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Social Networks Marketing and Consumer Purchase Behavior: The Combination of SEM and Unsupervised Machine Learning Approaches

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Abstract: The purpose of this paper is to reveal how social network marketing (SNM) can affect consumers' purchase behavior (CPB). We used the combination of structural equation modeling (SEM) and unsupervised machine learning approaches as an innovative method. The statistical population of the study concluded users who live in Hungary and use Facebook Marketplace. This research uses the convenience sampling approach to overcome bias. Out of 475 surveys distributed, a total of 466 respondents successfully filled out the entire survey with a response rate of 98.1%. The results showed that all dimensions of social network marketing, such as entertainment, customization, interaction, WoM and trend, had positively and significantly influenced consumer purchase behavior (CPB) in Facebook Marketplace. Furthermore, we used hierarchical clustering and K-means unsupervised algorithms to cluster consumers. The results show that respondents of this research can be clustered in nine different groups based on behavior regarding demographic attributes. It means that distinctive strategies can be used for different clusters. Meanwhile, marketing managers can provide different options, products and services for each group. This study is of high importance in that it has adopted and used plspm and Matrixpls packages in R to show the model predictive power. Meanwhile, we used unsupervised machine learning algorithms to cluster consumer behaviors.

Keywords: social networks marketing; consumer purchase behavior; Facebook Marketplace; structural equation modeling; machine learning; unsupervised clustering algorithms

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1. Introduction

With the advent of social networks, a lot of changes have happened in the marketplace. Nowadays, social networks (SN) have become the preferred platform of shopping for many consumers. Social networks make interactive communication among users and create substantial opportunities for marketers to connect with consumers [1].

Facebook is the prime social network service in the world and a tool that has become an important part of consumers' lives [2]. Facebook users, especially, tend to create commercial groups that allow them to conduct business. This kind of group that enables users to conduct consumer-to-consumer commercial activities is called a marketplace [3]. The marketplace is a kind of group which Facebook users create to sell their items. Many developed and developing countries are using social media platforms for purchasing products. COVID-19 has also significantly impacted the influence to purchase products in marketplaces. Moreover, popular social networks, such as Facebook and Twitter, are used by marketers to draw attention to their products and services and reach out to the customers [1,4]. Social networks marketing (SNM) has the potential to optimize the customer experience and journey [5], provide connection with customers [6], lower the marketing cost [7], and enable marketers to send messages to millions of consumers simultaneously [8]. Therefore, social network marketing is going to be more popular in every country, and it is not surprising that social networks are one of the most important tools to encourage the consumption of products. In Hungary, Facebook was launched in 2008 and rapidly played an important role in people's lives. As of 2020, almost 90 percent of Hungarian internet users had a Facebook account. According to recent statistics for 2021, this social network platform was almost equally popular among both men and women, with a moderately bigger share of female users. Moreover, in 2021, the biggest user group of Hungarian Facebook users comprised users between the ages of 25 to 34 years old, while the second group included the ages of people between 35 to 44 years [9]. As limited research has been conducted [4] about the Facebook Marketplace in Hungary in order to determine the factors which influence consumer purchase behavior, it has become an increasingly important issue for sellers using Facebook Marketplace. Social media is a platform that has transformed the interaction between companies and customers, allowing consumers to go through a more interactive purchasing experience [10]. In addition, the government, policymakers, and marketers of Hungary need to understand the consumer purchase behavior trend from the social media marketplace as well as what consumers think about the social media marketplace. Previously, only a few studies focused on the role of social network marketing in consumer purchasing behavior in developing and developed countries. For example, a study on SNM was carried out on consumer purchase decisions in Marketplace in the context of Pakistan [11], Italy [12]), Thailand [13], and Iran [14]. Some studies focused on location-based SNM [15], value co-creation of SNM [16], the effects of social networking sites, and marketing campaigns [17]. In spite of this, there is still a lack of studies around Europe on the effect of social networking marketing on consumer purchases. Therefore, this study aims to examine social networks marketing (SNM) and consumer purchase behavior (CPB) with evidence from Facebook Marketplace in Hungary. Moreover, this study investigates five dimensions of social network marketing such as entertainment, customization, interaction, word of mouth, and trends that can influence consumer purchase behavior (CPB). This current study tried to know the consumer choice behavior through Facebook platforms based on Glasser's choice theory. The research concentrates on a majority of young consumers as understanding the purchasing behavior. Young people are essential because they are both present and future consumers.

However, the novel contribution of this study is to apply both SEM (structure equation modeling) and machine learning approaches to investigate social network marketing (SNM) and consumer purchase behavior from Marketplace. To the best of the authors' knowledge, the current study is the first empirical survey that investigates how social network marketing can affect consumers' purchase behavior with evidence from Facebook Marketplace in Hungary.

The research question is 'How can social network marketing (SNM) affect consumers' purchase behavior through social media (Facebook) marketplaces?' To answer this question, the SEM and unsupervised machine learning algorithms method are used to cluster consumer behaviors at different levels. The findings can help digital marketing, online marketing, affiliate marketing, online advertising agency, company, and policy planners better understand the consumer's purchase behavior of products in light of social media and social network marketing.

This research is structured as follows: Section 2 describes the literature with theoretical background, social network marketing and consumer purchase behavior, as well as the proposed conceptual framework. Secondly, Section 3 describes the methodology, data processing, path modeling, hypothesis testing, and unsupervised machine learning approach with a model fit. Section 4 explains the results and discussion. Finally, the conclusions, recommendations, limitations with future research of consumer purchase behavior by social network marketing are presented in Section 5.

2. Literature Review and Hypotheses Development

2.1. Theoretical Background: Choice Theory

Prior studies have used several theories to identify consumer purchase behavior determinants over the last few decades. Among the most widely used theories for identifying the consumer online purchase behavior are theory of planned behavior (TPB) [18], theory of reasoned action (TRA) [19], diffusion of adoption (DOI) [20], technology acceptance model (TAM) and unified theory of acceptance and use of technology (UTAUT) [21]. This research is invoked and described Glasser's choice theory. This theory is an explanation of human behavior that helps explain our findings and consumer purchase behavior. Furthermore, the theory, in conjunction with our results, serves as a foundation for managerial implications. In generally, choice theory [22] suggests that human beings choose their behavior in an attempt to meet their basic needs, which have evolved over time and have become part of the genetic structure. The five basic needs according to Glasser are survival, belonging, freedom, fun and power. Glasser believes that all behaviors are purposeful, and people are motivated by the pleasure they experience when they satisfy these basic needs. He explains that people give their current knowledge and skills to meet one or more of their basic human needs, and these needs are the general motivation for everything they do. Our study extends choice theory by demonstrating its application in social networks marketing and consumer purchase behavior.

2.2. Social Networks Marketing

The use of social networks and artificial intelligence has increased, and it has become an essential part of the lives of most people around the world [5,23,24]. Statistics show that in 2021, 4.66 billion people were active internet users, encompassing more than half of the global population. At this time, the amount of active social media users is 4.2 billion people across the world [25]. Meanwhile, Facebook takes the leading position as a favored social network service in developed and developing countries [2] with more than 2.89 billion monthly active users [26].

The users of this platform are using the website for commercial activities, including buying or selling items from each other more and more [3,27]. These actions usually take place in a type of group which is called the marketplace. In Marketplace, Facebook works as the platform, just providing the functions; this platform is not involved in the transactions [28]. In these groups, users can see the selling posts of other group members and are able to communicate with them [3].

The possibility for communication in social networks enables retailers to understand the customers' needs better [6]. The important issue is that different demographic, cultural, geographic and behavioral consumer segments must be taken into consideration during social networks marketing activities [29]. Nonetheless, research shows that some businesses have joined social network platforms and spent a lot of money in social networks marketing without clear marketing plans and strategies. As a result, they may not completely benefit from these platforms [1,30].

Social network marketing offers better customer experiences and journeys [7], lowers marketing costs, and engages greater numbers of consumers [19].

2.3. Consumer Purchase Behavior

Social networks play an important role in changing consumer purchase behavior [6] and the development of online shopping [5,31]. Studies show that consumers commonly use social media to search for information before making purchase decisions [8,32].

Social networks make it possible to gather groups of consumers to talk about products and services and share ideas about certain brands [33]. This is one of the most important roles that these platforms play in shopping behavior. A study about the influence of likes on

Facebook on user's purchase behavior shows that when the number of likes on Facebook is higher, purchasing and recommending a product on the linked website is more likely [34]. Other researches also mention the positive effect of the number of likes [35], expressing subjectivity within online reviews [36], online recommendations [1], other consumers ratings [37] and influencer endorsements [38] on consumers' intention to make purchases on social networks. Previous studies indicate that there are several important aspects, such as the quality of information about products or services [14], emotional experiences, emotional engagement, [7], brand trust, brand community, and brand awareness [39], which can influence consumer purchase behavior.

Other studies have pointed out that the design of a post [28], trust of a social network community [40], message structure [41], attitude [42], cultural settings [43], AR (augmented reality) experience [44], ease of understanding [3] and pro-social consumer behaviors, such as social responsibility, empathy, moral reasoning, self-reported altruism (SRA), and past helpfulness [45] are able to influence consumer purchase behavior.

2.4. Conceptual Framework of Social Networks Marketing, Consumer Purchase Behavior and Its Five Measures

The rapid growth of social networks and gaining new followers causes many opportunities and challenges. Increasing the use of internet and social networks, consumers' purchase behavior has completely changed. Lower costs of marketing activities, improved brand awareness and increased sales are some of the opportunities provided for users through social network platforms [5]. On Facebook, the group function is connecting people who have the same interests for operating certain businesses [28]. Facebook users create commercial groups to buy and sell products and services [3]. Although Facebook remains the leading social network platforms all around the world, the users have differences in information processing with regard to messages [46], which is able to change consumer purchase behavior. The conceptual framework of this study is adapted from different types of social media marketing activities, such as entertainment, interaction, trend, customization, and word of mouth [14]. This study aims to investigate the possible influence of entertainment, customization, interaction, word of mouth and trends on customer purchase behavior on Facebook Marketplace.

Entertainment: A form of entertainment is a way of attracting audience's attention or pleasing them. The new era of social media entertainment refers to the emerging industry of native online cultural producers operating alongside legacy media industries and around global media cultures, including platforms, intermediaries, and fan communities [47]. The use of social media, particularly when gamification techniques are employed, provides users with a sense of fun and play, which encourages them to return and purchase. Consumer attitudes are positively influenced by entertainment, which results in increased engagement between brands and consumers [48]. A recent study by Ebrahimi et al. [14] found that entertainment has a positive impact on consumer sustainable consumption behavior. Thus, we propose the following:

H1. *Entertainment is capable of positively influencing CPB on Facebook Marketplace.*

Customization: Customization refers to the degree to which a service is customized to satisfy an individual's preferences. Customization means how a product or service meets customers' preferences, needs, and demands [49]. Customization in social media refers to how messages, information, and advertising materials correspond to what customers are looking for [14,50]. Through customization, a company can increase customer engagement and enhance the value of its products. Consumers are most satisfied after receiving their expected products and services [51]. Network marketing also helps a company to understand what types of products consumers need or seek. Therefore, a company can provide customized services. Thus, customization has positively influenced consumer purchase behavior in the Facebook marketplace. Therefore, we propose the following hypothesis:

H2. *Customization is capable of positively influencing CPB on Facebook Marketplace.*

Interaction: Interactions on social media platforms are dramatically changing how brands share information with their consumers [52]. Social media marketing has an impact on the purchasing behaviors of people who regularly use social networking sites for information. According to Daugherty et al. [53], social interaction facilitates marketers in evolving user-inspired themes. The interaction on social media allows customers to share their ideas while also providing a forum for discussion. Social networks allow users to express their opinions and exchange customer purchase experiences when it comes to brand-related services and goods. Interaction among users on social media platforms provides knowledge and insight [54]. Ebrahimi et al. [14] observed that interaction resulting from social network marketing has a positive influence on consumers' sustainable purchasing behavior. Sharing opinions or conversations (two-way interaction) with buyers or sellers through the Facebook marketplace is comparatively easy [48]. Thus, interaction in social network marketing significantly influences the purchase of products. Therefore, we propose the following hypothesis:

H3. *Interaction is capable of positively influencing CPB on Facebook Marketplace.*

Word of mouth (WoM): WoM (word-of-mouth) marketing is free advertising that is triggered by customers' experiences, which are usually more than what they were expecting [55,56]. The effectiveness of social network dimensions are electronic word-of-mouth marketing (eWoM), online advertising, and online communities in promoting brand loyalty and consumer purchase intention [57]. A social media platform is an excellent tool for eWOM since consumers generate and spread information about brands to their friends, peers, and acquaintances without restrictions [48,58]. Positive WoM influences consumers to purchase particular brands. For example, word of mouth on social media is critical in motivating consumers to purchase green cosmetics [10]. However, Ebrahimi [14] found that word of mouth of social media has a negative influence on consumer eco-friendly purchase behavior in Iran. When consumers share positive information on products or services from the Facebook Marketplace on their page, blog, or microblog with their friends, their friends are motivated to purchase the product or service [48]. As a result, WoM strongly influences consumers' behavior to buy products on the marketplace. Thus, we propose the following hypothesis:

H4. *Word of mouth is capable of positively influencing CPB on Facebook Marketplace.*

Trend: Social media platforms provide the most recent news and hot discussion topics [59], as well as primary product search channels [60]. In general, social media are considered a more trustworthy, timely and cheaper source of information than traditional promotional activities. Consumers more frequently use various types of social media to obtain information [8,60,61]. Trendiness is a social media tool used to take advantage of grabbing customer attention by providing the latest information on the most current trends. According to Muntinga et al. [54], there are four sub-motivations for sharing trendy information on social media: surveillance, knowledge, prepurchase information, and inspiration. Surveillance refers to consumers observing and staying informed about their social environment; knowledge refers to consumers gaining access to other consumers' knowledge and expertise in order to learn more about a product or brand; pre-purchase information refers to consumers learning more about a product or brand before purchasing it. Product reviews or threads on brand communities in order to make the right purchasing decisions are referred to as "pre-purchase information." Finally, inspiration refers to consumers' acquiring new ideas and how consumers are following brand-related information, which acts as a source of inspiration. Access to information through social networks plays an essential role in consumer behavior. As a result, consumer attitudes and purchase behavior regarding products and services are influenced by trendiness. Based on the literature, we propose the following hypothesis:

H5. *Trend is capable of positively influencing CPB on Facebook Marketplace.*

Based on the previous, above-mentioned literature, we propose the following research model in Figure 1.

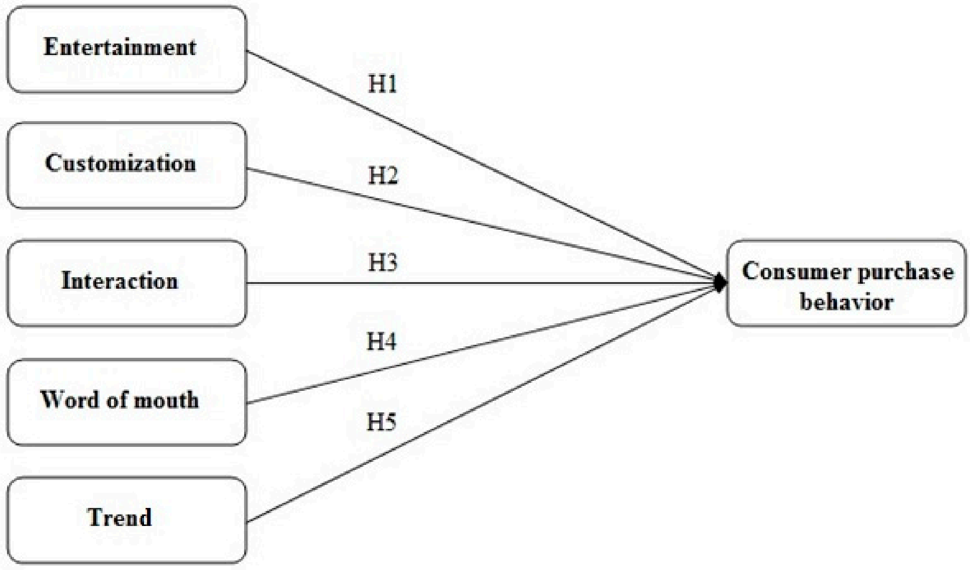

Figure 1. Theoretical model (five dimensions of social network marketing on CPB).

3. Research Method

Sample Size and Measurement of Constructs

This research uses the convenience sampling approach to gathering data. While this approach is commonly used in quantitative studies to overcome bias [62], we employed the common method bias (CMB) test as well [63]. Out of 475 surveys distributed (with an online link), a total of 466 respondents successfully filled out the entire sampling with a response rate of 98.1%. To ensure that the collected data do not have CMB, the Harman's single-factor was carried out with six variables. The six factors were then loaded into a single factor. The analysis shows that the largest variance explained by the newly created factor is 46.37% (for ENT), which is below the threshold value of 50% [63]. Hence, there were no concerns regarding the CMB in the collected data. Furthermore, a pilot study was performed for ensuring the content validity and reliability of the sample size of 25.

The statistical population of the study involved users living in Hungary and who had at least one online purchase experience in Facebook Marketplace. We shared the questionnaire with different groups on Facebook related to online purchases. The questionnaire was translated into both the Hungarian and English languages.

The questionnaire consists of two parts. The first one addresses demographic information and the second one, which is the main part of it, consists of 21 items. All items were scored based on the Likert 5-point scale (5 = strongly agree and 1 = strongly disagree). Five dimensions of SNM (e.g., four items for entertainment and interaction, five items for customization, three items for WoM, and two times for trend) were measured with a total of 18 items adapted from [64,65], and CPB with 3 items adapted from [66–68] was measured. Appendix A shows the items.

In the research sample, 57.7% and 42.3% of the respondents were males and females, in the respective order. The majority of the respondents (42.1%) were in the age group of 25–34 years. Moreover, 31.1% of the respondents had bachelor's degrees, revealing the levels of education of the majority of the respondents. Respondents were instructed to pay attention to the real condition while answering the questions with transparency and loyalty. Based on the time on Facebook, the majority of respondents (53.3%) spent at least 1 to 2 h on Facebook every day. Table 1 shows the demographic information report.

Table 1. Demographic data.

Respondent Profile		**(N = 466)**	
Attributes	Distribution	Frequency	Percent
Gender	Male	269	57.7
	Female	197	42.3
Age	16 to 24	148	31.7
	25 to 34	196	42.1
	35 to 44	86	18.5
	45 to 54	30	6.4
	55 and up	6	1.3
Education	Below diploma and diploma	124	26.6
	Bachelor's degree	145	31.1
	Associate degree	73	15.7
	Master	110	23.6
	PhD	14	3.0
Time on Facebook	Below 1 h	78	16.7
	1 to 2 h	248	53.3
	2 to 3 h	81	17.4
	3 to 4 h	41	8.7
	4 h and up	18	3.9

The paper used the combination of structural equation modeling (SEM) and unsupervised machine learning (ML) approaches. SEM was used in several previous research studies related to social network marketing [41,64] and consumer purchase behavior [69,70]. However, there are few studies with a combination of SEM and ML (for example, [62]). This paper aimed to use SEM as a powerful tool to predict the research model. SEM helps us to evaluate the performance of the model in both the inner and the outer models. We used the unsupervised ML approach to cluster different consumers. We used hierarchical cluster analysis (HCA) and K-means algorithms based on Python libraries. In fact, these two clustering algorithms are unsupervised machine learning algorithms. For example, if your customer data include age, education, and spending time in social media, a well-configured k-means or HCA model can help divide your customers into groups, where their attributes are closer together.

4. Results

4.1. Measurement Models

The reliability of the questionnaire was evaluated by Cronbach's alpha, composite reliability, Dillon–Goldstein's rho and by checking the first and second eigenvalues of the indicators' correlation matrix (Table 2). Some researchers suggest 0.7 and above as the favorable point for Cronbach's alpha [69,71–74] and DG rho [75]. As the value of these coefficients is higher than 0.7, it means that the reliability of the research is confirmed. The first eigenvalue should be much larger than 1, whereas the second eigenvalue should be smaller than 1 [75]. The outer loading values were above the 0.7 thresholds [76]. Meanwhile, the AVE (block communality) scores were above the threshold of 0.50 (Table 2), showing the internal consistency of the measurement model [77,78]. Figure 2 shows that all items have an acceptable outer loadings level based on the graphical outer loading figure (Plspm package with R).

Discriminant validity was assessed at the construct level by the Heterotrait–Monotrait ratio (HTMT), as shown in Table 3. Values less than 0.9 are considered favorable for this index [79]. To assess the discriminant validity of items, cross-loadings were used by adopting the plspm package with R (see Figure 3) which show reliable results and confirmed the discriminant validity in the items level.

Table 2. Measurement models and measures.

Items	Outer Loadings	AVE (Block Communality)	C.alpha	DG.rho	CR	Eig.1st	Eig.2nd
Social Media Marketing *adapted from* [64,65] *Entertainment* (SD = 0.711, M = 4.275)		0.707	0.862	0.907	0.908	2.83	0.523
ENT 1	0.871						
ENT 2	0.881						
ENT 3	0.819						
ENT 4	0.790						
Customization (SD = 0.638, M = 4.416)		0.725	0.904	0.929	0.931	3.63	0.835
CUS 1	0.884						
CUS 2	0.857						
CUS 3	0.853						
CUS 4	0.747						
CUS 5	0.908						
Interaction (SD = 0.692, M = 4.210)		0.808	0.919	0.944	0.944	3.24	0.448
INT 1	0.953						
INT 2	0.857						
INT 3	0.825						
INT 4	0.952						
Word of mouth (SD = 0.667, M = 4.343)		0.728	0.813	0.889	0.890	2.18	0.447
WOM 1	0.890						
WOM 2	0.824						
WOM 3	0.843						
Trend (SD = 0.645, M = 4.328)		0.771	0.705	0.872	0.875	1.54	0.455
TRE 1	0.903						
TRE 2	0.852						
Consumer Purchase Behavior *adapted from* [66–68] (SD = 0.629, M = 4.350)		0.701	0.787	0.876	0.880	2.10	0.473
CPB 1	0.851						
CPB 2	0.824						
CPB 3	0.836						

Note: C.alpha, Cronbach's alpha; CR, composite reliability; DG.rho, Dillon–Goldstein's rho; eig.1st, first eigen value; eig.2nd, second eigen value; AVE, average of variance extracted; SD, standard deviation; M, mean; ENT, entertainment; CUS, customization; INT, interaction; WOM, word of mouth; TRE, trend; CPB, consumer purchase behavior.

Table 3. Discriminant validity with HTMT.

Construct	ENT	CUS	INT	WOM	TRE	CPB
ENT						
CUS	0.831					
INT	0.801	0.771				
WOM	0.824	0.826	0.849			
TRE	0.824	0.812	0.804	0.848		
CPB	0.845	0.836	0.838	0.832	0.798	

Note: ENT, entertainment; CUS, customization; INT, interaction; WOM, word of mouth; TRE, trend; CPB, consumer purchase behavior.

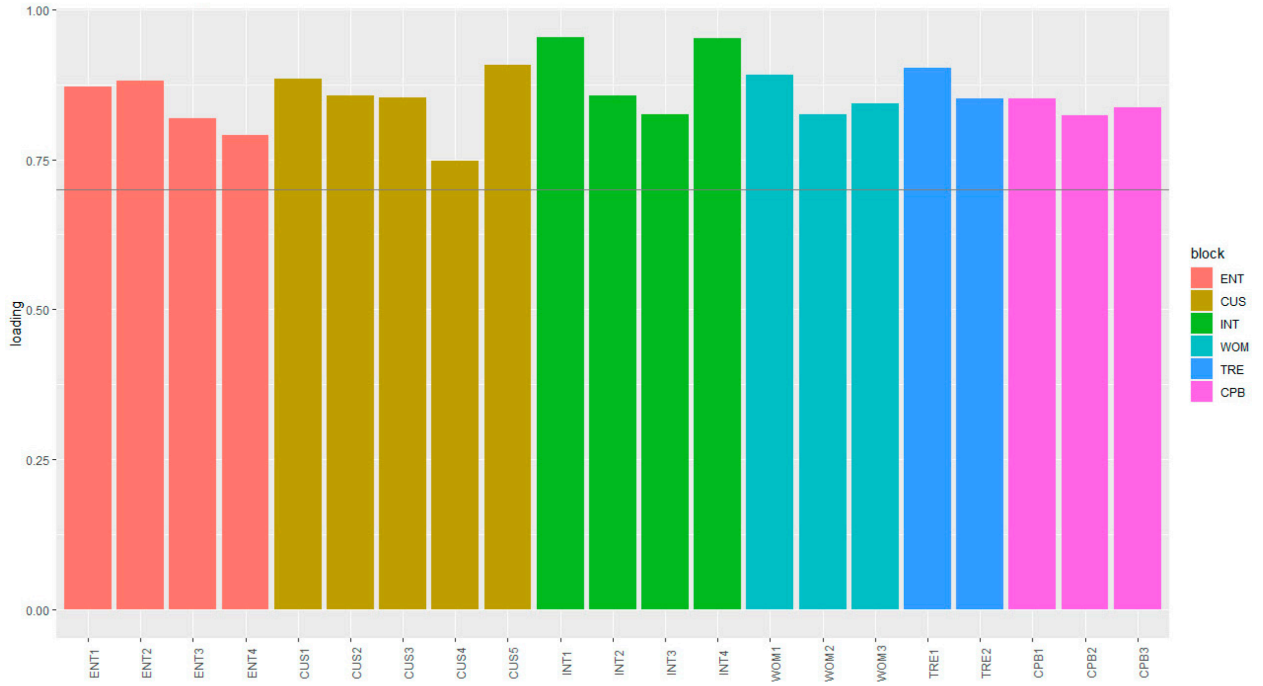

Figure 2. Graphical outer loadings scores with R.

Figure 3. Graphical cross-loadings with R.

4.2. Structural Model

The SEM approach was used with the help of the R software (Plspm and Matrixpls packages Version 4.1.2) to evaluate the structural model and test the hypotheses. For evaluating the model's in-sample fit, we calculated the R^2. The model explained 84.1% of the variance in consumer purchase behavior.

Furthermore, "Mean_Redundancy" was used as an amount of variance in an endogenous construct explained by its independent latent variables. It reflects the ability of a set of independent latent variables to explain variation in the dependent latent variable. Positive and high redundancy means good ability to predict [75]. GoF can be used as a global criterion that helps us to evaluate the performance of the model in both the inner and the outer models [75]. In this research, the value of GoF is 0.788, which is acceptable.

Henseler et al. [80] introduced the SRMR as a goodness-of-fit measure for PLS-SEM that can be used to avoid model misspecification [14,81], and SRMR < 0.1 is acceptable. In this study, SRMR was 0.058 in the output of the estimated model as an acceptable and ideal amount (Table 4).

Table 4. Results of research hypotheses and model fit.

Hypotheses	Direct Effect	SD	Low CI	High CI	Decision
H1	0.369	0.039	0.298	0.461	Supported
H2	0.136	0.038	0.066	0.212	Supported
H3	0.353	0.023	0.306	0.397	Supported
H4	0.069	0.024	0.025	0.114	Supported
H5	0.095	0.026	0.042	0.141	Supported
Model fit	R^2	Mean–Redundancy	GOF	SRMR (Henseler)	
Consumer purchase behavior	84.1%	0.589	0.788	0.058	

Note: SD, standard deviation; CI, confidence intervals; t > 1.96 at * $p < 0.05$; t > 2.58 at ** $p < 0.01$; t > 3.29 at *** $p < 0.001$; two-tailed test.

Entertainment significantly influenced CPB in Facebook Marketplace (β = 0.369, CI = [0.298; 0.461]). Thus, H1 is supported. Customization positively and significantly influenced CPB in Facebook Marketplace (β = 0.136, CI = 0.066; 0.212]). Thus, H2 is supported. Likewise, interaction (β = 0.353, CI = 0.306; 0.397]), word of mouth (β = 0.069, CI = 0.025; 0.114]) and trend (β = 0.095, CI = 0.042; 0.141]) positively and significantly influenced the consumer purchase behavior in Facebook Marketplace. Therefore, H3, H4 and H5 are supported (see Table 4).

4.3. Application of 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 [82] and predict [83]. Unsupervised learning algorithms are useful for making 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 each data value. It means that unsupervised association mining algorithms tend to identify rules that accurately represent relationships between features [84]. We used two different unsupervised algorithms to cluster consumers based on Python libraries (Box 1).

Box 1. # Python Libraries.

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from scipy.cluster.hierarchy import linkage, dendrogram, fcluster
%matplotlib notebook
%config InlineBackend.figure_format = "svg"
```

Hierarchical cluster analysis or HCA (Box 2) is an unsupervised clustering algorithm that involves creating clusters that have predominant ordering from top to bottom. HCA is an algorithm that groups similar objects into groups called clusters. The endpoint is a set of clusters, where each cluster is distinct from other cluster, and the objects within each cluster are broadly similar to each other.

Box 2. # Hierarchical Model.

```
hierarchical_model = linkage (data, method = "complete")
dendrogram (hierarchical_model)
plt.show ()
clusters = fcluster (hierarchical_model, 4, criterion = "distance")
```

K-means clustering is one of the simplest and most popular unsupervised machine learning algorithms. In other words, the K-means algorithm identifies k number of centroids, and then allocates every data point to the nearest cluster, while keeping the centroids as small as possible. Based on a dendrogram in Figure 4, we found that respondents of this research can be clustered in nine different groups based on behavior (regarding demographic variables and independent features to predict consumer behavior). It means that we can follow nine different marketing strategies for these nine groups. Meanwhile, marketing companies can provide different options, products and services for each group. Furthermore, based on Box 3 and Figure 5, we confirmed nine different groups of consumers regarding the K-means algorithm.

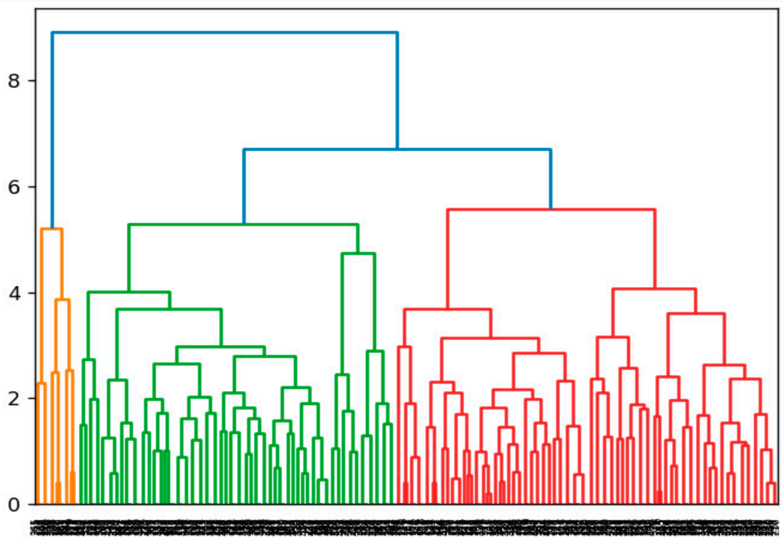

Figure 4. Hierarchical cluster analysis (dendrogram).

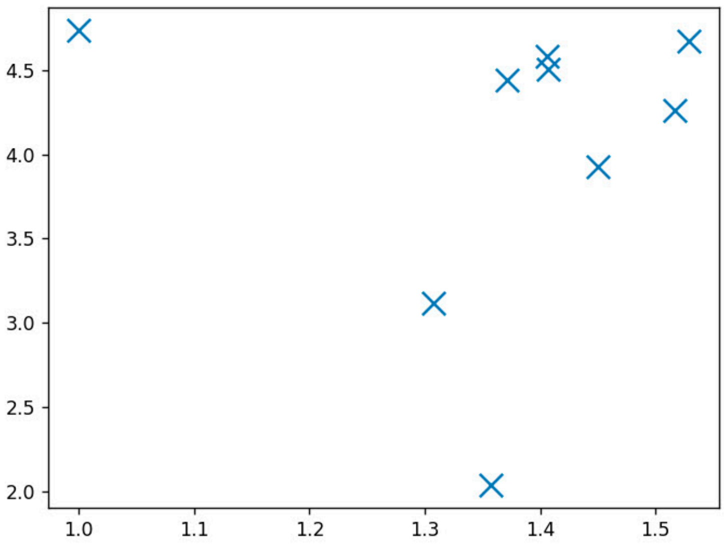

Figure 5. K-means algorithm.

Box 3. # KMeans model.

```
km_model = KMeans (n_clusters = 9)
km_model.fit (data)
clusters = km_model.predict (data)
array([R1,Ci = 5, 3, 8, 3, 3, 0, 5, 5, 0, 4, 3, 8, 3, 8, 0, 1, 2, 4, 3, 5, 0, 3,
2, 6, 3, 0, 1, 1, 3, 6, 6, 6, 4, 5, 1, 3, 6, 0, 8, 3, 5, 1, 5, 1,
3, 5, 1, 8, 2, 2, 2, 7, 5, 2, 1, 1, 2, 5, 1, 5, 4, 1, 5, 5, 5, 1,
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1, 1, 3, 6, 6, 6, 4, 5, 1, 3, 6, 0, 8, 3, 5, 1, 5, 1, 3, 5, 1, 8,
2, 2, 2, 7, 5, 2, 1, 1, 2, 5, 1, 5, 4, 1, 5, 5, 5, 1, 7, 7, 7, 7,
0, 5, 2, 0, 1, 6, 0, 1, 0, 3, 0, 6, 1, 3, 5, 6, 5, 3, 0, 6, 5, 3,
6, 5, 0, 7, 0, 6, 5, 7, 5, 1, 3, 3, 0, 5, 6, 6, 6, 5, 0, 5, 0, 6,
0, 2, 5, R466,Ci = C6])
Note: R, respondents; C, clusters
# cluster centroids
centroids = km_model.cluster_centers_
array([[1.52857143, 3.35714286, 1.74285714, 3.31428571, 4.625,
4.58285714, 4.52142857, 4.51904762, 4.67142857],
[1.42424242, 1.34848485, 1.90909091, 3.1969697, 4.41287879,
4.57878788, 4.45075758, 4.64646465, 4.5530303],
[1.2972973, 1.21621622, 3.18918919, 1.86486486, 3.42567568,
4.03243243, 3.73648649, 3.88288288, 3.86486486],
[1.59459459, 3.28378378, 1.56756757, 1.87837838, 4.51013514,
4.64594595, 4.49324324, 4.63513514, 4.39864865],
[1.26315789, 2.78947368, 2, 1.47368421, 2.06578947,
2.16842105, 1.86842105, 1.92982456, 2.15789474],
[1.39130435, 1.5326087, 1.68478261, 1.81521739, 4.29891304,
4.43478261, 4.30706522, 4.49637681, 4.4076087],
[1.40677966, 3.6440678, 3.16949153, 2.96610169, 4.52118644,
4.61016949, 4.44491525, 4.55932203, 4.50847458],
[1.15384615, 1.38461538, 3.88461538, 4.57692308, 4.83653846,
4.91538462, 4.13461538, 4.30769231, 4.75],
[1.34782609, 3.60869565, 1.17391304, 1.60869565, 3.90217391,
4.04347826, 3.45652174, 3.60869565, 3.69565217]])
```

5. Discussion

These days, shopping on social networks is more favored than ever before [1]. One of the most popular social networks websites is Facebook, which plays the role of the marketplace as well. Facebook users are using this website as a place for selling and buying items from each other more and more [3].

This study tested five factors (e.g., entertainment, customization, interaction, word of mouth and trend) of social networks that are capable of influencing consumer purchase behavior with evidence from Facebook Marketplace in Hungary. Our findings indicate that all five of our hypotheses are supported and confirmed. These findings are in line with the previous studies and the background theory.

For example, H1 points out that entertainment is capable of positively influencing CPB on Facebook Marketplace. The confirmation of this hypothesis is in accordance with Glasser theory that considers fun as a basic human need that acts as a motivation of human behavior. Other studies also show that feeling pleasure [1], emotional engagement [85], and entertainment [86] can affect consumer purchase behavior.

The second hypothesis proposed that customization is capable of positively influencing CPB on Facebook Marketplace. This proposition is in alignment with another study that proved the positive direct effect of behavioral targeting on purchase intent [87].

Similarly, many studies [39,56,86,88,89] indicate the relationship between interaction or communication and consumer purchase behavior, which is in line with the confirmation of the third hypothesis.

The fourth hypothesis refers to word of mouth as a factor which is capable of positively influencing CPB on Facebook Marketplace. This hypothesis is justified, and the results are in line with the statements of previous research. Gonda et al. [56] examined the effects of WoM on the purchasing behavior of consumers in fashion retail and concluded that it is a very important factor for creating consumer loyalty and makes a high contribution to the competitiveness of brands or companies. Meanwhile, Wiese et al. [2] concluded that electronic word of mouth shared with other Facebook users or friends is considered invasive and has a positive influence on consumers' purchase behavior [2].

Finally, the positive effect of influencer marketing is in line with the confirmation of H5. This hypothesis refers to trend as another factor that is capable of positively influencing CPB on Facebook Marketplace. Marketers can consider these factors in their marketing activities to influence customers' purchase behavior.

6. Conclusions, Managerial Implications, Limitations, and Suggestions

This research tested five dimensions of social network marketing that are capable of influencing consumer purchase behavior (CPB). The noble aim of this research was to examine the possible effect of entertainment, customization, interaction, word of mouth and trends on consumer purchase behavior with evidence from the Facebook marketplace in Hungary. Undoubtedly, the most important finding of this research is the emphasis on clustering consumers. Customers with different demographic characteristics and different attitudes must have different purchase behaviors. In fact, the results of this study emphasize that all aspects of social networks marketing have a positive and significant effect on consumer purchase behavior. However, the need to cluster customers is a missing link that has received less attention. From a managerial point of view, it is very important to pay attention to this point. Online businesses need to have different strategies for different consumers. Discussing the market segment and focusing on target customers according to their tastes and interests should be given more attention by marketing managers. In fact, from a managerial point of view, by examining the demographic characteristics of the respondents, long-term planning can be created based on their interests. For example, when a marketing company tries to introduce and sell a new product. It can have a comprehensive review of previous customer data obtained in the form of customer relationship management (e-CRM or CRM). It seems that marketing managers should not overlook the value of demographic information. By examining and analyzing demographic characteristics (big data) in a wide range of consumers, "customization" for customers can be implemented. From an economic point of view, this is very important for increasing the efficiency as well as the profitability of online businesses. What consumers want and what products are in their shopping cart is a priority. The "customization" of advertisements for consumers is one of the important results of market clustering.

There are also some limitations in the present study; the results during the COVID-19 crisis is one of the most important challenges and limitations of this research. It means that under normal conditions, respondents may have had a different attitude to social networks marketing in comparison with the COVID-19 situation. The long-term impact of the pandemic requires further research in this field. Furthermore, to extrapolate the findings of this study, keep in mind that the respondents in this study answered the questionnaire based on their experiences with various online social platforms in Hungary, and that different outcomes and/or experiences may be observed in other nations and/or cultures. Future researchers are encouraged to use other clustering methods (DBSCAN or mean shift) to cluster consumers. Additionally, using supervised methods (ANN, K-NN, SVM, decision tree or Naive bayes) can provide more results and findings based on "Classification". A qualitative study in the future can divide the available data into nine different groups and examine the characteristics of individuals in each group separately and provide appropriate planning and strategies according to the characteristics of each group, including age and interests, etc. A qualitative study based on open coding in different cluster can provide a lot of important notes for marketing managers.

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Appendix A

SNM adapted from [63,68]

Entertainment

ENT 1: The contents on Facebook Marketplace are believed to be thought-provoking.

ENT 2: Using Facebook Marketplace is exciting.

ENT 3: Gathering data on services and products through Facebook Marketplace is fun.

ENT 4: Using Facebook Marketplace saves time easily.

Customization

CUS 1: Looking for tailored data on Facebook Marketplace is possible.

CUS 2: Customized services are offered by Facebook Marketplace.

CUS 3: Facebook Marketplace offers sparkling feed data that users are interested in.

CUS 4: Using Facebook Marketplace is easy.

CUS 5: Facebook Marketplace is everywhere.

Interaction

INT 1: Conveying opinions with buyers/sellers through Facebook Marketplace is easy.

INT 2: Exchange opinions or conversation with buyers/sellers through Facebook Marketplace is easy.

INT 3: Two-way interaction through Facebook Marketplace is done easily.

INT 4: Sharing data with buyers/sellers through Facebook Marketplace is done easily.

Word of mouth

WOM 1: I like to share information on products or services from Facebook Marketplace to my friends.

WOM 2: I like uploading contents from Facebook Marketplace on my page, blog or microblog.

WOM 3: I like sharing thoughts on items, or services acquired from Facebook Marketplace with my friends.

Trend

TRE 1: It is a leading branding by using Facebook Marketplace.

TRE 2: Contents on Facebook Marketplace are fresh.

CPB adapted from [67–69]

CPB 1: Many buyers/sellers perform online shopping following Facebook Marketplace advertisements.

CPB 2: Based on the advertisements on Facebook Marketplace, I am faithful to buy or sell in Facebook Marketplace.

CPB 3: If I want to repurchase an item, my priority is with Facebook Marketplace.

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