

Benefit Segmentation of Internet Users and Their Addictive Behavior

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Abstract

The dominance of technology is in consumers' daily life. Some of them prefer to use technology for business purposes; some integrate their basic needs of entertainment and fun over the internet and social media usage. This research aims to understand the different levels of integration and the deepness of the Internet users' needs and connection of online time, which might be an indication of online addictions and addictive behavior. With this purpose internet user groups are compared by the main purpose of the internet and social media usages. It is also aimed to define the behavioral differences based on the leading addictive signs of internet users.

Keywords: Internet Usage, Internet Addiction, Benefit Base Segmentation, Social Online Behavior

1 Introduction

An increasing number of people use internet and mobile technologies for different purposes of their daily lives. Most of the behavior patterns have changed since the benefits of the internet have reached to more and more people every day. Especially, the younger population tends to have a better rate of integration and show different behavior patterns compared to previous generations. With the available information flowing online, people no longer memorize phone numbers or have phonebooks, use paper maps or check transportation schedules on paper.

However the usage of internet and related technologies are not limited to information search anymore, people are depended on computer and communication technologies for business/work and writing; but they also use internet for gaming, and some are depended on social media for socializing and self-expressing. The purpose of using the same technologies brings the question of if the benefit based segmentation for internet users a viable option to reach different need profiles of internet users. Is this internet reliability a general profile which leads the users to a total addiction and dependency or is there still different attachment levels and behavior patterns?

The addiction is a very complex psychological research area with different types. Psychology literature defines addiction as a response to the need to outside stimuli and the feeling of discomfort without and attaching such stimuli or behavior and disconnect with others and other activities (Young, 1996). These stimuli can be material like alcohol or drug addictions or some behaviors in cases of gambling addiction. Despite the benefits of internet are well known and accepted, the relationship with internet is also transforming to a level of addiction, an impulse control matter at least (Young,

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1998). Different types of addictive profiles might be a sign of different internet user profiles and even segments.

The segmentation of the internet users could be based on many criteria, but with the possible technology integration perspective usually the demographic base segmentation is preferred (Kotler and Armstrong, 1980). However, segmenting with multiple criteria can be the new era for the consumer studies.

Benefit based or benefit segmentation was defined in the 1960s with a new perspective of achieving a better understanding of consumers' reasons to have same behavior patterns then their descriptive qualities (Haley, 1968). This basic perspective of understanding how the consumers think, rather than where they live or what their demographic profile is still an important aspect for psychographic, behavioral or value based segmentation approaches (Hendricks et al., 2004).

This study focuses on the different reasons for using internet and tries to understand the benefit based segmentation difference on the addictive profiles of these segments. In order to determine the different addictive profiles of the business/work related internet users and social and entertainment related users, a discriminant analysis was applied.

2 Literature Review

For this study, it is important to understand the nature of consumer segmentation and how addiction could be a differentiation point of constructing the benefit based consumer segments. Therefore, we would like to look through market segmentation and addiction literature.

Unlike taking the whole market as a homogeneous sum, segmentation basically divides the market based on different criteria to more homogenous pieces. It is aimed to have different segments, which have different characteristics when compared to each other by increasing the heterogeneity between different segments (Kotler and Armstrong, 1980; Kotler et al., 2014). The segmentation considers each unit/person as an individual data to place it in the right segment (Gunter and Furnham, 2014). Literature of segmentation depends on finding the best criteria to divide the market into segments and completing the process with targeting the right segment (Kotler and Armstrong, 1980; Aghdaie et al., 2013; Simkin L, 1998). While targeting the best market segment or segments first considers profitability, market growth and market size (Simkin L, 1998), effective segmentation should focus more on the homogeneity, measurability and accessibility of the segments (Kotler et al., 2014; McDonald and Dunbar, 2004; Eckrich, 1984; Weinstein, 2004). While the most commonly used consumer market segmentation criteria are, demographic, geographic, psychographic and behavioral (Kotler and Armstrong, 1980) , new segmentation studies consider multi-criteria segmentation to be a better solution in some industry and markets.

Benefit based segmentation considers the benefit that the consumer hopes to get from the product and their reasons for using/choosing products are more important than defining the demographics (Haley, 1968). Lewis (1981) alters the benefit based segmentation definition and takes the level of importance of the product or the services for consumers into consideration. Some of the studies directly preferred the terminology of ?motivation? based segmentation and considers perceptions on benefits as the motivation of consumer choices (Ryan and Glendon, 1998). Attribute evaluation, true benefit evaluation and value-based evaluation of the consumers and their perceptions as segmentation criteria is also linked to each other but found different as segmentation evaluation (Botschen et al., 1999). Briefly, benefit perception is recognized as a motivation reflecting over the behaviors of the consumers and should be taken into consideration.

Since the motivation is a part of the consumers' choice, could addictive stimulus be considered as any other product? What if the impulse control problems or addictive stimuli's are not really leaving the consumer a choice of their behavior? Is it still the same if the addictive people and non-addictive people still have the same motivations?

Addiction is a state of a person's high-level attachment to stimuli, where he has a high level of attention and time commitment which leads to losing interest to other things, and creates social and physical problems (Young, 1996). In most cases addiction is considered as a sickness, which requires more drastic precautions.

The periodic checks of social media and internet and increasing time spent online makes the internet an ?impulse control disorder? for psychology literature (Young, 1996, 1998). The behavior is defined as a mental disorder, yet some resources define behavior as ?overuse? of internet rather than an ?addiction? (Spada, 2014; Young, 1996).

The addiction of internet refers to the need of acceptance, anonymity, information search need, or the computer usage behavior as the source of addiction (Beard and Wolf, 2001). Almost most of the reasons creating any addiction seems to be replaced by internet addiction too. Classical symptoms like avoiding problems, feeling better with the behavior and even lying about the behavior, repeating the behavior and inability to stop the behavior and increase time/energy consumption for the behavior are also seen as Internet addiction (Young, 1999). Liu and Kuo (2007) links internet addiction to parent and peer problems, while Kardefelt-Winther (2014) refers to avoiding problems and focusing on feeling better.

Different dimensions of internet addiction are also defined by the literature. Addiction to the computer games is examined under the need of gaming as a class of addiction. While online pornography is accepted as a part of sex/cybersex addiction, web surfing is linked with information need and also named as information overload. The compulsive behaviors over the internet are also examined like online shopping addiction or online gambling and named as net compulsion. Addictive behavior of online relations could be named as cyber-relationship addiction (Young, 1999).

Social network or social media gets more excessive use of time online in Turkey as well (TUIK, 2013). Social media allows people to have the freedom to be anonymous, create their own profiles to communicate and even create new societies (Hughes et al., 2012; Kuss and Griffiths, 2011). People are eager to join and actively use social media for many reasons, including feeling better, avoiding problems, the need to be accepted in a group, etc. (Davenport et al., 2014; Andreassen et al., 2012) which are all considered as motivating factors. In this study, business/work related and social related motivations are divided into two different groups and the behavioral profile on addictive scale adapted from psychology Kurtuluş K. (2014) literature are compared.

3 Research Methodology

The aim of the research is to determine the differences between business/work related and social related internet users' (as benefit based segments) differences on internet and social media addictive behavior bases. It is also aimed to develop a forecasting model to estimate such addictive or compulsive behavior patterns of internet usage purposes. For this reason, we used the previously adapted 37 item Likert scale (1 totally disagree-5 totally agree) from Young's studies. We prefer to use the whole scale without eliminating it into dimensions and conducted a reliability test the scale and reached 0.982 Cronbach Alpha coefficients which indicate excellent fit. Addition to the demographic and internet using pattern questions, the primary purpose of using the internet was also examined. Information search, mailing, business/work/studying purposes, buying goods and services, news following categorized as business/work related behaviors while, social media content creation, content following, chats, games, and entertainment were considered as social purposes. Finally, discriminant analysis is used to determine these two groups' differentiation items from 37 item scale.

4 Findings

For this study, 255 participants are reached via an internet survey. Participants report using internet at the average of 6.47 hours per day (std. dev. 3.31). The average usage period of internet was 11.39 years (std. dev. 7.47). The participants state laptop computers are the most frequently used device for internet connection (%49.8) followed by desktop computers (%22.7).

?Following social media? is the most important reason for internet usage (%21.6), followed by ?data search? (%19.6) and ?content creation over social media? (%17.6). The fourth important reason seems to be ?business purposes? with %15.3.

The demographic profile of the sample is also examined. %52.2 of the participants are male. The average age is 19.18 (std. dev. 6.02). The majority of the participants have undergraduate degree (%52.2) and the average household is 4 people. The two highest income groups are; 2001 TL- 3000 TL (with %26.7) and 1001 TL-2000 TL (with %18.9). All of these data show that participants of this survey are very young, highly educated, mid-income class, average household size. Therefore, they are very homogeneous group of individuals.

Table 1: Eigen value and Wilk's Lambda of the discriminant analysis Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	$.547^{a}$	100.0	100.0	.595

a. First 1 canonical discriminant functions were used in the analysis.

Table 2: Wilks' Lambda	Table	ole 2:	Wilks	' Lambda
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Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.646	102.305	37	.000

In order to test the differences between the groups, a discriminant analysis was applied to the 37 item scale, which measures addictive attitudes of the internet use. Enter method discriminant analysis was chosen. Grouping variable was the work or social related user purposes.

Tests of Equality of	Wilks'	F	Sig.	Business	Social
Group Means	Lambda			group	Group
				Mean	Mean
I think I should spend	0.957	11.327	0.001	3.407	3.896
less time online					
People around me com-	0.954	12.186	0.001	2.343	2.852
plains that I spend so					
much time online					
I usually spend more	0.985	3.821	0.052	3.336	3.635
time online then I antic-					
ipated					
I don't feel satisfied	0.949	13.624	0.000	2.829	3.391
when I use internet less					
now					

I am trying to control	0.991	2.313	0.130	2.514	2.739
myself about being on-					
line					
I feel like I am spending	0.971	7.482	0.007	2.664	3.070
too much time online	0.001	0.040	0.100	2 507	0.700
I am trying to limit my	0.991	2.242	0.136	2.507	2.722
time online	0.005	1.00.4	0.956	2 000	2 400
I feel lost without inter- net connection	0.995	1.294	0.256	3.229	3.409
I feel anxious without	0.986	3.689	0.056	3.186	3.496
internet connection	0.900	5.009	0.000	5.100	5.490
I don't know what to do	0.997	0.758	0.385	2.343	2.470
when I don't have inter-	0.001	0.100	0.000	2.010	2.110
net connection					
I am using internet more	0.964	9.461	0.002	2.907	3.348
than it is necessary					
I usually don't realize	0.912	24.392	0.000	2.757	3.461
how much time I spend					
online					
My work/school per-	0.911	24.829	0.000	1.821	2.417
formance decreases be-					
cause of internet					
My relationship with	0.981	4.998	0.026	1.721	1.948
my family had weak-					
ened because of internet					
My relationship with	0.995	1.379	0.241	1.771	1.904
my friends had weak-					
ened because of internet	0.000	2.000	0.001		1.0.10
I feel like I can spend	0.988	3.066	0.081	1.757	1.948
enough time with peo- ple I care about because					
of internet					
I lied to peo-	0.997	0.637	0.426	1.414	1.478
ple around me	0.001	0.001	0.420	1.111	1.110
(friends/family/therapist					
etc.) about my fre-					
quency of using internet					
I lied to peo-	0.999	0.360	0.549	1.400	1.443
ple around me					
(friends/family/therapist					
etc.) about my time					
frame been online					
I use internet to avoid	0.952	12.891	0.000	1.814	2.296
my problems					
I use internet to avoid	0.966	8.779	0.003	1.843	2.209
my responsibilities					
(school. work etc.)					

I want to be online when	0.981	4.905	0.028	2.614	2.965
I am troubled					
I want to be online when	0.980	5.057	0.025	2.479	2.826
I feel unhappy					
I feel anxious unless I	0.936	17.225	0.000	2.421	3.026
control my social media					
accounts frequently					
I feel like I miss some-	0.933	18.038	0.000	2.736	3.391
thing unless I connect to					
Social media frequently					
I got my smartphone be-	0.947	14.291	0.000	2.636	3.270
cause I want to be able					
to check my social me-					
dia accounts everywhere					
Even I am online. just	0.950	13.341	0.000	1.664	2.070
not to show people		1	0.000		
around me that I am al-					
most always online. I					
seem like offline on so-					
cial media					
I use social media to	0.975	6.556	0.011	1.750	2.078
avoid my problems	0.310	0.000	0.011	1.100	2.010
I am aware that I am	0.893	30.298	0.000	2.157	3.000
spending more time on	0.095	00.290	0.000	2.107	0.000
social media					
I am aware that I am	0.920	22.029	0.000	2.207	2.896
	0.920	22.029	0.000	2.207	2.090
sharing so many per-					
sonal details about my life online					
	0.943	15.214	0.000	1.721	2.183
My work/school per- formance decreases be-	0.945	10.214	0.000	1.721	2.185
cause of social media	0.005	00 501	0.000	0.001	9.049
I think I should spend	0.895	29.581	0.000	2.221	3.043
less time on social me-					
dia	0.000	01.101	0.000	0.407	0.070
I feel more like sharing	0.923	21.161	0.000	2.407	3.070
when people "like" my					
shares	0.004		0.0.10	2.400	2 2 2 2
I like to increase	0.984	4.170	0.042	2.493	2.800
the number of					
friends/followers over					
social media					
I need to speak up my	0.971	7.647	0.006	1.700	2.052
thoughts online by us-					
ing a nick name which I					
can't say in my real life					

I like to be included to	0.940	16.081	0.000	1.836	2.391
strangers life as a fol-					
lower over social media					
I feel happy when peo-	0.982	4.631	0.032	2.129	2.443
ple "like"s my location					
check ins					
I want to share every in-	0.897	28.966	0.000	1.729	2.417
teresting thing I do or					
place I been to					

Table 3: Test of Equality of Group Means

The Wilk's Lambda Sig. level is 0.000 which indicates the discriminant analysis meaningful to differentiate these two groups. The canonical Correlation coefficient is 0.595 which indicates %35.4 of the differences between these two groups could be explained by this discriminant function (1). Even though the explanation rate is not very high, the function is still significant for classification.

Table 3 shows that 26 of 37 items are significant at p=0.05 in order to discriminate two groups of internet users. Among 26 discriminating items 15 items are significant at p = 0.000 (3). Table 3 clearly indicates that social users have significantly higher means than business users of internet. Social media users have higher means which groups them as internet addicts.

	Predicted Group Membership		
	social	business	Total
Original Count business	115	25	140
social	28	87	115
% business	82.1	17.9	100.0
social	24.3	75.7	100.0

Table 4:	Correct Classification Probablities
	$Classification Results^a$

a. %79.2 of original grouped cases correctly classified.

Finally, the correct classification rate of business group by the function is %82.1 while social group %75.7 and overall %79.2 from discriminant function determined. (Table 4) This result indicates that discriminant functions correct classification rate is significantly higher than the correct classification rate of random probability model at p = 0.000 (random classification model gives %50.6 correct classification probability) This means that discriminating function model has a very strong prediction power. Therefore, it can be used for predicting internet users' benefit seeking behavior from internet namely business or social.

5 Conclusion

When the test of equality of group means are examined, the addictive red flag items like ?I am trying to limit my time online?, ?I lied to people around me (friends/family/therapist etc.) about my time frame been online? or ?I am trying to control myself about being online? found not to be significant. Even though the lying behavior pattern is very rarely seen in both group, the limiting of internet, or feeling the withdraw when the user is without internet seems to be in the middle range.

Most significant differences between groups observed to be on the items like; ?I don't feel satisfied when I use internet less now?, ?I usually don't realize how much time I spend online?, ?My work/school performance decreases because of internet/social media?, ?I am aware that I am sharing so many personal details about my life online?, ?I got my smartphone because I want to be able to check my social media accounts everywhere ?, ?Even I am online, I just not to show people around me that I am almost always online. I seem like offline on social media? or ?I use internet to avoid my problems/responsibilities?. These significant differences show that the Social purposed internet users are more keen on Social media and started show symptomatic results of overuse or addiction. Social users express the withdraw feeling with less usage, the time consumption of their behavior and avoiding the problems or responsibilities with the stimuli of internet.

The differences between these two groups based on their purpose of usage seem to be a good classification of these groups. The groups show similarities on not lying about their behavior, but the need and the attitude is clearly differentiates these two segments of internet users.

This research clearly indicates that benefit based segmentation of internet users; namely social and business is a viable approach to segment the internet users. Since the model has a very significant predicting power, we advise the researchers to look and use benefit perceptions of users in addition to classical segmentation methods based on users' characteristics. Although this method of using the benefits is more complex, it gives us more insights of this phoneme of addictive behavior.

Although this study is limited to internet addiction with a limited sample size of 255, studies with larger and different sample sizes and sample profiles are encouraged to retest the findings of this research. Therefore, further research is recommended to test this hypothesis of very high significance predicting the power of benefit based segmentation not only in addictive behavior but also different consumer choice behaviors.

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