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Segmentation of Social Media Platforms in Terms of Perceived Benefits: Cluster Analysis on Brand Followers*

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Abstract: *This study was designed to determine clusters of brand followers on social media platforms and a cluster analysis was carried out to obtain information about the functional, social and communication benefits of social media platforms. The population of this research, which was carried out on social media users, consists of 414 people selected by convenience sampling method. The online survey method was used to collect the data. The research model variables were analyzed by two-step cluster analysis and K mean cluster analysis. Then, discriminant and chi-square analysis were performed. Findings indicate that Instagram users in the cluster 1 have the highest perception of benefit, YouTube users in the cluster 3 have a high perception of benefit, and Facebook and Twitter users in the cluster 2 have an average perception of benefit in terms of brand follow-up.*

Keywords: Social Media Segmentation, Brand Followers, Cluster Analysis, Functional Benefits, Social Benefits, Communication Benefits

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1. Introduction

Since 2003, social media platforms, especially the ones based on web 2.0 technology, have shown a dramatic improvement. To date, social media has evolved into countless mobile applications that have become an important part of people's lives, rather than primitive internet-based computer applications (Ye et al., 2021: 136). According to Raman and Menon (2018), it is predicted that social media, which refers to internet-based applications that allow users to create and share content, will be used 63% more by marketing experts, especially in the coming years. Facebook, Twitter, Instagram, and YouTube platforms are popular social media channels where users share their ideas, relevant moments, and interests. Facebook allows users to interact with other users by sharing, liking, and clicking on their posts and comments. Twitter is a microblogging platform that allows users to express themselves, or "tweet", up to 280 characters. Thanks to Instagram, users can create, share, like and comment on photos. Finally, YouTube is a social media platform that offers its users the opportunity to upload, watch and share videos (Kim et al., 2021: 361).

Consumers increasingly consider brand information obtained from blogs and social networking sites more important than sources provided by brands themselves. Based on this, marketing and advertising agency managers believe that the strategic use of social media will develop stronger customer relations with brands (Foster et al., 2011: 5). In the past years, companies trying to reach consumers with traditional marketing activities such as public relations, reward programs and direct marketing have started to develop direct relationships with potential consumers through social networks. For this purpose, companies have

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created their own brand pages on social media platforms. Companies generally use social media platforms as an open channel of brand communication and interaction. This way, brand followers are more likely to post comments, communicate, review messages and offers, and interact with other followers. In short, with social media platforms, brands both offer content related to products or services and develop a two-way interaction between the consumer and the brand (Tsimonis et al., 2020: 218).

Social media platforms provide users with some social (e.g., easy/fast access to information and two-way interaction), psychological (e.g., belonging, identity development, and relationship building), and hedonic benefits (e.g., entertainment). While doing market segmentation, the benefits, motivation, and preferences of the consumers are taken into consideration (Özdemir & Arzık, 2022: 55-56). The market segmentation is the process of dividing or segmenting a market so that people in a group can have similar characteristics compared to the ones in other groups. Thanks to market segmentation, companies can identify the clusters of potential buyers for whom they will implement their marketing strategies. Identification of market segments with similar characteristics will be beneficial in achieving sustainable competitive advantage in the future (Bannor et al., 2022: 78).

Many different approaches are suggested in the literature considering market segmentation. Tynan and Drayton (1987) and Kotler (2003) determined market segmentation criteria as “geographical”, “demographic”, “psychological”, “psychographic”, “geodemographic”, and “behavioral”. Sarvary and Elberse (1995) mentioned that a market can be segmented in two ways: “Segmentation based on benefits” and “segmentation based on observable features”. They also recommended that marketers conduct comprehensive market analyses that will typically group customers according to the benefits and needs they expect from particular product or service groups. In this way, companies can design their products or services in accordance with customer expectations and transform the relevant segments into a more efficient ones. One of the most frequently used methods in market segmentation is cluster analysis. Churchill and Lacobucci (2007) suggested that cluster analysis is a very useful market segmentation tool for identifying groups with similar characteristics. Ho and Hung (2008) stated that the most appropriate statistical technique for market segmentation is cluster analysis.

The aim of this research is to determine clusters of brand followers on social media platforms. In this context, a cluster analysis was carried out regarding the functional, social and communication benefits of social media platforms. In the second part of the study, the literature was reviewed based on the research model. In the third part, information about the methodology of the research was given. In the fourth part, the findings of the research were mentioned. In the fifth part, the research findings and limitations were discussed.

2. Literature Review

Considering the development stages of marketing, it can be stated that a customer-oriented approach is dominant today. Realizing the importance of developing and managing relationships with customers, companies seek ways to offer their customers not only a product or service but also some additional benefits. Particularly with the increasing digitalization in recent years, companies have started to offer some additional benefits to their customers through social media platforms. Gwinner et al. (1998) stated that the benefits that consumers desire to perceive regarding the use of social media are “trust”, “sociability” and “special treatment”, while according to Reynolds and Beatty (1999), they are classified as “sociability” and “functional” benefits. In another study, Gummerus et al. (2012) grouped the perceived relational benefits of Facebook users as “sociability”, “entertainment” and “economic”. Finally, Zhang and Luo (2016) found that benefits such as “trust”, “social” and “honor” positively increase the satisfaction level of social media users.

Several studies have used cluster analysis to identify consumer segments. Pedersen (2008) classified customers according to certain criteria such as customers’age, gender, ethnicity, income, number of households, occupation, and homeownership. Foster et al. (2011) identified four different types of consumers that differ in their needs to socialize and acquire information through online technology and these are “uninterested”, “social”, “information seeker”, and “social media technologist” clusters. Sütterlin et al. (2011) segmented the energy consumers with a behaviorally-based approach through the cluster analytical method. Accordingly, customers are segmented according to age, education, income, and gender. In a cluster analysis study conducted on 706 people in Switzerland, customers were segmented according to age, gender, income, number of households, and homeownership. Cluster analysis was also used by Raman and Menon (2018) to identify groups of entrepreneurs using social media as part of their digital marketing strategy and it was found that, according to their social media usage behaivors of the entrepreneurs, the market group was divided into four main segments, which are “high roles”, “ignorant residients”, “trendsetters” and “quarrelsome crowd”. Tumbaz and Mogulkoç (2018) investigated the attitudes and behaviors of Turkish consumers towards energy efficiency with cluster analysis and the consumers were segmented according to their age, gender, and education level. Slupik et al. (2021), on the other hand, partitioned 1237 Polish consumers by income and number of households in order to understand the underlying causes of energy-saving behaviors.

Various studies have used cluster analysis focusing on social media platforms. Tsimonis et al. (2020) focused on the consumer-brand relationship in the social media environment. According to the results of their research, the followers of the brand pages on Facebook and Twitter perceived the benefits of “social”, “functional”, “entertainment”, “special treatment”, “self-improvement”, “advice”, and “situation”. Malebran and Gaitan (2021) segmented fashion consumers through mobile social networks and the consumers were classified under “purchase intention”, “privacy concern”, and “trend perception”. With the cluster analysis performed by Ihm and Lee (2021) on 723 people in South Korea, public health in the Covid-19 period was examined over social media. According to the results of the research, it was revealed that a cluster of young people is more unhealthy than a cluster of older people due to the lack of social resources. Ye et al. (2021) examined three social media platforms, namely Facebook, Twitter, and Instagram, and found that Twitter is used only to connect with university friends, Facebook is used to connect with university friends, relatives, and family members, and Instagram, on the other hand, is designated as a popular social media platform for all kinds of relationships. Halgamuge et al. (2021) conducted another study on social media and, in their study, social media platforms were subjected to a categorical segmentation with Hashtag data. With this research, an algorithm is proposed to segment Hashtags. In this way, a 29.7% improvement was achieved by optimizing customer segmentation calculation times. Finally, a cluster analysis was conducted on social media users who are interested in travelling by Özdemir and Arzik (2022). The aim of their research is to determine whether there are differences in perceived benefits between customer segments. Accordingly, customers are grouped as “information seekers”, “contact seekers”, “interaction seekers”, and “hybrids”.

In addition to these studies, there are many studies conducted in recent years regarding customer segmentation (Chen et al., 2019; Funk et al., 2021; Abu-Bakar et al., 2021; Moon et al., 2021; Hedhilia et al., 2021; Špička & Zdeňka, 2022; Budhathoki et al., 2022; Wang et al., 2022; Caracciolo et al., 2022; Vigneau et al., 2022; Carla Kuesten et al., 2022). It has been observed that these studies on customer segmentation are mostly about organic products, food, and supplements.

3. Methodology

3.1. Research Sample

The population of the research consists of social media users living in Turkey. The sample consists of 422 people selected by convenience sampling method. The eight participants were eliminated as outliers. Therefore, the sample size was accepted as 414. The participants, who formed the sample obtained, were selected among those who follow the brand through a social media platform. The 276 participants (66.7%) are Instagram followers, 59 (14.3%) are Twitter, 33 (8.0%) are Facebook and 46 (11.1%) are YouTube followers.

3.2. Scale Development and Collection of Research Data

The social media benefits scale was adapted from Özdemir and Arzık (2022). While choosing the scale for the research, the criterion of having been applied before in Turkey and in a similar research area was taken into consideration. In addition, the reliability and validity values of the related scale were also taken into consideration.

The e-survey method was used to collect data. A five-point Likert-type scale was used to in the questionnaire. The research e-survey form consists of 3 sections and 14 items. The first section of the e-survey focuses on thequestions about the use of social media platform, the second section on the questions about the benefits variables, and the thirdsection on the demographic questions. Research data was obtained in March and April in 2022. The data obtained through the electronic google survey was transferred to SPSS programs and analyzed. Ethics committee approval, numbered 2022/79 and dated 26.05.2022, was obtained from Sirnak University Ethics Committee for this study.

3.3. Analysis of Research Data

Current research aims to determine clusters of brand followers on social media platforms through using cluster analysis based on the functional, social and communication benefits of social media platforms. In the analysis of the research data, firstly, descriptive statistics and data about the participants were obtained. In the second stage, the correlation levels between the variables were examined. In the third stage, validity and reliability analyses were carried out. Accordingly, Cronbach's alpha (Cα), explained mean variance (AVE), combined reliability (CR) and confirmatory factor analysis (CFA) values were examined. In the fourth stage, the research model variables were analyzed by two-step cluster analysis and K mean cluster analysis. Then, discriminant and chi-square analyses were performed. At this stage, cluster of the social media users, distances between final cluster centers, significancy of cluster by ANOVA and, tests of equality of group means were measured.

4. Findings

4.1. Participants

Table 1 details the demographic characteristics of the participants according to gender, age, occupation, income, and educational status. The 414 participants who completed the questionnaire, 253 (61.1%) of them were male; 175 (42.3%) of them were between the ages of 19 and 24; 130 (31.4%) of them received an education at the high school level; 178 (43.0%) of them had an income of 2000TL and below; and 170 (41.1%) of them are students.

Table 1. Demographic Characteristics of the Participants

Variables	Groups	N	%
Gender	Female	161	38.9
	Male	253	61.1
Age	18 and below	20	4.8
	19-24	175	42.3
	25-30	117	28.3
	31-36	61	17.2
	37-42	19	4.6
	43-48	5	1.2
	49 and above	7	6.2
Education	Primary-Middle School	34	8.2
	High School	130	31.4
	Associate Degree	97	23.4
	Bachelor's Degree	118	28.5
	Master	26	6.3
	PhD	9	2.2

Table 1. Demographic Characteristics of the Participants (Continued)

Variables	Groups	N	%
Income Status	2000TL and below	178	43.0
	2001TL-4000TL	65	15.7
	4001TL-6000TL	58	14
	6001TL-8000TL	29	7
	8001tl -10000TL	36	8.7
	10001TL-12000TL	18	4.3
	12001TL and above	30	7.2
Profession Group	Public Sector Employee	82	19.8
	Private Sector Employee	88	21.3
	Industrialist and Businessman	9	2.2
	Tradesman and Craftsman	14	3.4
	Employee	21	5.1
	Student	170	41.1
	Housewife	29	7
Total		**414**	**100**

Table 2 presents the data on the social media usage of the participants in terms of which social media platforms the participants use and how often the participants use them. The participants, who formed the sample obtained, were selected among those who follow the brand through a social media platform. The 276 participants (66.7%) are Instagram followers, 59 (14.3%) are Twitter, 33 (8.0%) are Facebook and 46 (11.1%) are YouTube followers. Furthermore, 164 (39.6%) of the participants stated that they use social media platforms 3-4 hours a day.

Table 2. Social Media Usage of the Participants

Variables	Groups	N	%
Social Media Platform	Instagram	276	66.7
	Twitter	59	14.3
	Facebook	33	8.0
	YouTube	46	11.1
Frequency of Social Media Use	0-2 Hours	127	30.6
	3-4 Hours	164	39.6
	5-6 Hours	80	19.3
	7-8 Hours	25	6.0
	9-10 Hours	12	2.9
	>10 Hours	6	1.4
Total		**414**	**100**

4.2. Correlation Analysis

Before analyzing the hypotheses of the study, it is necessary to observe the relations between the research variables. Therefore, correlation analysis was applied to the variables of ‘functional benefits (FNC)’, ‘social benefits (SCL)’ and, ‘communication benefits (CMN)’. Pearson correlation analysis values, means and standard deviations were shown in table 3. Based on these data, it was found that there were significant relationships between the variables.

Table 3. Values of Variables

Variables	Mean	S.D.	CMN	SCL	FCN
CMN	3.3688	0.99004	1		
SCL	3.3414	0.75232	0.869*	1	
FCN	3.4622	0.85357	0.979**	0.856*	1

FNC: Functional Benefits, SCL: Social Benefits, CMN: Communication Benefits, *p<.05; **p<.01; ***p<.001

4.3. Reliability and Validity Analysis

Within the scope of the research, Cronbach's alpha (Cα) values were examined for the reliability of the dimensions, and the average explained variance (AVE) and composite reliability (CR) values for the validity. It was determined that the skewness and kurtosis values of the research data were between +2.0 and -2.0. According to George and Mallery (2010), the kurtosis and skewness values of the study show normality. Table 4 shows the values of the dimensions of research. As a result of confirmatory factor analysis, it was decided not to include the CMN (0.380) item with low factor loading into the analysis. George and Mallery (2010) stated that when the factor loading of an item is higher than 0.50, the item can be considered acceptable. The data analysis showed that the factor loadings consisted of statistically significant values ranging from 0.690 to 0.893. According to Kalaycı (2006), if the alpha value is 0.70 and above, the relevant scale is reliable. According to Fornell and Larcker (1981), the AVE value must be above 0.50 and the CR value above 0.70.

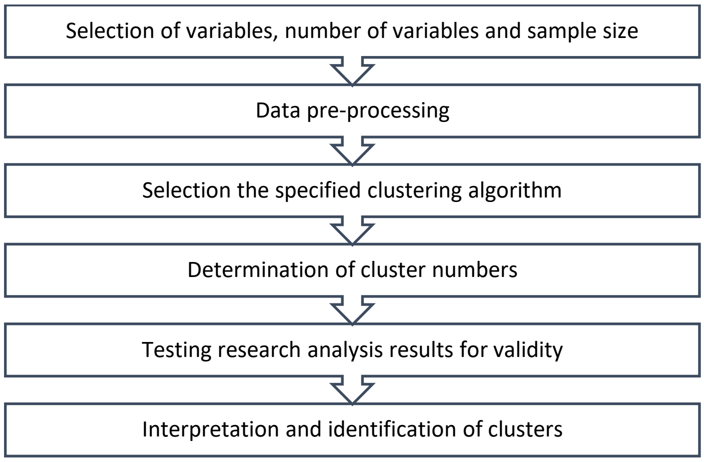
Table 4. Reliability and Validity Analysis

Scale Dimensions	Scale Items	Skewness	Kurtosis	Factor Weights	Cα	CR	AVE
Functional Benefits	FNC1	-0.478	-0.822	0.836	0.853	0.913	0.539
	FNC2	-0.660	-0.516	0.893			
	FNC3	-0.851	-0.084	0.864			
Social Benefits	SCL1	-0.090	-0.104	0.663	0.761	0.898	0.747
	SCL2	-0.172	-0.110	0.690			
	SCL3	-0.614	-0.661	0.749			
	SCL4	-0.460	-0.817	0.729			
	SCL5	-0.852	0.066	0.785			
	SCL6	-0.872	0.177	0.792			
Communication Benefits	CMN1	-0.785	-0.069	0.793	0.726	0.848	0.650
	CMN2	-0.757	-0.438	0.802			
	CMN3	-0.617	-0.271	0.825			
Overall Scale Cα: 0.886							

4.4. Cluster Analysis

According to Shoemaker (1989), cluster analysis is defined as “a statistical method for classifying participants into separate unique groups”. The techniques used in cluster analysis allow the variables to form homogeneous groups within themselves and heterogeneous groups among themselves. In general, clustering techniques are grouped under two headings. These can be classified as hierarchical and non-hierarchical clustering techniques. In both techniques, the common goal is to increase the homogeneity values within the cluster, while decreasing the homogeneity values between the clusters. It is important to use both techniques together in order to obtain more appropriate results (Yılmaz & Patır, 2011: 101-102). The stages of cluster analysis are shown in Figure 1.

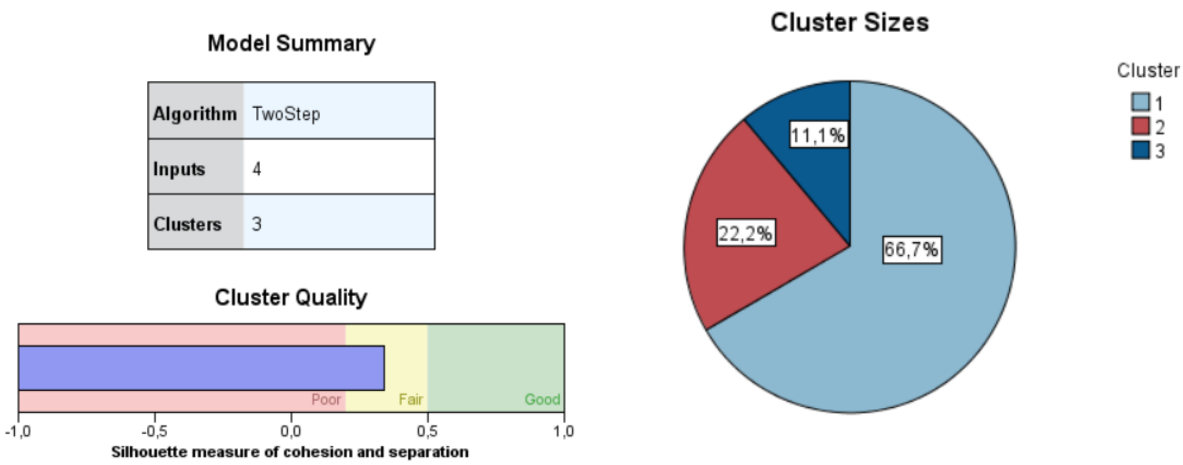
Figure 1. Stages in the Clustering Process



Resource: Tuma et al. (2011).

As a result of the tests performed with two-stage clustering analysis, the best averages, namely the "Silhouette" coefficient, are obtained. The research model is divided into 3 clusters. The cluster separation compatibility of the model with a Silhouette coefficient between 0.0 to 0.5 is at a sufficient (fair) level. Cluster sizes and segregation compatibility values of the research model are shown in Figure 2. The size of the smallest cluster 46 (11.1%), the size of the largest cluster 276 (66.7%) and the ratio of sizes (from the largest cluster to the smallest one) were found at 2.50.

Figure 2. Cluster of the Benefits by Social Media Users



The functional benefit average for cluster 1 was 3.42, the social benefit average was 3.49, and the benefit of the communication was 3.44. The functional benefit average for cluster 2 was 3.04, the social benefit average was 3.00, and the benefit of the communication was 3.09. The functional benefit average for cluster 3 was 3.42, the social benefit average was 3.41, and the benefit of the communication was 3.24. The averages of the social media clusters and significancy are shown in Table 5. While interpreting the determined cluster groups, the significance values on the ANOVA table were also taken into account. Described as cluster groups, cluster 1 (p=0.000), cluster 2 (p=0.000) and cluster 3 (p=0.000) groups differ significantly from each other.

Table 5. Cluster of Social Media Users and Significancy

	Cluster 1 n= 276 (66.7%)	Cluster 2 n= 92 (22.2%)	Cluster 3 n= 46 (11.1%)	F	Sig.
FNC	3.42	3.04	3.42	479.792	0.000
SCL	3.49	3.00	3.41	139.199	0.000
CMN	3.44	3.09	3.24	162.252	0.000

K means cluster analysis, the distance between the variables, is taken into account in the formation of the groups. While distance expresses the relative positions of objects or events, it also shows similarity and proximity. The most used index is the squared euclidean distance (Yılmaz & Patır, 2011: 106). The averages showing the distances of the created clusters to each other are shown in Table 6. According to the results of the K means cluster analysis, it was determined that the most distant clusters were cluster 1 and cluster 2 respectively, while the closest clusters were cluster 1 and cluster 3.

Table 6. Distances Between Cluster

	Cluster 1	Cluster 2	Cluster 3
Cluster 1		3.060	1.394
Cluster 2	3.060		2.216
Cluster 3	1.394	2.216	

In order to evaluate the validity and reliability of the findings obtained from the cluster analysis, discriminant analysis was performed. Wilks' Lambda results for canonical discriminant for utility variables are presented in Table 7. Wilks' lambda values for each of the utility variables were determined as 0.583, 0.502, and 0.588, respectively. The discriminant analysis results of the clusters were determined as ($p \leq 0.05$). Accordingly, the distinctiveness meaning of the clusters was somehow accepted.

Table 7. Tests of Equality of Group Means

	Wilks' Lambda	F	Sig.
Cluster 1	0.583	173.933	0.000
Cluster 2	0.502	240.588	0.000
Cluster 3	0.588	170.204	0.000

4.5. Description of Final Clusters

Within the scope of the research, the clusters obtained as a result of the evaluations of 414 participants are shown in Table 5. According to the results of the analysis, it was determined that cluster 2, which is the Facebook and Twitter users, perceived the functional benefit, social benefit, and communication benefit the least, and cluster 1, which is the Instagram users, who perceived them the highest. The chi-square test was conducted to reveal the demographic profiles of the threeclusters that emerged as a result of the analyses. Accordingly, the participants were distributed to the relevant clusters according to gender, age, education level, income status and occupation group. The details of the cluster analysis are shown in Table 8.

Cluster 1 (Instagram users): 100% of the participants in this cluster are Instagram platform users. It is understood that the functional, social, and communication benefit perceptions of the participants regarding brand follow-up on Instagram are high. In addition, it is seen that the participants forming the cluster are predominantly male (55.8%), between the ages of 19-24 (47.1%), high school graduates (31.4%), with an income of 2000TL or less (47.1%) and housewives (47.1%). *Cluster 2 (Facebook & Twitter users):* 100% of the participants in this cluster are Facebook and Twitter users. It is understood that the functional, social, and communication benefit perceptions of the participants regarding brand following on Facebook and Twitter are at an average level. In addition, it is seen that the participants forming the cluster are predominantly male (82.6%), between the ages of 31-36 (32.6%), with a bachelor's degree (31.5%), with an income of 2000TL or less (30.4%) and public sector employees (28.3%). *Cluster 3 (YouTube users):* 100% of the participants in this cluster are YouTube platform users. It is understood that the functional, social, and communication benefit perceptions of the participants regarding brand tracking on YouTube are high. In addition, the participants forming the cluster are predominantly female (52.2%), in the 19-24 age group (41.3%), high school graduates (37.0%), with an income of 2000TL or less (43.5%) and private sector employees (39.1%).

Table 8. Details on Cluster Analysis

Variables	Groups	Total n= 414 (100%)	Cluster 1 n= 276 (66.7%)	Cluster 2 n= 92 (22.2%)	Cluster 3 n= 46 (11.1%)	Chi-square	p value
			Instagram	Facebook & Twitter	YouTube		
Gender	Female	161 (38.9%)	122 (44.2%)	16 (17.4%)	24 (52.2%)	23.506	0.000
	Male	253 (61.1%)	154 (55.8%)	76 (82.6%)	22 (47.8%)		
Age	18 and below	20 (4.8%)	16 (5.8%)	2 (2.2%)	2 (4.3%)	42.044	0.000
	19-24	177 (42.8%)	130 (47.1%)	26 (28.2%)	19 (41.3%)		
	25-30	117 (28.3%)	82 (29.7%)	18 (19.6%)	17 (37.0%)		
	31-36	59 (16.7%)	37 (13.4%)	30 (32.6%)	4 (8.7%)		
	37-42	19 (4.6%)	8 (2.9%)	9 (9.8%)	2 (4.3%)		
	43-48	5 (1.2%)	1 (0.4%)	3 (3.3%)	1 (2.2%)		
	49 and above	7 (6.2%)	2 (0.7%)	4 (4.3%)	1 (2.2%)		
Education Status	Primary-Middle School	34 (8.2%)	21 (7.6%)	8 (8.7%)	5 (10.9%)	17.502	0.064
	High School	130 (31.4%)	88 (31.9%)	25 (27.2%)	17 (37.0%)		
	Associate Degree	97 (23.4%)	72 (26.1%)	18 (19.6%)	7 (15.2%)		
	Bachelor's Degree	118 (28.5%)	79 (28.6%)	29 (31.5%)	10 (21.7%)		
	Master	26 (6.3%)	11 (4.0%)	8 (8.7%)	7 (15.2%)		
	PhD	9 (2.2%)	5 (1.8%)	4 (4.3%)	0 (0.0%)		
Income Status	2000TL and below	178 (43.0%)	130 (47.1%)	28 (30.4%)	20 (43.5%)	32.282	0.001
	2001TL-4000TL	65 (15.7%)	44 (15.9%)	11 (12.0%)	10 (21.7%)		
	4001TL-6000TL	58 (14%)	39 (14.1%)	14 (15.2%)	5 (10.9%)		
	6001TL-8000TL	29 (7%)	21 (7.6%)	7 (7.6%)	1 (2.2%)		
	8001tl -10000TL	36 (8.7%)	21 (7.6%)	12 (13.0%)	3 (6.5%)		
	10001TL-12000TL	18 (4.3%)	12 (4.3%)	6 (6.5%)	0 (0.0%)		
	12001TL and above	30 (7.2%)	9 (3.3%)	14 (15.2%)	7 (15.2%)		
Profession Group	Public Sector Employee	82 (19.8%)	49 (17.8%)	26 (28.3%)	7 (15.2%)	37.641	0.001
	Private Sector Employee	88 (21.3%)	53 (19.2%)	22 (23.9%)	18 (39.1%)		
	Industrialist and Businessman	9 (2.2%)	11 (4.0%)	3 (3.3%)	0 (0.0%)		
	Tradesman and Craftsman	14 (3.4%)	2 (0.7%)	6 (6.5%)	1 (2.2%)		
	Employee	21 (5.1%)	12 (4.3%)	7 (7.6)	3 (6.5%)		
	Student	170 (41.1%)	19 (6.9%)	6 (6.5%)	4 (8.7%)		
	Housewife	29 (7.0%)	130 (47.1%)	22 (23.9%)	13 (28.3%)		

5. Discussion, Conclusion and Limitations

Today's consumers obtain information about a product or service based on user experiences rather than corporate information sources of brands. With the popularization of social media platforms, user experiences have also started to take place more on digital platforms. Realizing this, businesses have started to promote their brands, products, or services through social media platforms. Thanks to these digital platforms that allow two-way interaction, businesses can conduct brand-consumer communications more effectively. Considering the functional, social, and communication benefits that social media provides to its users, the use of related platforms has become more important for both businesses and consumers. Realizing this, businesses can now perform customer segmentation according to social media user types. In particular, the benefits obtained by consumers form the basis of customer segmentation. Thanks to customer segmentation, businesses can identify potential buyer clusters to which they will implement their marketing strategies. With this research, digital platforms, on which social media users track brands, products, or services, are evaluated in terms of functional, social, and communication benefits. In addition, demographic differences regarding social media platform users were determined by creating natural clusters. Thus, the perceived benefits and demographic characteristics of Instagram, Facebook, Twitter, and YouTube users were determined.

Cluster 1 (i.e., Instagram users) is perceived to be higher than cluster 2 (i.e., Facebook and Twitter users) and cluster 3 (i.e., YouTube users) in terms of perceived social media usage benefits. Cluster 3 is perceived to be higher than cluster 2 in terms of social media usage benefits. Based on this information, it was found that YouTube users (i.e., Cluster 3) perceived functional, social, and communication benefits at a higher rate than Facebook and Twitter users (i.e., cluster 2). The specific studies on social media segmentation have been examined in the literature. Tsimonis et al. (2020) examined Facebook and Twitter platforms in terms of benefit, cost, and demographic variables. Based on the results of their research, according to cluster 1, Facebook users, are predominantly male (59.1%) and aged 25-34 (28.0%). Twitter users are similarly male (68.9%) and 25-34 years old (40.3%). According to cluster 2, Facebook users are predominantly female (54.3%) and aged 25-34 (47.9%). Twitter users are male (61.9%) and 25-34 years old (41.3%). Tsimonis et al. (2020)'s demographic findings on Facebook and Twitter platforms and the findings of the study support each other. Ye et al. (2021) analyzed the Facebook, Twitter, and Instagram platforms. According to their study, Twitter is used only to connect with university friends, Facebook is used to connect with university friends, relatives, and family members. Instagram, on the other hand, has been designated as a popular social media platform for all kinds of relationships. Finally, in a study conducted by Özdemir and Arzik (2022), social media users were segmented according to their perceived usefulness and demographic variables. In this direction, social media users are divided into four different clusters. These clusters are named "information seekers", "contact seekers", "interaction seekers" and "hybrids". Cluster 1 (interaction seekers) make up 25% of social media users. It is the cluster with the highest perceived communication utility and users with a master's degree. Cluster 2 (contact seekers) make up 10% of social media users. The cluster with the highest number of single (66.7%), young and undergraduate users. Cluster 3 (hybrids) make up 50% of social media users. Users aged 19-29 (46%) and 29-39 years (33.3%) with high perceived functional utility are the clusters with the highest number of users. Cluster 4 (information seekers) make up 25% of social media users. Married (52.7%), 19-29 years old (38.2%), and 50 years old and above (34.6%) are the clusters with the highest number of users.

The benefits offered by social media platforms to their users offer different opportunities than previous digital media channels. Brand pages on social media platforms organize raffles, contests and games. With these activities, deeper and instant interactions with consumers can be established. This strengthens the emotional bond between the brand and the users. With social media platforms, consumers can exchange ideas about brands and share their feedback and experiences. In this way, businesses can identify new consumer needs and marketing strategies. The clues obtained from Instagram, Facebook, Twitter, and YouTube users through this research will contribute to the brands' presentation of their social media pages with more interactive, useful, social, innovative, and informative content. Obtaining information about the demographics or perceived benefit levels of the followers of the brand pages on social media platforms will be useful in differentiating the content of social mediaand turning it into a pleasant experience.

The sample size of the study was limited to 414. It can be stated that the participants follow the brand groups they frequently prefer on Instagram, compared to Facebook, Twitter, and YouTube. In this respect, the number of samples can be increased in order to obtain more generalizable findings in future studies. In addition, reaching different types of social media users from different countries, and collecting data in different time periods will be useful for presenting comparative findings.

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References

Abu-Bakar, H., Williams, L., & Hallett, S. H. (2021). An empirical water consumer segmentation and the characterisation of consumption patterns underpinning demand peaks. Resources. *Conservation & Recycling,* 174, 1-18. https://doi.org/10.1016/j.resconrec.2021.105792

Bannor, R. K., Abele, S., Kuwornu, J. K. M., Oppong-Kyeremeh, H., & Yeboah, E. D. (2022). Consumer segmentation and preference for indigenous chicken products. *Journal of Agribusiness in Developing and Emerging Economies,* 12(1), 75-93. https://doi.org/10.1108/JADEE-08-2020-0162

Budhathoki, M., Zølner, A., Nielsen, T., Rasmussen, M. A., & Reinbach, H. C. (2022). Intention to buy organic fish among Danish consumers: Application of the segmentation approach and the theory of planned behaviour. *Aquaculture,* 549, 1-11. https://doi.org/10.1016/j.aquaculture.2021.737798

Caracciolo, F., Furno, M., D'Amico, M., Califano, G., & Vita, G. D. (2022). Variety seeking behavior in the wine domain: A consumers segmentation using big data. *Food Quality and Preference,* 97, 1-10. https://doi.org/10.1016/j.foodqual.2021.104481

Chen, T. Y., Cheng, H. A., & Chen, Y. M. (2019). Developing a personal value analysis method of social media to support customer segmentation and business model innovation. *Expert Systems,* 36, 1-19. https://doi.org/10.1111/exsy.12374

Churchill, G. A., & Iacobucci, D. (2007). *Marketing research: Methodological foundations*. Peking: Peking University Press.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39-50.

Foster, M., West, B., & Francescucci, A. (2011). Exploring social media user segmentation and online brand profiles. *Journal of Brand Management,* 19, 4-17. https://doi.org/10.1057/bm.2011.27

Funk, A., Sütterlin, B., & Siegrist, M. (2021). Consumer segmentation based on stated environmentally-friendly behavior in the food domain. *Sustainable Production and Consumption,* 25, 173-186. https://doi.org/10.1016/j.spc.2020.08.010

George, D., & Mallery, M. (2010). *SPSS for Windows step by step: A simple guide and reference*. Boston: Pearson Edition.

Gummerus, J., Liljander, V., Weman, E., & Pihlström, M. (2012). Customer engagement in a Facebook brand community. *Management Research Review,* 35, 857-877. https://doi.org/10.1108/01409171211256578

Gwinner, K. P., Gremler, D. D., & Bitner, M. J. (1998). Relational benefits in services industries: The customer's perspective. *Journal of the Academy of Marketing Science,* 26, 101-114. https://doi.org/10.1177/0092070398262002

Halgamuge, M. N., Caliskan, H., & Mohammad, A. (2021). Computation time optimization on hashtag segmentation for social media data. *IEEE Wireless Communications and Networking Conference (WCNC).*

Hedhilia, A., Lubbersb, S., Bou-Marounb, E., Griffona, F., Akinyemic, B. E., Hussonb, F., & Valentin, D. (2021). Moringa Oleifera supplemented biscuits: Nutritional values and consumer Segmentation. *South African Journal of Botany,* 138, 406-414. https://doi.org/10.1016/j.sajb.2021.01.017

Ho, H. F., & Hung, C. C. (2008). Marketing mix formulation for higher education: An integrated analysis employing analytic hierarchy process, cluster analysis and correspondence analysis. *International Journal of Educational Management,* 22(4), 328-340. https://doi.org/10.1108/09513540810875662

Ihm, J., & Lee, C. J. (2021) Toward more effective public health interventions during the COVID-19 pandemic: Suggesting audience segmentation based on social and media resources. *Health Communication,* 36(1), 98-108. https://doi.org/10.1080/10410236.2020.1847450

Kalaycı, Ş. (2006). *SPSS applied multivariate statistics techniques*. Ankara: Asil Broadcast Distribution.

Kim, J., Uddin, Z. A., Lee, Y., Nasri, F., Gill, H., Subramanieapillai, M., Lee, R., Udovica, A., Phan, L., Lui, L., Lacobucci, M., Mansur, R. B., Rosenblat, J. D., & McIntyre, R. S. (2021). A Systematic review of the validity of screening depression through Facebook, Twitter, Instagram, and Snapchat. *Journal of Affective Disorders,* 286, 360-369. https://doi.org/10.1016/j.jad.2020.08.091

Kotler, P. (2003). *Marketing Management* (International Edition). Upper Saddle River, NJ: Pearson Education International.

Kuesten, C., Dang, J., Nakagawa, M., Bi, J., & Meiselman, H. L. (2022). Japanese consumer segmentation based on general self-efficacy psychographics data collected in a phytonutrient supplement study: Influence on health behaviors, well-being, product involvement and liking. *Food Quality and Preference,* 99, 1-9. https://doi.org/10.1016/j.foodqual.2022.104545

Malebran, J. S., & Gaitan, J. A. (2021). When does personalization work on social media? A posteriori segmentation of consumers. *Multimedia Tools and Applications,* 80, 36509-36528. https://link.springer.com/article/10.1007/s11042-021-11303-2

Moon, S., Jalali, N., & Erevelles, S. (2021). Segmentation of both reviewers and businesses on social media. *Journal of Retailing and Consumer Services,* 61, 1-14. https://doi.org/10.1016/j.jretconser.2021.102524

Özdemir, G., & Arzık, V. A. (2022). Segmentation of social media users for destinations: A clustering approach. *An International Interdiscipliner Journal Tourism,* 70(1), 53-66. https://doi.org/10.37741/t.70.1.4

Pedersen, M. (2008). Segmenting residential customers: Energy and conservation behaviors. In Proceedings of the ACEEE Summer Study on Energy Efficiency in Buildings, Pacific Grove, CA, USA, 229-241.

Raman, R., & Menon, P. (2018). Using social media for innovation - market segmentation of family firms. *International Journal of Innovation Science,* 5, 1757-2223. https://doi.org/10.1108/IJIS-08-2017-0078

Reynolds, K. E., & Beatty, S. E. (1999). Customer benefits and company consequences of customer-salesperson relationships in retailing. *Journal of Retailing,* 75, 11-32. https://doi.org/10.1016/S0022-4359(99)80002-5

Sarvary, M., & Elberse, A. (1995). Market segmentation, target market selection, and positioning. In: A. J. Silk, *What is marketing.* Boston, MA: Havard Business School Press,

Shoemaker, S. (1989). Segmentation of the senior pleasure travel market. *Journal of Travel Research,* 27(3), 14-21. https://doi.org/10.1177/004728758902700304

Špička, J., & Náglová, Z. (2022). Consumer segmentation in the meat market: The case study of Czech Republic. *Agricultural Economics - Czech,* 68(2), 68-77. https://doi.org/10.17221/334/2021-AGRICECON

Sütterlin, B., Brunner, T. A., & Siegrist, M. (2011). Who puts the most energy into energy conservation? A segmentation of energy consumers based on energy-related behavioral characteristics. *Energy Policy,* 39, 8137-8152. https://doi.org/10.1016/j.enpol.2011.10.008

Tsimonis, G., Dimitriadis, S., & Omar, S. (2020). An integrative typology of relational benefits and costs in social media brand pages. *International Journal of Market Research,* 62(2), 216-233. https://doi.org/10.1177/1470785318822270

Tuma, M. N., Decker, R., & Scholz, S. W. (2011). A survey of the challenges and pitfalls of cluster analysis application in market segmentation. *International Journal of Market Research,* 53(3), 391-414. https://doi.org/10.2501/IJMR-53-3-391-414

Tumbaz, M. N. M., & Mogulkoç, H. T. (2018). Profiling energy efficiency tendency: A case for Turkish households. *Energy Policy,* 119, 441-448. https://doi.org/10.1016/j.enpol.2018.04.064

Tynan, C., & Drayton, J. (1987). Market segmentation. *Journal of Marketing Management,* 2(3), 301-335. https://doi.org/10.1080/0267257X.1987.9964020

Vigneau, E., Cariou, V., Giacalone, D., Berget, I., & Llobell, F. (2022). Combining hedonic information and CATA description for consumer segmentation. *Food Quality and Preference*, 95, 1-12. https://doi.org/10.1016/j.foodqual.2021.104358

Wang, Y., Wang, J., & Shen, Q. A. (2022). Consumer segmentation study of nutrition information seeking and its relation to food consumption in Beijing, China*. Foods,* 11, 453, 1-14. https://doi.org/10.3390/ foods11030453

Ye, S., Ho, K.W., & Zerbe, A. (2021). The effects of social media usage on loneliness and well-being: Analysing friendship connections of Facebook, Twitter and Instagram*. Information Discovery and Delivery,* 49(2), 136-150. https://doi.org/10.1108/IDD-08-2020-0091

Yılmaz, Ş. K., & Patır, S. (2011). Kümeleme analizi ve pazarlamada kullanımı. *Journal of Academic Approaches*, 2(1), 91-113.

Zhang, M., & Luo, N. (2016). Understanding relationship benefits from harmonious brand community on social media. *Internet Research,* 26, 809-826. https://doi.org/10.1108/IntR-05-2015-0149

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