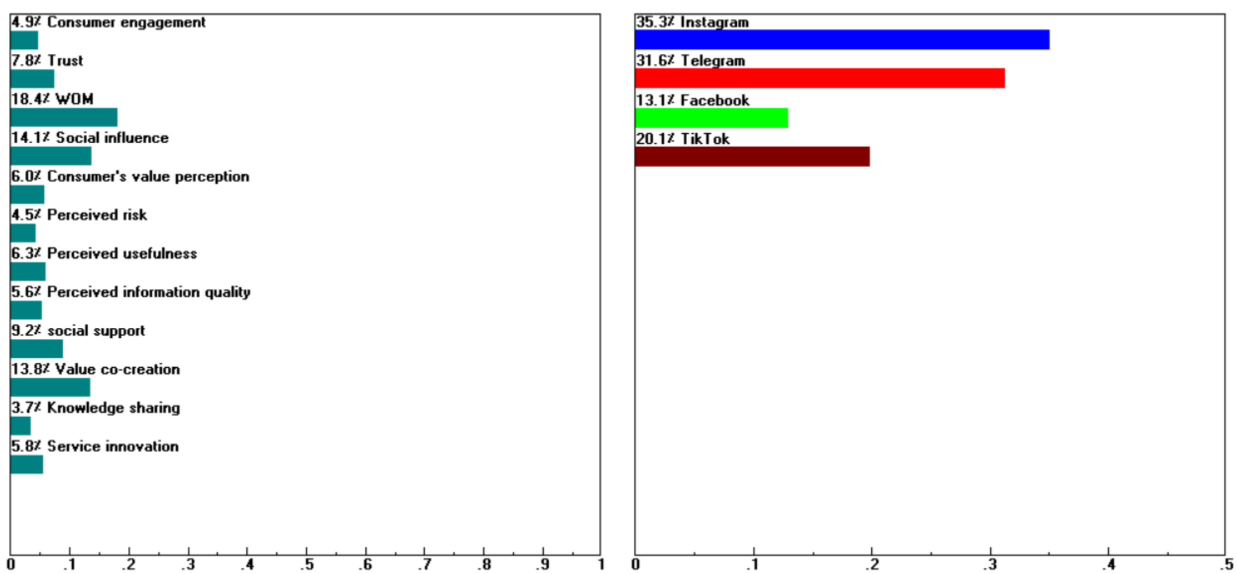

Figure 11. Dynamic sensitivity analysis of criteria and alternatives

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

Figures 12 to 17 utilize a 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.

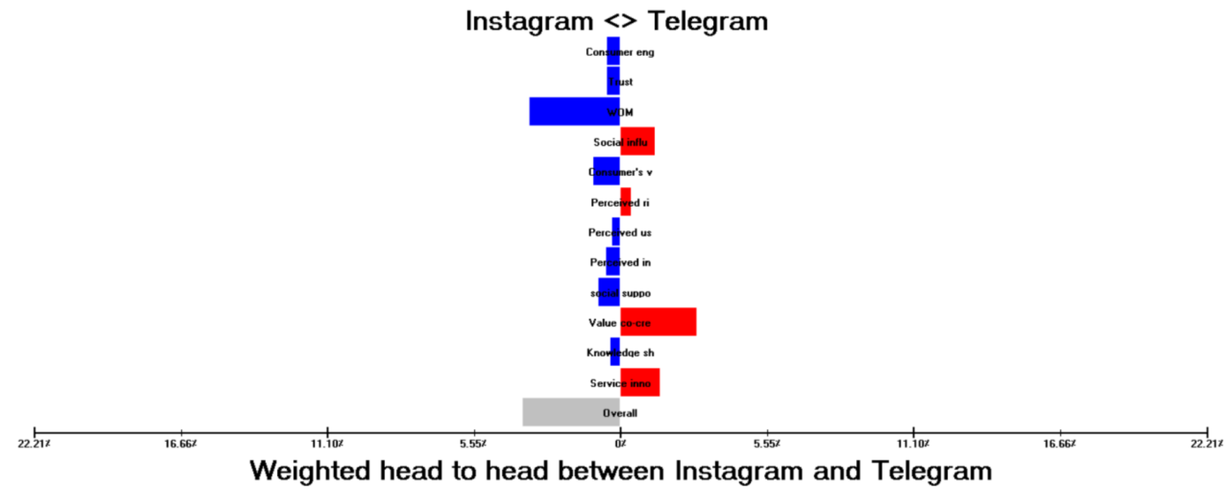

Figure 12. Weighted head to head analysis Instagram & Telegram

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

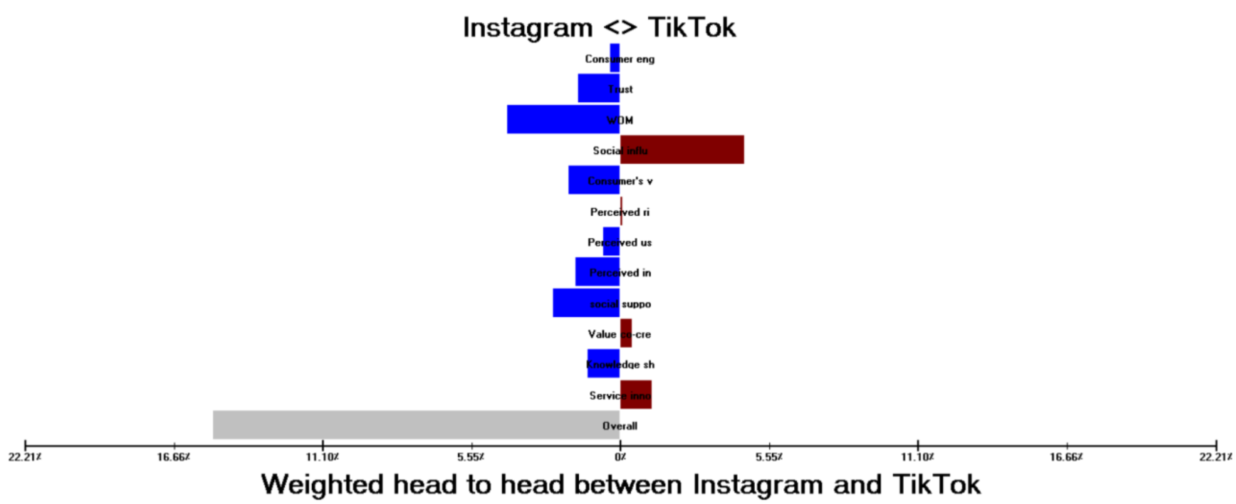

Figure 13. Weighted head to head analysis Instagram & TikTok

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

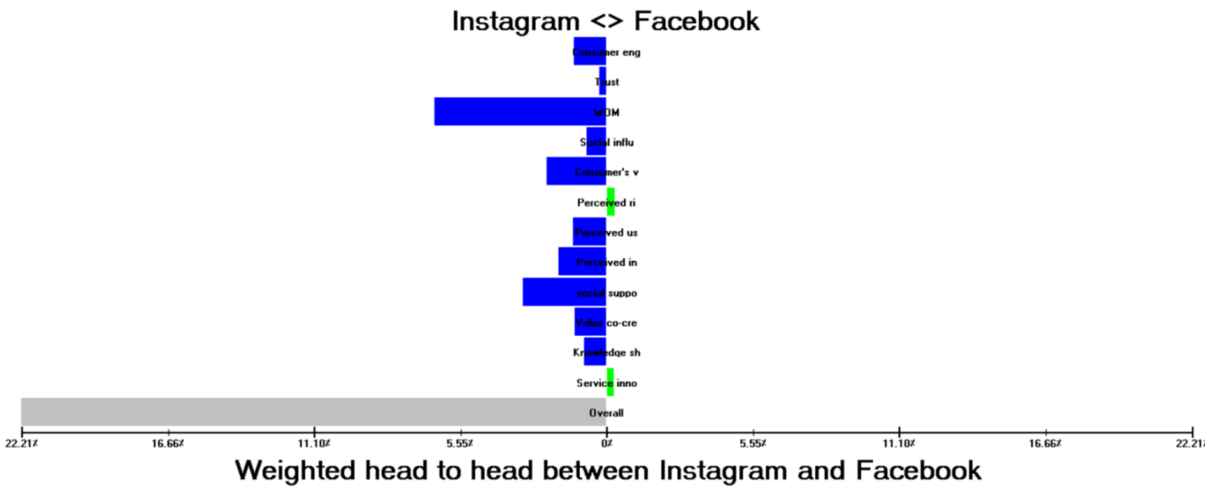

Figure 14. Weighted head to head analysis Instagram & Facebook

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

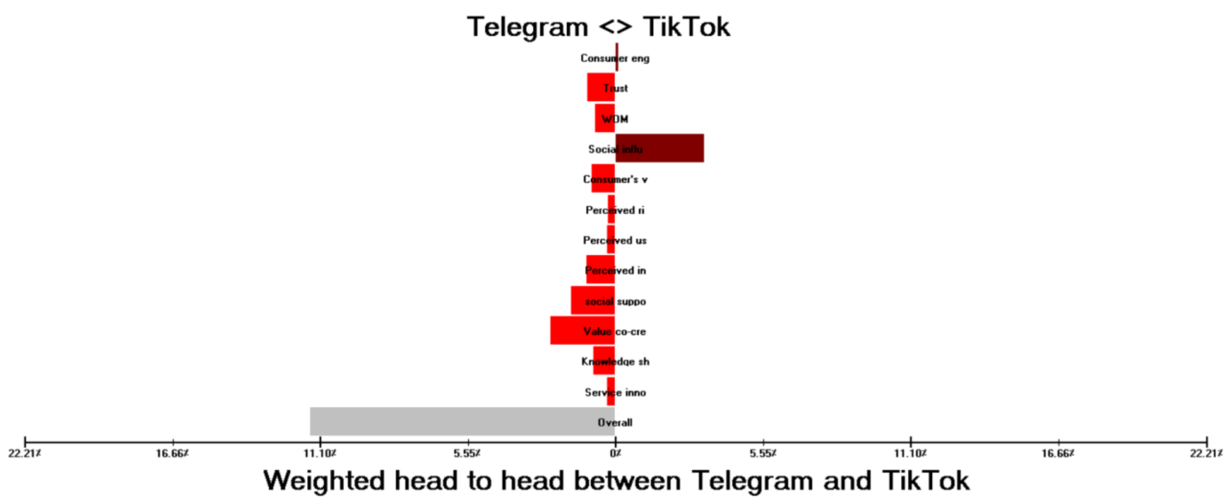

Figure 15. Weighted head to head analysis Telegram & TikTok

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

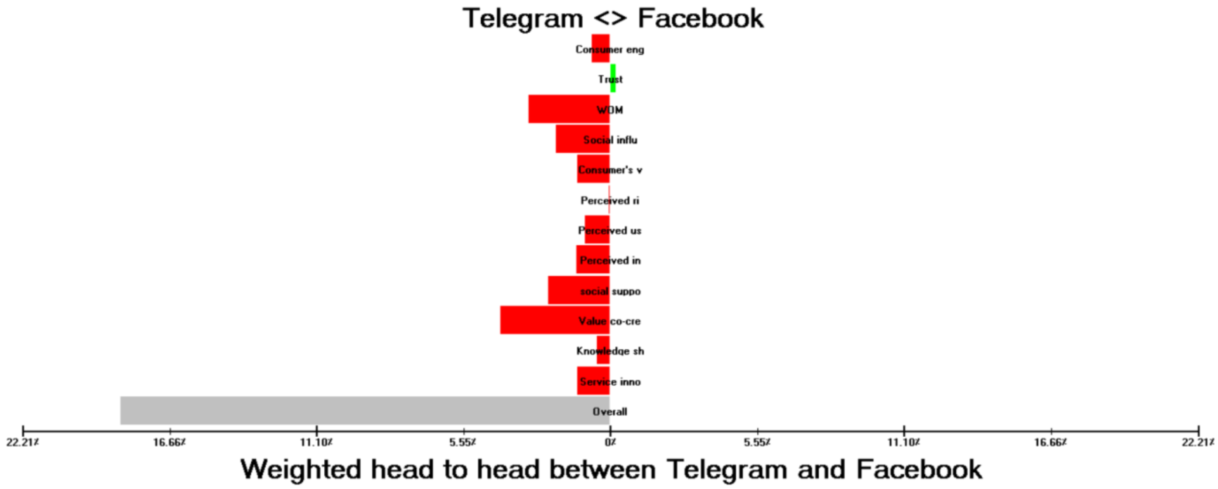

Figure 16. Weighted head to head analysis Telegram & Facebook

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

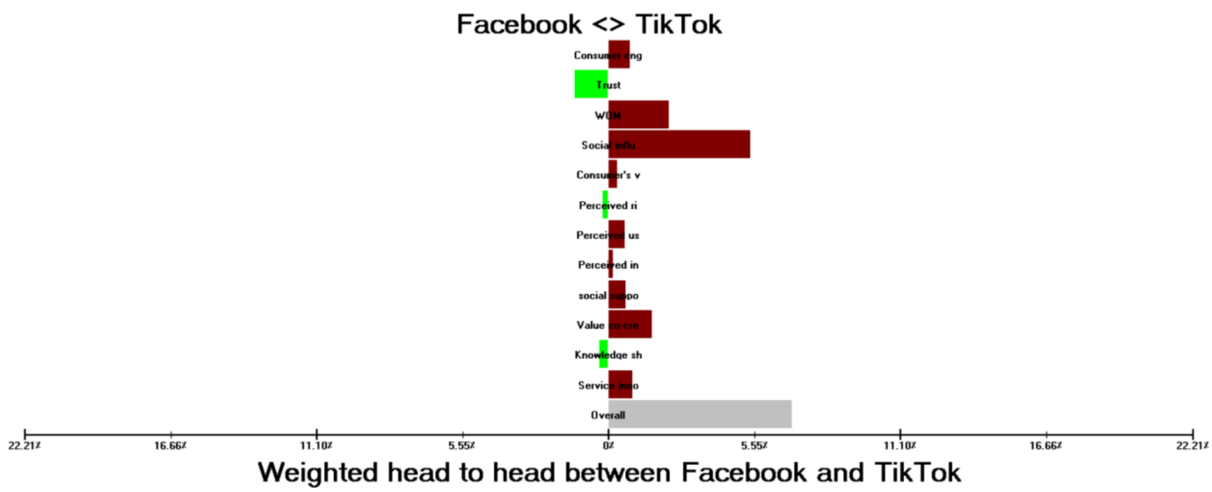

Figure 17. Weighted head to head analysis TikTok & Facebook

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

Concentrating on the analysis of performance sensitivity, Figure 18 additionally illustrates that, within the scope of the study objective, the various criteria exhibit fluctuating trends in their plots contingent upon distinct social networks.

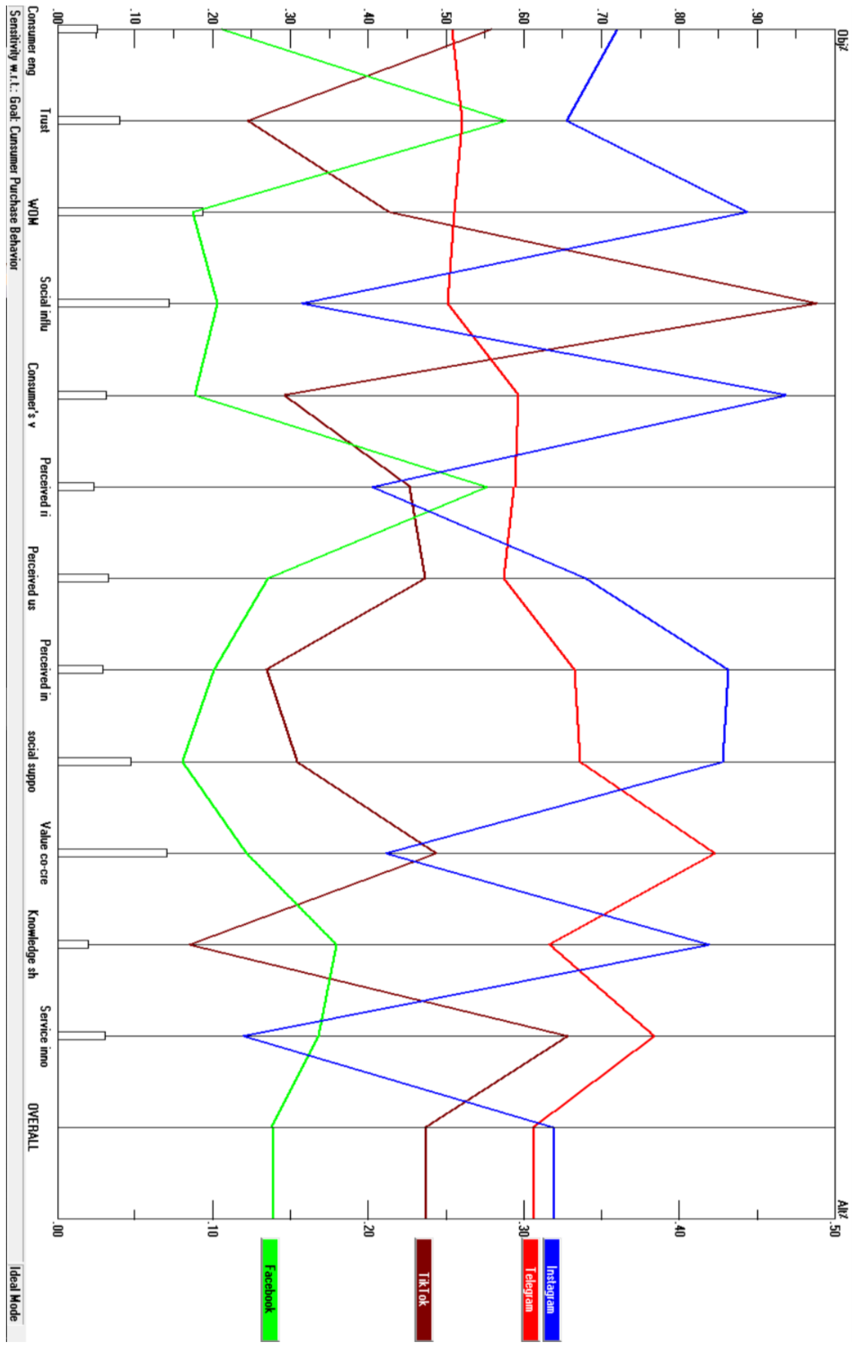

Figure 18. Performance sensitivity analysis

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

5.3. Case study 1, A decision tree model to predict consumer purchase behavior in Iran

Figure 19 displays a pair plot of demographic data, highlighting Instagram as the most popular online platform across various demographic variables.

A pair plot is a type of visualization commonly used in exploratory data analysis to examine relationships between pairs of variables in a dataset. It typically consists of a grid of scatterplots, where each pair of variables is plotted against each other. Along the diagonal of the grid, histograms or kernel density plots may be displayed for each variable individually, showing the distribution of values for that variable. In each scatterplot, the x-axis represents one variable, while the y-axis represents another variable. By examining the scatterplots, patterns such as linear relationships, clusters, outliers, and correlations between variables can be visually identified. Additionally, the pair plot may include correlation coefficients or other statistical measures to quantify the strength and direction of relationships between numerical variables.

The pair plot of the respondents' demographic data is a visual representation that illustrates the relationships between pairs of demographic variables. It provides a comprehensive overview of the data by displaying scatterplots for each pair of variables along the diagonal and correlation coefficients for numerical variables. This visualization technique is particularly useful for identifying patterns, trends, and potential correlations within the dataset. In this specific context, the pair plot was generated using Python programming language and the Seaborn package within a Jupyter notebook environment. Python offers a wide range of libraries for data visualization, and Seaborn is known for its simplicity and elegance in creating complex visualizations with minimal code.

By leveraging Seaborn's pair plot function, the authors were able to efficiently generate the visualization directly within the Jupyter notebook, facilitating seamless integration of data analysis and visualization tasks. The pair plot serves as a valuable tool for exploring and understanding the relationships among different demographic variables, such as age, gender, income, education level, etc., among respondents. By examining the patterns revealed in the pair plot, researchers can gain insights into potential correlations or dependencies between demographic factors, which can inform further analysis.

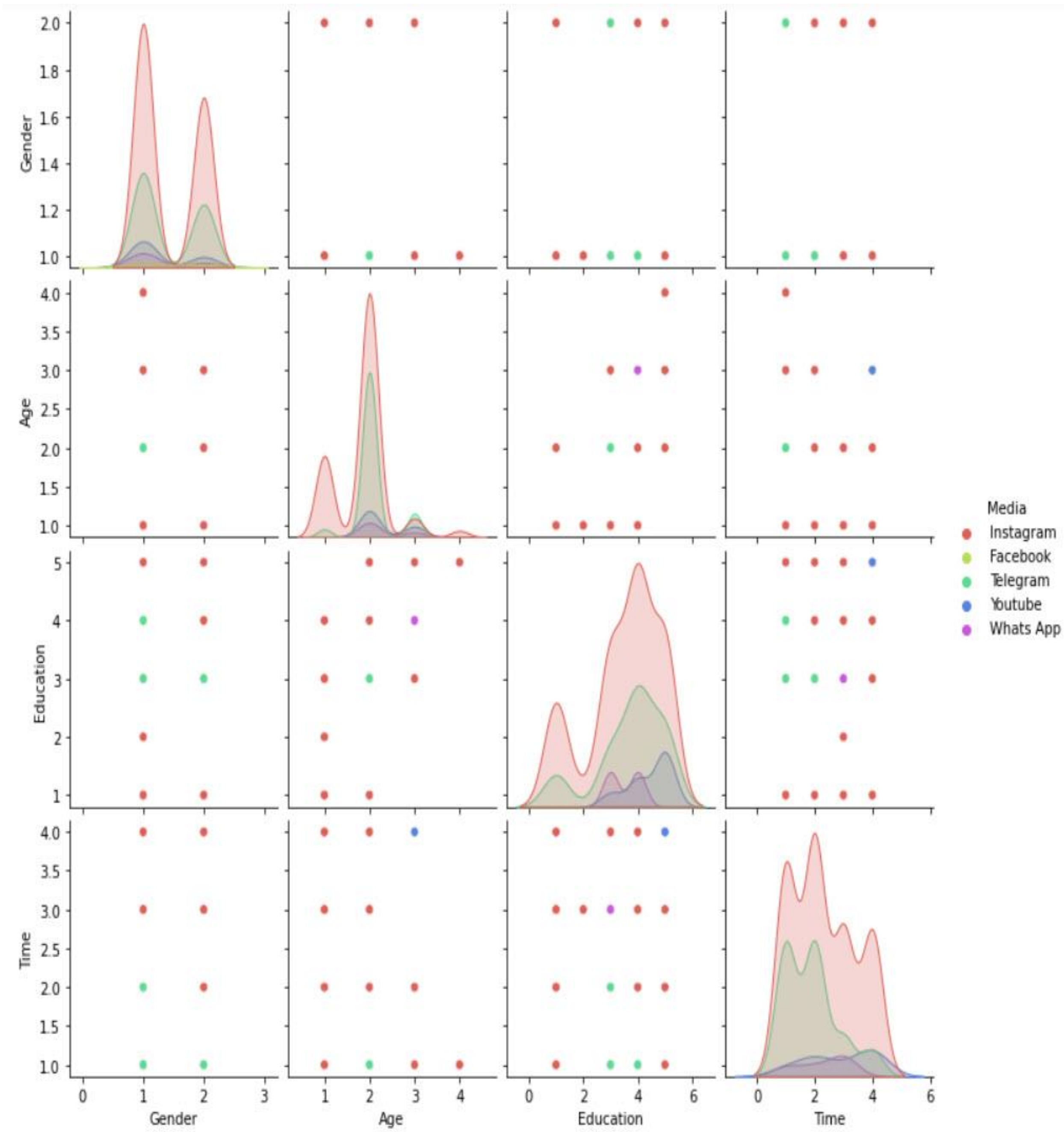

Figure 19. The pair plot of the respondents' demographic data

(Source: authors' calculations based on Python programming/Seaborn package in Jupyter notebook)

Figure 20 illustrates an expansive schematic of online consumer behavior incorporating demographic variables, encompassing a comprehensive array of predictive modes (map visualization). 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.

By incorporating map visualization into the decision tree model, the author likely aim to leverage spatial information to enhance the predictive power of the model. This could involve features such as behavior, proximity to certain stores or demographics, or other spatial attributes that may influence consumer behavior. The use of map visualization within the decision tree model can offer several benefits in understanding consumer behavior:

1. Spatial Patterns: By visually representing consumer behavior on a map, patterns and trends specific to consumer desires can be easily identified. This can provide valuable insights into regional variations in purchasing preferences, which may inform marketing strategies and targeted advertising campaigns.
2. Targeted Marketing: Decision trees generated from map visualization can help identify key areas or customer segments with high purchase likelihoods. Marketers can then tailor their promotional efforts and product offerings to better meet the needs and preferences of these specific consumer groups.
3. Predictive Accuracy: Incorporating spatial data into the decision tree model can improve its predictive accuracy by capturing additional factors that influence consumer behavior beyond traditional demographic or behavioral variables. This can lead to more accurate predictions of future purchase decisions, facilitating better resource allocation and strategic decision-making.

Overall, the combination of decision tree modeling with map visualization offers a powerful approach to analyzing and understanding consumer purchase behavior, enabling businesses to gain actionable insights and drive more effective marketing and sales strategies.

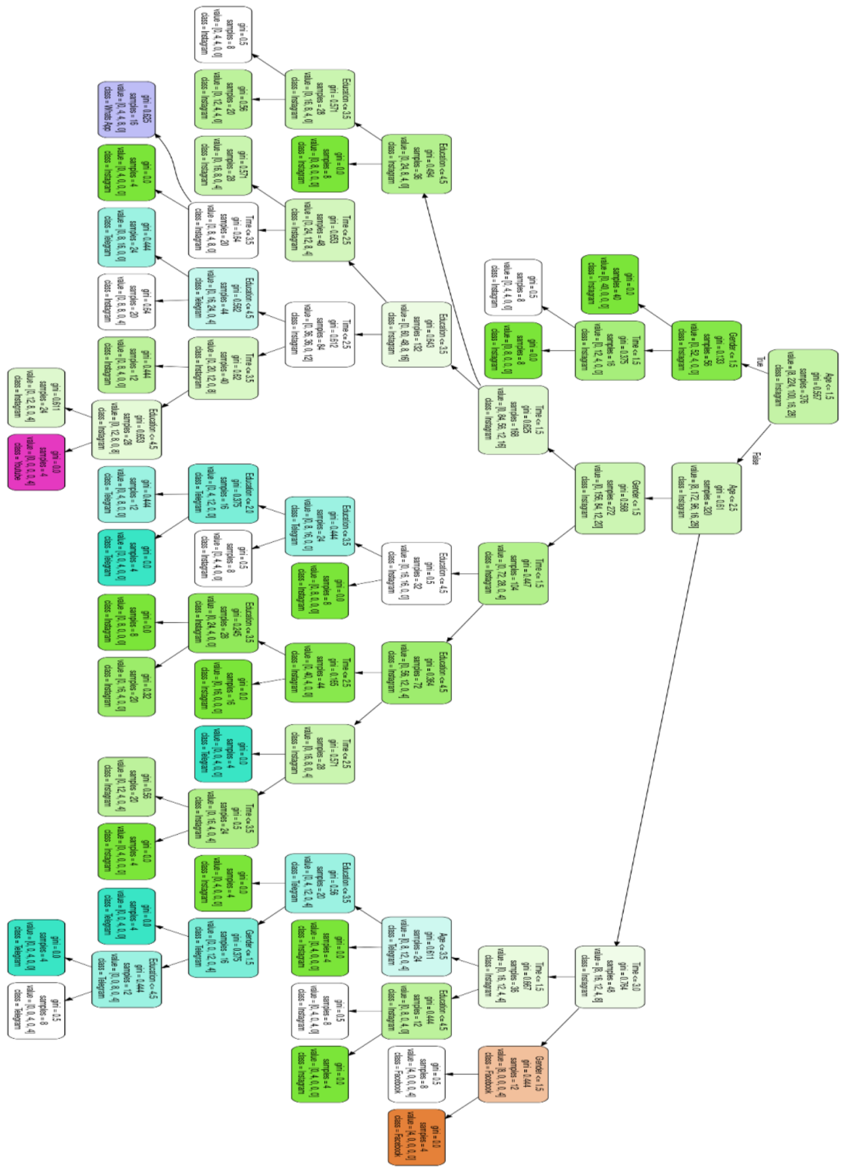

Figure 20. The decision tree model based on map visualization of consumer purchase behavior (Source: authors' calculations based on Python programming/ Visualization with Visual Studio Code).

To achieve this pivotal objective, program codes have been developed utilizing the decision tree model. In the program (refer to Appendix H), 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. 20), 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.

5.4. Case study 2, Grocery apps and consumer purchase behavior

Figures 21 and 22 present noteworthy insights through pair plots and comparative analyses of demographic data pertaining to Iran and Hungary.

Figure 21 presents a pair plot analysis of demographic data specific to Iran. The plot showcases relationships between pairs of demographic variables, including gender, age, education level, online shopping experience, and the popular grocery app used in Iran (such as Snappfood, Jimomarket, or Digikala). Each scatterplot in the pair plot visualizes the relationship between two variables, offering insights into potential correlations or patterns within the data. For example, the scatterplots may reveal how age correlates with online shopping experience or how education level influences the choice of grocery app. Additionally, histograms along the diagonal provide distributions of individual demographic variables, aiding in understanding their overall characteristics.

Figure 22 illustrates a pair plot analysis of demographic data specific to Hungary. Similar to Figure 21, this plot examines relationships between pairs of demographic variables, including gender, age, education level, online shopping experience, and the popular grocery app used in Hungary (such as FoodPanda, Wolt, Spar, Tesco online, or myLidl). By visualizing these relationships, Figure 22 offers insights into how demographic factors may interact with each other and influence consumer behavior in Hungary. For instance, the plot may reveal how age and gender affect online shopping experience or how education level correlates with the choice of grocery app.

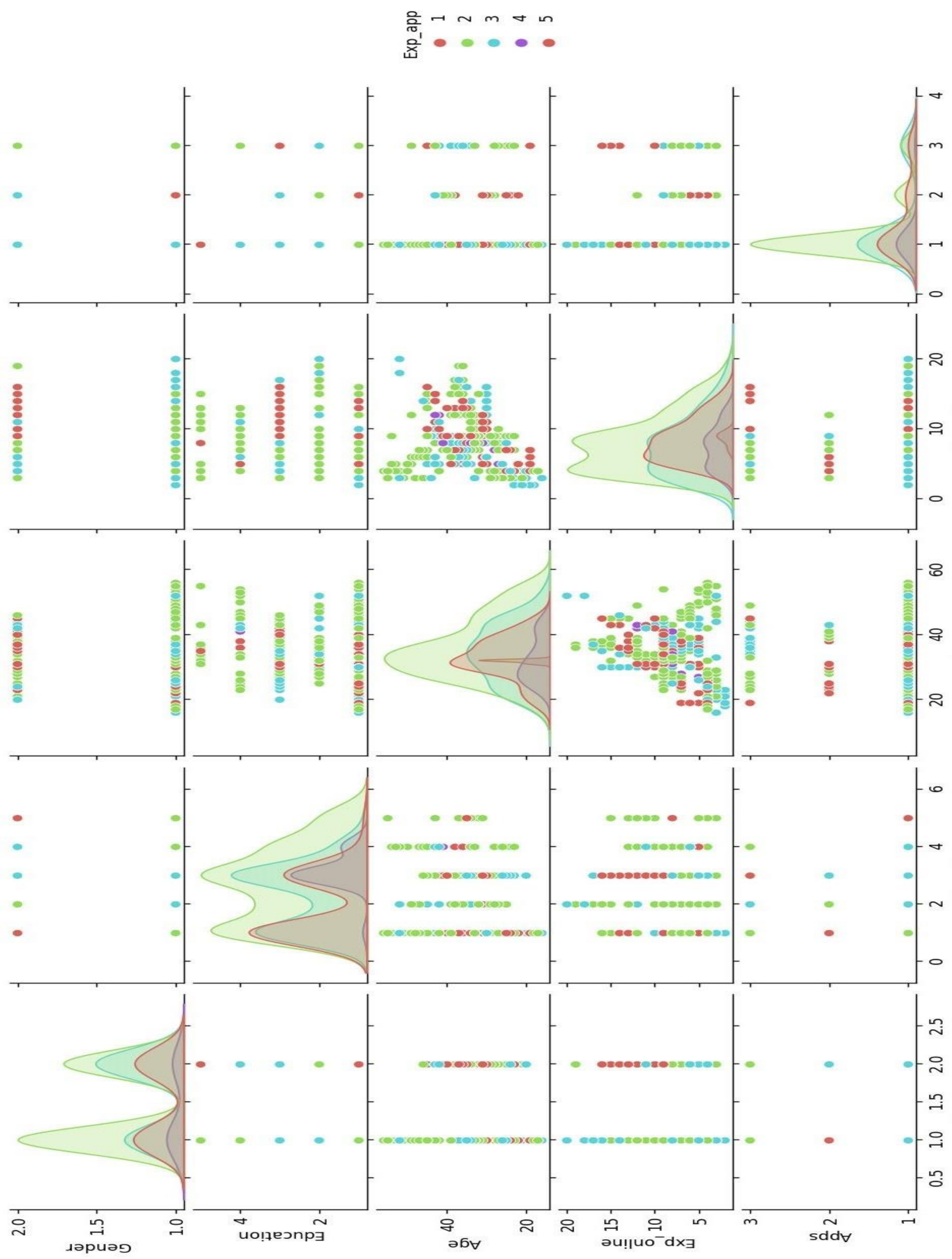

Figure 21. The pair plot of the respondents' demographic data in Iran (Source: authors' calculations based on Python programming; Seaborn package; VS Code editor)

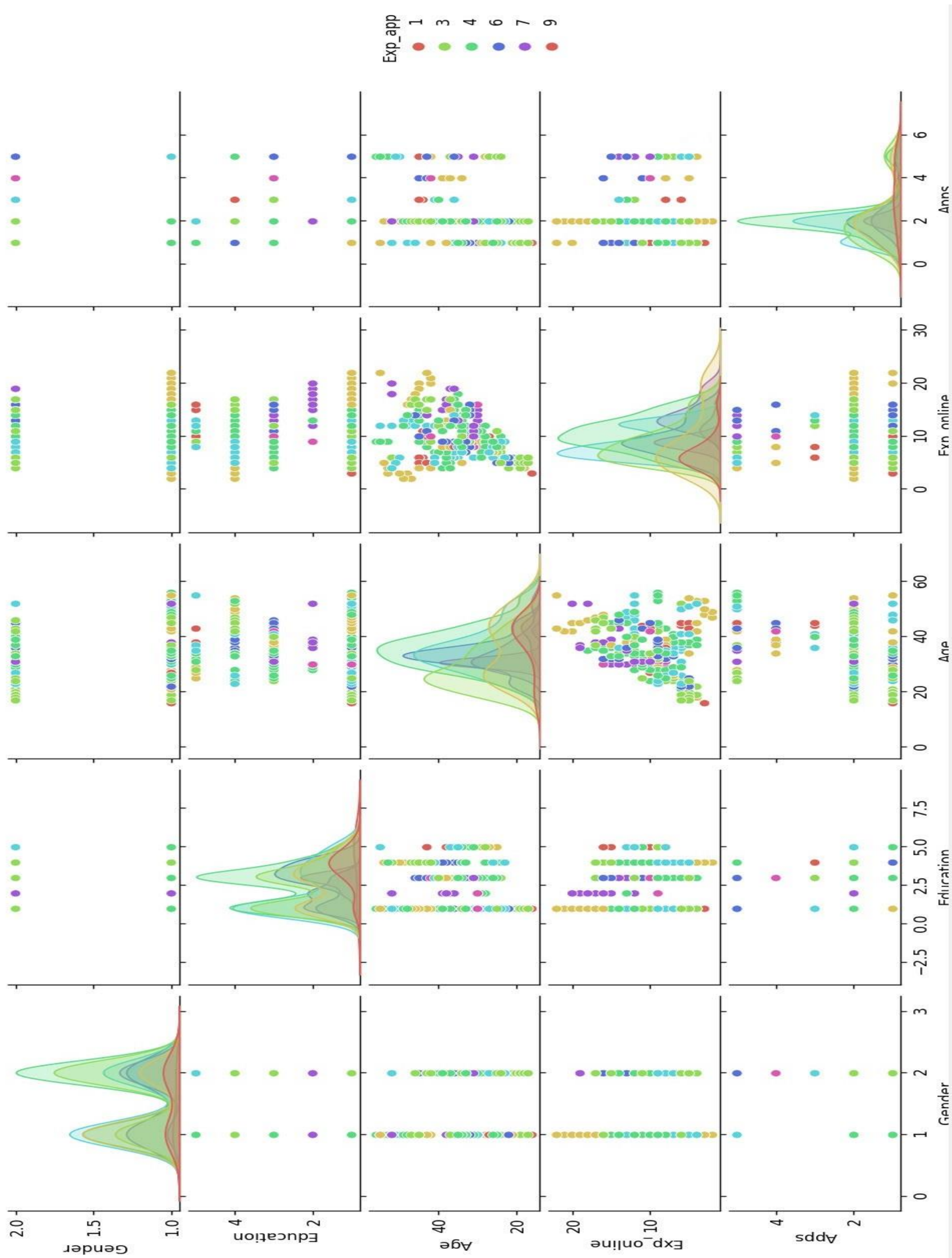

Figure 22. The pair plot of the respondents' demographic data in Hungary (Source: authors' calculations based on Python programming; Seaborn package; VS Code editor)

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 23 and 24 depict the evaluation of model accuracy across these four covariance types. In Figure 23, 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 24, 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.

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.

This live demo deployment of the two models in Iran and Hungary represents an innovative application of machine learning in real-world scenarios, facilitated by the Flask framework. Flask serves as the backbone for the backend infrastructure, enabling seamless integration between the predictive models and the user interface. By hosting the models on PythonAnywhere, a cloud-based platform, accessibility, and scalability are ensured, allowing users from anywhere to access the prediction service through the provided URLs: https://arad1367.pythonanywhere.com/predict_iran for Iran and https://arad1367.pythonanywhere.com/predict_hungary for Hungary.

The deployment process involves creating endpoints within the Flask application, which handle incoming requests from users seeking predictions about the preferred grocery app in Iran and Hungary. These endpoints interact with the deployed machine learning models to generate predictions based on user input, such as demographic data. The user-friendly interface provided by the Flask app guides users through the prediction process, making it accessible to individuals with varying levels of technical expertise. Furthermore, the incorporation of a database to store user predictions enhances the utility of the deployed models for future use cases and analysis.

The project is also available on GitHub, fostering collaboration and transparency. Access to project in GitHub: https://github.com/arad1367/PhD_live_demo_ML_NLP_LLM

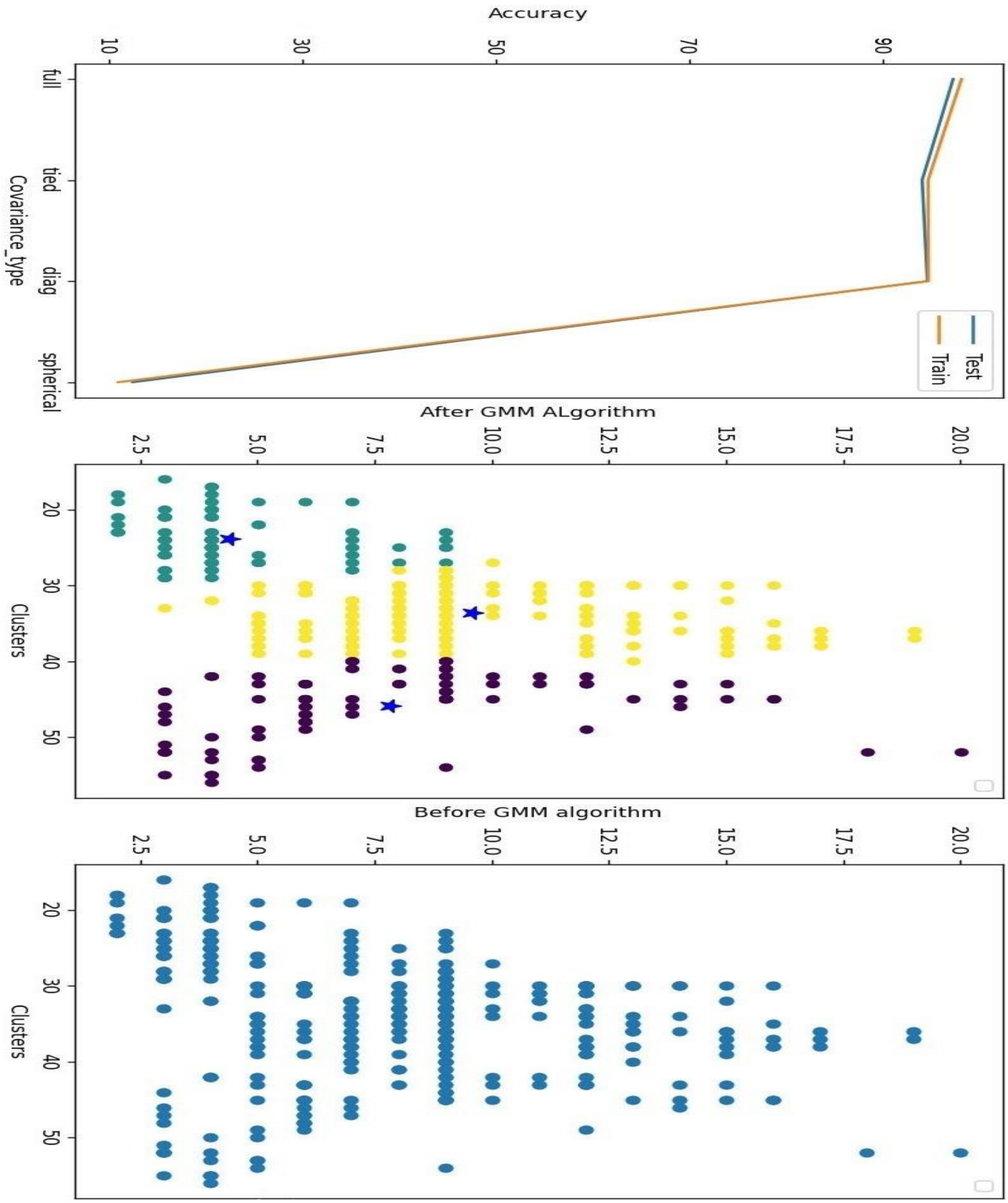

Figure 23. GMM algorithm output based on Iran data (Source: authors' calculations based on Python programming)

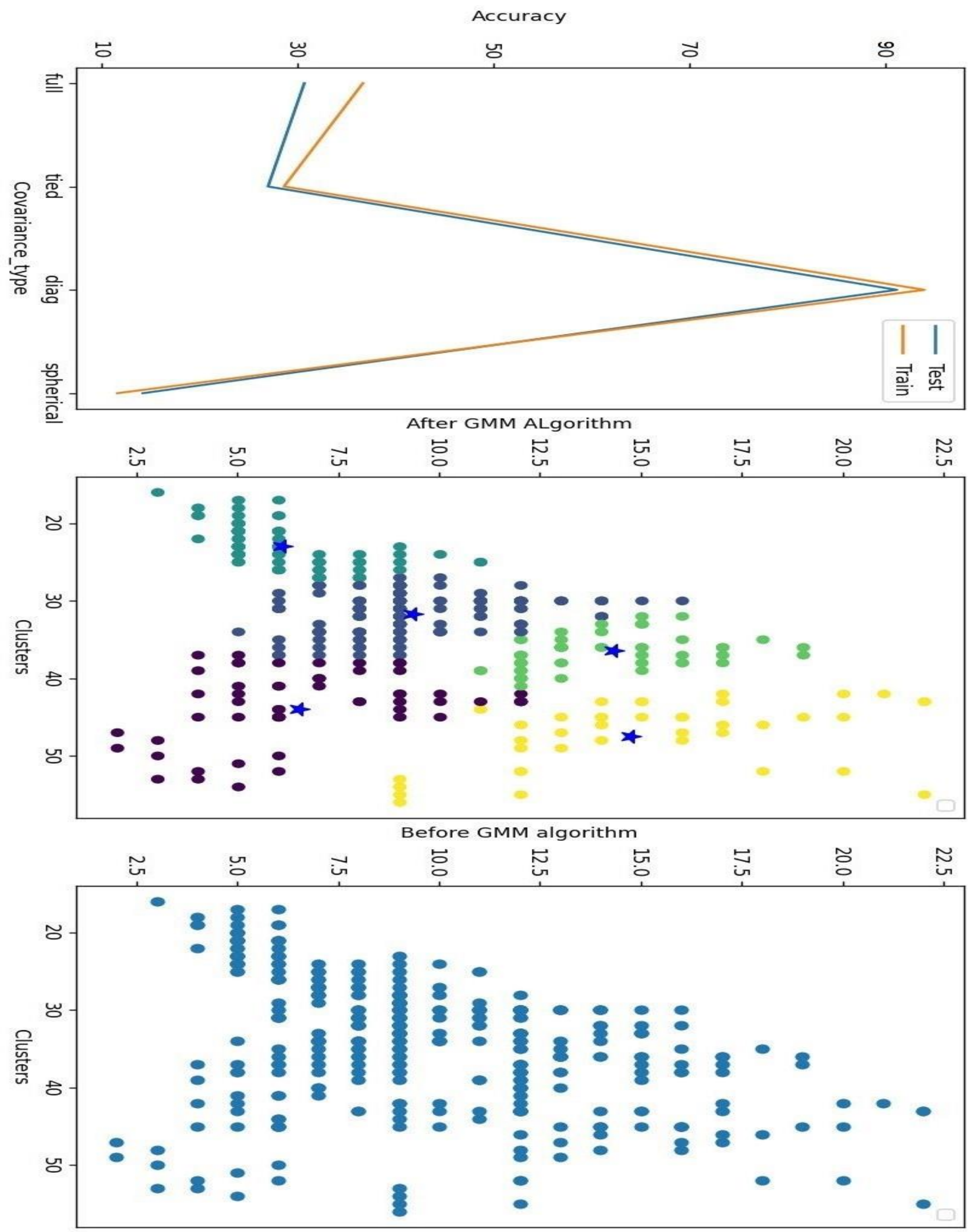

Figure 24. GMM algorithm output based on Hungary data

(Source: authors' calculations based on Python programming)

5.5. Case study 3, Sentiment analysis of Instagram comments using NLP

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 each 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 25 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 9 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. In addition, you can access a live demo of the embedding projector and make predictions on sentiment analysis at the following address: https://arad1367.pythonanywhere.com/sentiment_analysis

Table 9. 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

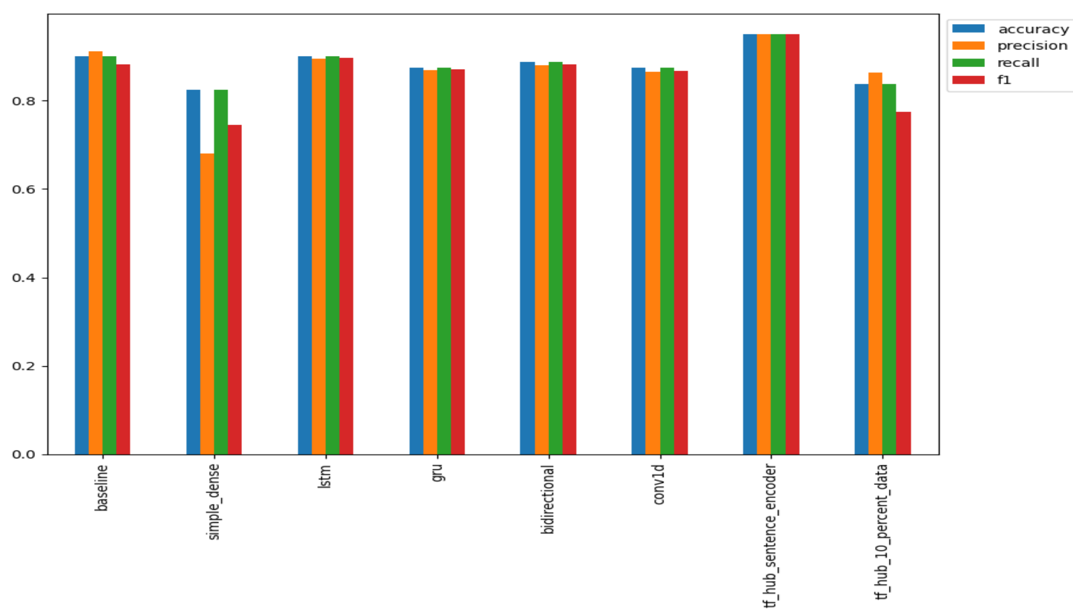

Figure 25. Models accuracy comparison

(Source: authors' calculations based on Matplotlib library using google colab and TensorFlow 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 26 to 28 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.

The TensorFlow Embedding Projector stands as a cornerstone tool within the Natural Language Processing community, offering a multifaceted approach to understanding and refining word embeddings. By providing an interactive visual interface, it empowers users to navigate and comprehend the intricate relationships encoded within high-dimensional embedding spaces. Through intuitive clustering and overlaying metadata, researchers can unveil semantic nuances and uncover subtle patterns that may elude traditional analyses.

Moreover, the Embedding Projector serves as a dynamic playground for model exploration and fine-tuning, enabling researchers and developers to iteratively refine their NLP architectures for optimal performance. Beyond its visualization capabilities, the TensorFlow Embedding Projector facilitates deeper insights into the inner workings of NLP models. Its ability to visualize embeddings not only aids in understanding semantic relationships between words but also sheds light on how models generalize and capture linguistic structures. By dissecting these embeddings, researchers can diagnose biases, identify areas of improvement, and iteratively enhance model robustness and fairness.

Furthermore, the TensorFlow Embedding Projector democratizes NLP research by offering an accessible platform for both experts and newcomers to the field. Its user-friendly interface lowers the barrier to entry for experimenting with embeddings, fostering collaboration and knowledge-sharing within the community. As NLP continues to evolve, the Embedding Projector remains an indispensable tool, empowering researchers to push the boundaries of language understanding and develop more sophisticated and inclusive AI models.

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.

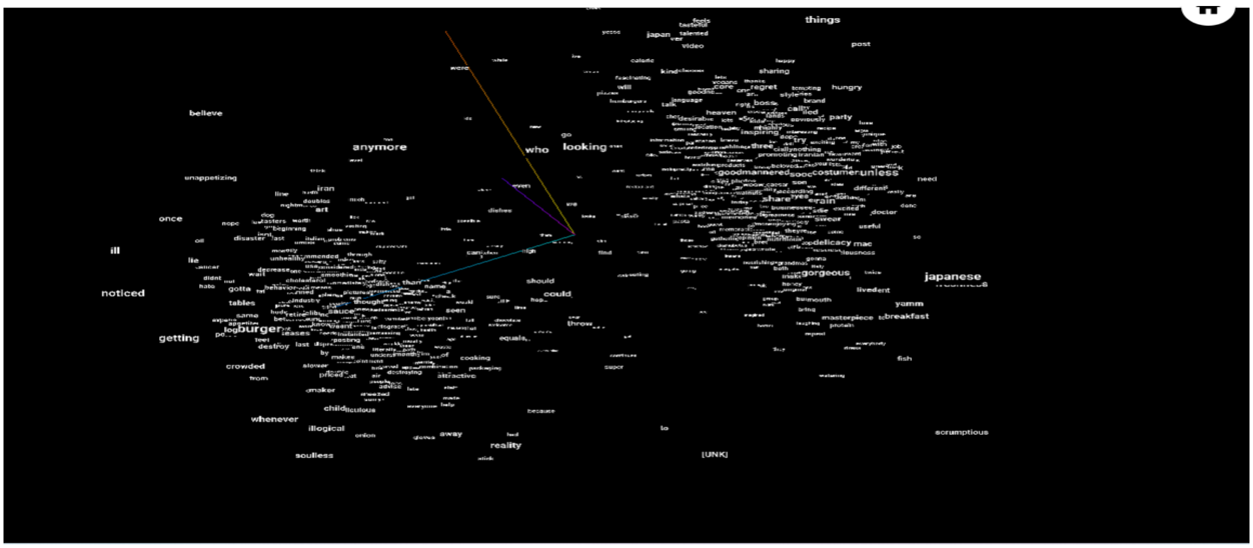

Figure 26. Embedding projector white and black

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

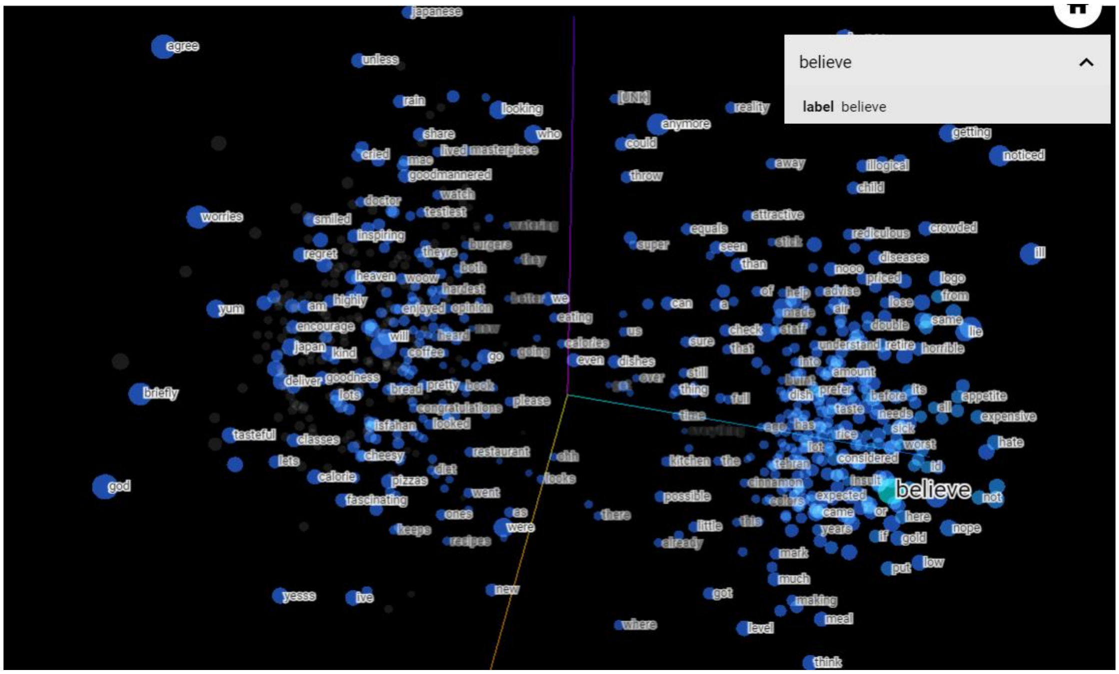

Figure 27. Embedding projector blue and black

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

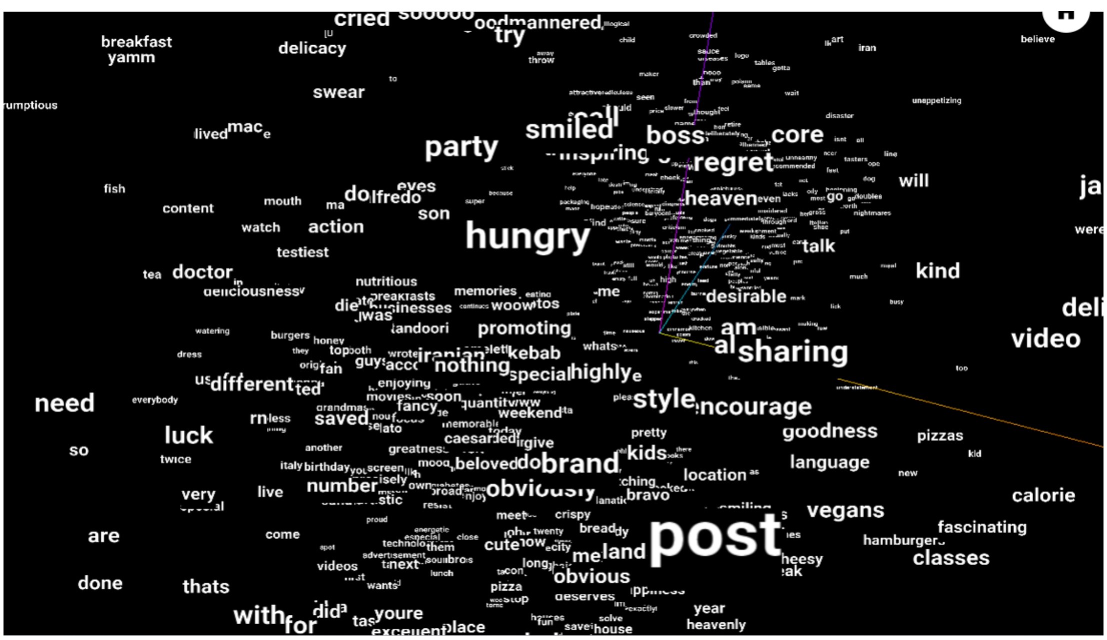

Figure 28. Embedding projector frequency words

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

5.6. Discussion and Findings

5.6.1. 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 (SCHAMARI & SCHAEFERS, 2015). 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).

Prior studies (HOLLEBEEK ET AL. 2014; KUMAR ET AL. 2010; PRENTICE ET AL. 2019; SANTINIi ET AL. 2020) have established the significant impact of consumer engagement on online purchase behavior. This study builds on these findings, highlighting the crucial role of consumers' value perception in shaping online shopping behavior. Value perception consistently emerges as a key factor influencing decisions in the online shopping realm (WU ET AL. 2018).

Extensive research supports the pivotal role of consumer value perception. LIN ET AL. (2020) found positive effects of functional and emotional value on purchase intention. ANDERSON ET AL. (2014) confirmed the impact of time-saving (utilitarian values) on purchase intention. ALALWAN (2018) showed hedonic motivation's role in predicting reactions to social media ads, and IRSHAD ET AL. (2020) affirmed the positive effects of remuneration and social motivation on online purchase intentions. Together, these studies contribute to the growing evidence linking consumers' value perception to online purchasing decisions.

Furthermore, an additional crucial aspect in comprehending online consumer purchase behavior is perceived risk. Numerous studies (AGHEKYAN-SIMONIAN ET AL. 2012; CUI ET AL. 2019; KIM & LENNON, 2013) consistently affirm the negative impact of perceived risk on online consumer purchase behavior. Perceived risk stands as a significant obstacle to purchase intentions within the online shopping environment, as evidenced by AGHEKYAN-SIMONIAN ET AL. (2012) findings.

Recognizing perceived risk as a substantial factor underscores the intricate nature of consumer decision-making in online contexts, where concerns about potential downsides associated with a purchase significantly shape consumer behavior. Heightened perceived risks, encompassing product, financial, time, psychological, physical, equipment, and social factors, diminish the likelihood of online consumer purchases (AGHEKYAN-SIMONIAN ET AL. 2012; CUI ET AL. 2019; TSENG & WANG, 2016). Meanwhile, the perceived usefulness of social networks for purchasing proves pivotal, positively influencing online consumer behavior (AGAG & EL-MASRY, 2016; AMOAKO-GYAMPAH, 2007; FU ET AL. 2018). These dynamics underscore the intricate interplay of risk perceptions and perceived utility in shaping online consumer decisions (EBRAHIMI, KHAJEHEIAN, SOLEIMANI, GHOLAMPOUT & FEKETE-FARKAS, 2023).

Online social support, deemed a pivotal strategic variable, commonly materializes in intangible expressions, encompassing emotional and informational aids for users within social networks (LIANG et al., 2011). In the context of social media platforms, users perceive others as benevolent and supportive when they share valuable product or life-related information. The reception of such information instills a disposition among users to exchange or disseminate valuable shopping insights within their network. This reciprocal exchange of supportive information not only fortifies trust and companionship among users but also amplifies the inclination to partake in commercial activities (BAI ET AL. 2015). The cultivation of trust and camaraderie through the systematic sharing of supportive information accentuates the dynamic role of online social support in influencing user behaviors and molding commercial intentions within the realm of social network platforms.

From a consumer behavior perspective, the influence wielded by information disseminated by fellow consumers often surpasses that emanating from suppliers. Consequently, the informational and emotional support a consumer garners from peers on social media assumes a pivotal role for marketers. Prior research consistently affirms the positive repercussions of social support on diverse dimensions of relationship quality, encompassing commitment, satisfaction, and trust (CUI ET AL. 2019; HAJLI, 2014a), as well as propensities to engage in social business (Liang et al., 2011), customer satisfaction (ZHU, Sun, & CHANG, 2016), and online consumer purchase behavior (BAI ET AL. 2015; OLAH ET AL. 2019). Given the recognition of social support as a strategic variable in the current study, marketing managers are urged to cultivate an environment conducive to support, thereby fostering optimal consumer interactions on social networks. Furthermore, it is imperative to furnish comprehensive and valuable information about the company and its products on virtual pages within social networks. Augmented investment in social support is poised to enhance the efficacy of marketing endeavors, underscoring the importance of nurturing consumer relationships in the online domain.

Therefore, trust emerges as a critical strategic variable closely linked to social support and consumer purchase behavior. Establishing a climate of trust between online consumers and sellers is imperative. Given the psychologically distant and unregulated nature of online communications, consumers who perceive trust-building as overly complex may choose to abstain from online purchases. Consequently, social platform marketers must prioritize reinforcing the trust of online consumers. Prior research (HAJLI, 2014b; IRSHAD ET AL. 2020) has consistently affirmed the positive impact of trust on online consumer purchase behavior (EBRAHIMI ET AL. 2023).

Social influence is another integral strategic variable introduced in the online consumer behavior model. Individuals are indeed influenced by the opinions of others when making purchases through social networks. The influence of social factors on the online purchase intentions of consumers has been corroborated in previous studies (FU ET AL. 2020; KUAN ET AL. 2014). Among the most pivotal variables and concepts is value co-creation. Opportunities for co-creation represent strategic avenues for suppliers to imbue enhanced brand meaning for customers. Suppliers can devise successful co-creation initiatives based on customer experiences, utilizing these encounters to educate customers on engaging in co-creation behaviors (EBRAHIMI ET AL. 2023).

The affirmative influence of value co-creation on shopping intention has been substantiated in earlier research, as evidenced by studies conducted by KUNJA & ACHARYULU (2018). Additionally, the work of SEE-TO & HO (2014) underscores the theoretical justifications supporting the impact of value co-creation on purchase intention. Further support is found in research conducted by CHOI ET AL. (2016) and SALEM ET AL. (2019), both confirming that characteristics of the value co-creation encounter significantly affect purchase intention, brand value, and customer value.

Among the independent variables, knowledge sharing emerges as a pivotal component of social activities within virtual communities (CHEN & KUO, 2017). Previous studies (ALBERT

ET AL. 2014; GHAHTARANI ET AL. 2020; TRAN, 2020) have consistently affirmed the influence of knowledge sharing on consumer purchase behavior. Service innovation within social networks stands as another independent variable in the online consumer behavior model. Leveraging the technological capabilities of social networks enables the provision of novel services to online consumers.

Service innovations, known for their attractiveness to online consumers, exert an impact on their purchase behavior. The positive influence of service innovations on online consumer purchase behavior has been validated in earlier research (AGAG & EL-MASRY, 2016; FUCHS ET AL. 2010; KIM ET AL. 2020).

Social media word of mouth stands out as another independent factor wielding substantial influence with high driving power and minimal dependence in the online consumer behavior model. Word of mouth over social media represents a form of communication recognized as a significant influential source of information on social media platforms (PARK ET AL. 2021). Previous research (MEKAWIE & HANY, 2019; YUSUF & BUSALIM, 2018) has consistently validated the impact of social media word of mouth on online consumer purchase behavior. Perceived information quality is another identified independent variable within the online consumer behavior model. Indeed, the perceptions of online consumers regarding the quality of information provided by sellers on social platforms can significantly impact online consumer purchase behavior. Earlier studies (FILIERI ET AL. 2018; GAO ET AL. 2017; KIM ET AL. 2020) have confirmed the positive influence of perceived information quality on online consumer behavioral tendencies.

5.6.2. Discussion on AHP section

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.

5.6.3. 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 role of artificial intelligence and technology, in a broader sense, serves as a powerful tool capable of significantly intensifying competition among online businesses. Recognizing the imperative for precise market predictions in the face of heightened competition, marketing executives have embraced the decision tree algorithm and the model outlined in this study. These elements provide a pragmatic framework for online businesses in Iran, exerting influence over strategic planning across economic, CRM, social, and individual dimensions. The accurate anticipation of consumer and market conditions is pivotal for resource allocation, and in this context, machine learning algorithms and artificial intelligence emerge as adept instruments for guiding strategic management decisions in marketing. Hence, the model advanced in case study

1 represents a positive advancement in this realm, with potential avenues for further refinement and expansion on a broader scale.

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.

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.

VI. CONCLUSION AND RECOMMENDATIONS

6.1. 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. The study has revealed a nuanced hierarchy of influential criteria, with Word of Mouth (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.

6.2. 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.

6.3. 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.

VII. 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.

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 provides 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.

VIII. SUMMARY

In synthesis, this comprehensive study delves into the intricate dynamics of online consumer behavior within the Iranian context, spanning diverse domains including e-commerce, social media, and sentiment analysis. The research strategically identifies key variables, such as social support and linkage factors, using MicMac analysis, emphasizing their pivotal role in shaping online consumer choices and signaling areas for potential future investments. The nuanced hierarchy of influential criteria, highlighting Word of Mouth (WOM) and recognizing Instagram as the most potent social network, provides actionable insights for marketers seeking to optimize their advertising strategies. The decision tree model introduces a pragmatic avenue for achieving customer customization, especially in environmentally conscious advertising on Instagram. Concurrently, the sentiment analysis results shed light on a predominantly positive online environment, offering practical opportunities for businesses and marketers to enhance brand image and refine content strategies. The AHP findings contribute a nuanced understanding of factors shaping consumer purchase behavior in Iranian social networks. While the study acknowledges limitations, such as the contextual impact of the COVID-19 crisis and potential biases in social platform selection, its scientific contributions span strategic variable identification, insights into social network dynamics, sentiment analysis, and AHP outcomes, with practical implications for targeted advertising and consumer customization. Future research directions include quantitative model testing, exploration of additional demographic characteristics, and the integration of multimodal analysis to provide a more comprehensive understanding of sentiment dynamics in the ever-evolving landscape of digital consumer behavior.

IX. APPENDICES

Appendix 1. References

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Appendix B. ISSM Questionnaire

This questionnaire is intended to support the research regarding the study An ISM-MICMAC approach to identify key strategic factors in online consumer purchase behavior. To attain this objective we design an expert questionnaire. we appreciate it if you could fill in the next questionnaire. It takes only a few minutes.

A1. Respondents' characterization

- Gender: ______________________
- Age: ______________________
- Education: ______________________
- Expertise area: ______________________
- Job of the respondent: ______________________________

A2. The following table intends to register the perception of professionals and academics about An ISM-MICMAC approach to identify key strategic factors in online consumer purchase behavior. Please, fill in the table considering the following symbols**:**

V: F1 variable I leads to F2 variable j
A: F2 variable j leads to F1 variable i
X: Both variables i and j lead to each other
O: Both variables i and j are unrelated

	j=F12	F11	F10	F9	F8	F7	F6	F5	F4	F3	F2	F1
i=F1												
F2												
F3												
F4												
F5												
F6												
F7												
F8												
F9												
F10												
F11												
F12												

Thanks for your responsiveness and collaboration

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.

Appendix C. Questionnaire of case study 1

Gender:
1- Male
2-Female

Age:
1- 20 and Lower than 20 years
2- Between 21 and 30 years
3- Between 31 and 40 years
4- Higher than 41 years

Education:
1- Diploma and lower
2- Associate
3- Bachelor
4-Master
5- Ph.D.

Time on online social platforms (Daily average) :
1- below one hour
2. One to two hours
3. Two to three hours
4. More than 3 hours

Prefatable online social platform :
1- Instagram
2- Facebook
3- Telegram
4- YouTube
5- WhatsApp

Appendix D. Questionnaire of case study 2

Gender: ["1. Male", "2. Female"]
Please enter your gender

Age:
Please enter your age.

Education: ["1. Under Diploma and Diploma", "2. Associate", "3. Bachelor", "4. Master", "5. PhD"]
Please enter your education level.

Online shopping experience:
Please enter a number.

What is your popular grocery app in your country :
In Hungary : [1. 'FoodPanda', 2. 'Wolt', 3. 'Spar', 4. 'Tesco online', 5. 'myLidl']
In Iran : ['Snappfood', 'Jimomarket', 'Digikala']

Appendix E. power iteration analysis program with MATLAB

```
function [ T i ] = ISMpower( x )
   [n, ~]=size(x);
   x= eye(n)+x;

   x(x~=0)=1;
   F=cell(n);

   F{1}=x;
   D=x;

   for i=2:n
      D=D^i;
      D(D~=0)=1;
      F{i}=D;

      if F{i} == F{i-1}
        break
      end
   end;


   T=zeros(n);

   for j=1:i
   T=F{j}+T;
   end
   T=T+eye(n);
   T(T~=0)=1;

end
```

Appendix F. Level partitioning program with MATLAB

```
function level=ISMLevels(x)

[n,~]=size(x);
xx= 1:n;
counter=1;
level={};

while isequal(x,[]) == 0

    [n,~]=size(x);

    [r, s, ~] = find(x);


    enter={n};
    exit={n};
    same={n};
    c=[];
    for i=1:n
        enter{i}=r(s==i);
        exit{i}=s(r==i);
        same{i}=intersect(enter{i},exit{i});

        if isequal(exit{i},same{i}) == true
            c=[c i];
        end

    end

    x(:,c)=[];
    x(c,:)=[];
    level{counter}=xx(c);
    counter=counter+1;
    xx(c)=[];

end
```

Appendix G. Criteria Pairwise Comparisons

F1 vs. F2

1: Equally important

3: F1 is slightly more important

5: F1 is moderately more important

7: F1 is strongly more important

9: F1 is extremely more important

F1 vs. F3

1: Equally important

3: F1 is slightly more important

5: F1 is moderately more important

7: F1 is strongly more important

9: F1 is extremely more important

F1 vs. F4

1: Equally important

3: F1 is slightly more important

5: F1 is moderately more important

7: F1 is strongly more important

9: F1 is extremely more important

...

(Continue this pattern for all pairs of criteria)

…

F11 vs. F12

1: Equally important

3: F11 is slightly more important

5: F11 is moderately more important

7: F11 is strongly more important

9: F11 is extremely more important

Alternative Pairwise Comparisons:

Instagram vs. Telegram

1: Equally preferable

3: Instagram is slightly more preferable

5: Instagram is moderately more preferable

7: Instagram is strongly more preferable

9: Instagram is extremely more preferable

Instagram vs. Facebook

1: Equally preferable

3: Instagram is slightly more preferable

5: Instagram is moderately more preferable

7: Instagram is strongly more preferable

9: Instagram is extremely more preferable

Instagram vs. TikTok

1: Equally preferable

3: Instagram is slightly more preferable

5: Instagram is moderately more preferable

7: Instagram is strongly more preferable

9: Instagram is extremely more preferable

...

(Repeat this pattern for all pairs of alternatives)

…

Facebook vs. TikTok

1: Equally preferable

3: Facebook is slightly more preferable

5: Facebook is moderately more preferable

7: Facebook is strongly more preferable

9: Facebook is extremely more preferable

Appendix H. Decision tree model training and visualization

DecisionTreeClassifier codes to predict consumer purchase behavior based on demographic variables

```
# Import necessary libraries for python programming
import numpy as np
import pandas as pd
import seaborn as sb
import matplotlib.pyplot as plt
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
import joblib
from sklearn import tree

# Import data
media_data = pd.read_excel ("MediaData.xlsx")
# or input a data with pd.DataFrame
# Creat a model and fit
model_tree = DecisionTreeClassifier ()
x = media_data.drop(columns = ["Media"])
y = media_data ["Media"]
model_tree.fit (x, y)
# Predict the model
prediction = model_tree.predict ([[1,2,5,3],[2,3,3,4]])
print (prediction)
# Train and Test
x_train, x_test, y_train, y_test = train_test_split (x, y, test_size = 0.3)
print (x_train.shape)
print (x_test.shape)
# Model accuracy and score
model_tree = DecisionTreeClassifier ()
model_tree.fit (x_train, y_train)
```

```
y_predict = model_tree.predict (x_test)

y_predict

print (model_tree.score(x_test, y_test))

#score = accuracy_score (y_test, y_predict)
```

 # Visualization

```
joblib.dump (model_tree, "media-vis.joblib")

tree.export_graphviz (model_tree, out_file = "media-vis.dot", feature_names = ["Gender", "Age", "Education", "Time"], class_names = sorted(y.unique()), label = "all", rounded = True, filled = True)
```

Appendix I. Evaluation function for our model experiments (Sentiment analysis)

```
# Function to evaluate: accuracy, precision, recall, f1-score
from sklearn.metrics import accuracy_score, precision_recall_fscore_support

def calculate_results(y_true, y_pred):
  """
  Calculates model accuracy, precision, recall and f1 score of a binary classification model.

  Args:
  -----
  y_true = true labels in the form of a 1D array
  y_pred = predicted labels in the form of a 1D array

  Returns a dictionary of accuracy, precision, recall, f1-score.
  """
  # Calculate model accuracy
  model_accuracy = accuracy_score(y_true, y_pred) * 100
  # Calculate model precision, recall and f1 score using "weighted" average
  model_precision, model_recall, model_f1, _ = precision_recall_fscore_support(y_true, y_pred, average="weighted")
  model_results = {"accuracy": model_accuracy,
                  "precision": model_precision,
                  "recall": model_recall,
                  "f1": model_f1}
  return model_results
```

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