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SEGMENTATION OF USERS OF SOCIAL NETWORKING WEBSITES

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The typology of networked consumers in The Netherlands presented in this study, was based on an online survey and obtained using latent segmentation analysis. This approach is based on the frequency with which users perform different activities, their sociodemographic variables, social networking experience, and patterns of interaction. The findings present new insights for marketing strategists wishing to use the communication potential of online social networks and for marketers willing to explore the potential of online networking as a low-cost, efficient alternative to traditional networking approaches. The findings also present researchers of social behavior with interesting insights into the role of online social networks as a platform for social interaction and communication.

Keywords: social media marketing, social networking websites, user profiles, latent segmentation.

Social networking websites (SNSs) are understood to be "*a web-based service which is based on certain meaningful and valuable relationships including friendship, kinship, interests, and activities, and which allows individuals to network for a variety of purposes including sharing information, building and exploring relationships, and so on*" (Kwon & Wen, 2010, p. 255). Both the widespread adoption of SNSs and that more and more applications and possibilities are being incorporated into these social websites, provide justification for the analysis of the nature and dimensions of individuals' interactions from

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sociological and anthropological perspectives. Moreover, the increasing value of online social networks, as part of the business strategy (Constantinides & Fountain, 2008; Kaplan & Haenlein, 2010; Mangold & Faulds, 2009), underlines the need for a better understanding of the impact of online social networks on customer behavior and decision-making processes. Two issues are important. Firstly, because of the diffusion and adoption processes while the number of new social networking applications have been growing exponentially since its first serious introduction at the beginning of the 21st century (Boyd & Ellison, 2008) the homogeneity of early adopters has evolved to include multiple user segments and various motivations for adoption. Second, the technologies and applications associated with SNSs have been growing simultaneously with user needs, motivations, and experiences. An increasing number of SNSs are moving from general or global websites to more specialized structures, targeting individuals with common motivations and interests. In a comScore (2011) study about digital trends in the European market, it was found that Europe showed the most growth in SNSs between December 2009 and December 2010 (up 10.9%), compared with North America (up 6.6%), Latin America (up 5.5%), and the Middle East and Africa (up 2.7%). North America has the highest number of Internet users who are also SNSs users (89.8%), followed by Latin America (87.7%), and Europe (84.4%). Within Europe, 85.1% of Internet users in The Netherlands are also SNSs participants.

The dynamism and marketing potential of social media, particularly SNSs, highlight the need for a better understanding of SNSs users. From academic and practitioner perspectives, market segmentation and classification are important steps in this direction. Although some general research has been published on the segmenting and profiling of social media users, segmentation studies of SNSs users, in particular, are rare. Researchers have demonstrated various segmentation approaches and classification patterns that underline the heterogeneity of SNSs users and help to better frame this line of research (see Alarcón-del-Amo, Lorenzo-Romero, & Gómez-Borja, 2011). They have analyzed the sociodemographic differences in SNSs usage, that is, gender, self-identity, belongingness, and addictive tendencies (Barker, 2009; Joiner et al., 2005; Magnuson & Dundes, 2008), to predict the intention of the user to participate in online social networks (Pelling & White, 2009; Pi, Liao, Liu, & Hsieh, 2010). Park, Kee, and Valenzuela (2009) analyzed the gratifications of Facebook group users and the relationship between users' gratifications and their political and civic participation offline. Four primary needs were identified for participation in Facebook groups: socializing, entertainment, self-status seeking, and information. Park et al. argued that gratifications vary depending on sociodemographics of users, such as gender, hometown, and educational background. Practitioners also offer some interesting insights on this topic. One of the well-known examples is the Social Technographics® approach, developed by Forrester Research (Li, 2007). This approach to the segmentation of the online population is based on people's attitudes and use of social media, but does not specify their attributes and use of SNSs. Using this approach, Forrester produced a ladder with six levels of participation or user segments in social technologies, ranging between two extreme positions: intensive participants (*creators*) and nonparticipants (*inactives*). In between, the segments of *critics*, *collectors*, *joiners*, and *spectators* were identified. Of the six segments, the joiners, who represent 19% of the adult online population, are the main users of SNSs (Li, 2007).

The rapid pace of adoption of social media is clearly reflected by the inclusion in the 2010 Social Forrester's Technographics® ladder of a new segment, *conversationalists*. This reflects two important changes: the rapid increase in the use of social media applications and changes in the way people use them. Conversationalists represent 33% of the population and is the category of users who update their SNSs status weekly and post updates on Twitter. The number of joiners increased to 59% in this ladder (Bernoff, 2010).

Previous SNSs researchers (Alarcón-del-Amo et al., 2011; Magnuson & Dundes, 2008; Park et al., 2009) have focused on the study of user behavior in specific SNSs, using mainly psychological (self-identity, addictive tendencies, belongingness) or sociodemographic variables. We have proposed a classification of users based on all SNSs in which they actively participate, and on their participation level. We have identified and described user profiles according to sociodemographic variables (e.g., gender and age), experience in the use of SNSs, and interaction patterns (e.g., frequency of participation and time spent in these websites). To achieve this objective, we applied a latent segmentation approach not used previously in this context, which allows for the introduction of additional variables, and obtains a more reliable and accurate segmentation result.

Method

Participants and Procedure

Our study was based on a survey conducted in the fall of 2009 in The Netherlands by Constantinides, Alarcón-del-Amo, and Lorenzo-Romero, and published in 2010. The sample population comprised 400 individuals who were SNSs users from throughout the country, ranging in age from 16 to 74. The nonprobability method, using quota sampling, ensured that the sample was representative of the Dutch population concerning gender, age, and area of residence. Participants completed a questionnaire based on a combination of closed-ended, dichotomous, and multichotomous questions with single and multiple responses. The main objective was to obtain information about Dutch consumers' experiences and usage of the Internet, in general, and their use of SNSs, in particular. This meant assessing their level of involvement and use of SNSs, user motivations to participate in these websites, types of profiles (public or private) preferred, the extent of network-based contacts, the ways people access SNSs, the number of accounts held in different SNSs, and the sociodemographic variables of the users.

Data Analysis

Latent segmentation methodology was used to define segments and profiles of the SNS users. This type of procedure allows for the assignment of individuals to segments based on the probability of belonging to the clusters. This avoids the restrictions of deterministic assignments that are inherent in nonhierarchical cluster analysis (Dillon & Kumar, 1994). The advantage of latent class models is that they allow for the inclusion of variables with different measurement scales (continual, ordinal, or nominal). In addition, the models can usually incorporate independent variables that can be used to describe (rather than to define) the latent classes. These exogenous variables are known as covariates or grouping variables (Hagenaars, 1993; Vermunt & Magidson, 2005).

Measures

The indicators for the cluster analysis were based on the frequency of different activities performed by the users in the SNSs on a 4-point scale (*never*, *rarely*, *sometimes*, or *frequently*). Different sociodemographic characteristics were introduced as covariates to profile the resulting segments. Other covariates included in the model were user experience with SNSs, frequency of participation, time spent browsing in SNSs, profile location(s), the number and nature of contacts, the number of SNSs used, and motives for using these websites. We obtained different grouping patterns, based on these variables, which fulfill the principles of maximum internal coherence and maximum external differentiation. We used Latent GOLD®4.5 software to conduct data analysis (Vermunt & Magidson, 2008) and also used the earlier 4.0 user's manual which includes all the theory concerning the latent class cluster (Vermunt & Magidson, 2005).

Results

The optimum number of segments were selected: The model estimated from 1 (no existing heterogeneity) to 8 (i.e., eight existing segments or heterogeneity). Table 1 contains a summary of the estimation process and the fit indices for each model.

The model fit was evaluated according to the Bayesian information criterion (BIC), as it allows for identification of the model with the least number of classes that best fit the data. The lowest BIC value was considered to be the best model indicator (Vermunt & Magidson, 2005). The best alternative was represented by three different user groups. The model fit likelihood ratio chi-squared statistic (L^2) can be interpreted as "indicating the amount of the observed relationship between the variables that remain unexplained by a model; the larger the value, the poorer the model fits the data and the worse the observed relationships are described by the specified model" (Vermunt & Magidson, 2005, pp. 107-108). On the other hand, the *p* value can be interpreted as a "formal assessment of the extent to which the model fits the data (the null hypothesis of this test is that the specified model holds true in the population)" (Vermunt & Magidson, 2005, p. 108). The entropy statistics (E_s) and R^2 in our analysis have a value close to 1. Therefore, we determined that our model had a good fit (see Table 1).

In Table 2, the Wald statistic, which evaluates the statistical significance within all groups of estimated parameters, is shown. We obtained a significant *p* value associated with the Wald statistics for all the indicators. This finding corroborates that each indicator discriminates between the clusters in a significant way (Vermunt & Magidson, 2005).

Table 2 also contains the profiles of the three clusters, including only the significant estimated parameters. In the first row, the names assigned to the groups and their relative sizes are shown. To complete the composition of the groups, we have analyzed the profile of the resulting groups according to the information from the covariates included in the model. The composition of the groups based on the descriptive criteria obtained in the analysis, including only the significant estimated parameters is shown in Table 3. Chi-square tests revealed that significant differences exist between the groups regarding frequency of participation in SNSs, weekly time spent on SNSs, location of the profile of these websites, and the number and nature of the contacts maintained. No significant differences are evident in the following two elements: persons known to participate in the past but now have contact only through the Internet, and the number of SNSs actively used.

The main characteristics of the three groups are detailed below, listed in ascending order from lesser to greater frequency of SNSs use.

Introvert Users

This group (Cluster 2) included 41.30% of SNSs users in The Netherlands. This is the least active group, using SNSs mainly to send private messages and contact friends. They update their profiles, but not very often. In other words, introvert users mainly use these sites as an email substitute and include mostly females with a high percentage aged over 51 years. These users connect to SNSs with low frequency (less than once a week) for a short time (less than one hour per week). They usually have a private profile and have fewer than 50 contacts.

Table 1. *Summary of the Results of the Models*

Number of conglomerates	LL	BIC(LL)	Npar	L^2	p	Class. Err.	E_s	R^2
1-Cluster	-8388.3321	17136.1520	60	16776.6642	3.0e-3285	0.0000	1	1
2-Cluster	-7483.5478	15614.1738	108	14967.0956	6.1e-2941	0.0182	0.9307	0.9442
3-Cluster	**-7256.9279**	**15448.5242**	**156**	**14513.8558**	**4.0e-2886**	**0.0327**	**0.9098**	**0.9145**
4-Cluster	-7114.0080	15450.2748	204	14228.0160	1.3e-2868	0.0406	0.9131	0.9105
5-Cluster	-7022.5604	15554.9699	252	14045.1209	1.9e-2875	0.0489	0.9076	0.9003
6-Cluster	-6923.1160	15643.6714	300	13846.2321	5.3e-2882	0.0444	0.9275	0.9170
7-Cluster	-6845.0906	15775.2109	348	13690.1812	8.1e-2903	0.0261	0.9573	0.9506
8-Cluster	-6780.0176	15932.6552	396	13560.0352	2.0e-2941	0.0266	0.9568	0.9489

Notes: LL = log-likelihood; BIC = Bayesian information criterion; Npar = number of parameters; Class. Err. = classification error; E_s = entropy statistic (entropy R^2); R^2 = multiple correlation squared.

Boldface type indicates the most important relatively by segments.

Table 2. *Cluster Profiles Obtained (Indicators)*

Indicators		Introvert (Cluster 2)	Versatile (Cluster 1)	Expert communicator (Cluster 3)	Total	Wald	p	R^2
	Cluster size	41.30%	47.38%	11.31%	100.00%			
Share or upload photos	Never	**0.3518**	0.0731	0.0005	0.1800			
	Sometimes	0.2819	**0.5784**	0.3271	0.4275	87.8370	8.4e-20	0.3304
	Frequently	0.0189	0.1217	**0.6590**	0.1400			
Comment on friends' photos	Never	**0.6606**	0.2640	0.0183	0.4000			
	Rarely	0.2647	**0.3585**	0.1172	0.2925	80.3864	3.5e-18	0.3503
	Sometimes	0.0715	0.3284	**0.5069**	0.2425			
Comment on what the people they follow do/say	Never	**0.7728**	0.2403	0.0170	0.4350	88.4956	6.1e-20	0.4383
	Sometimes	0.0380	**0.3642**	**0.4797**	0.2425			
Browse across SNSs and user profiles	Never	**0.9026**	**0.6035**	0.2319	0.6850			
	Sometimes	0.0084	0.1128	**0.3367**	0.0950	59.4232	1.2e-13	0.2625
	Rarely	0.5441	0.3698	0.0889	0.4100			
	Sometimes	0.1672	**0.5233**	**0.5786**	0.3825			
Send private messages	Sometimes	**0.4129**	**0.5687**	0.4419	0.4900	64.9520	7.9e-15	0.2321
	Frequently	0.0603	0.2685	**0.5117**	0.2100			
Send public messages	Never	**0.6505**	0.2840	0.1260	0.4175	64.3263	1.1e-14	0.2157
	Sometimes	0.1053	**0.3196**	**0.3983**	0.2400			
Label friends in pictures	Never	**0.9475**	**0.6629**	0.2613	0.7350	63.2649	1.8e-14	0.2882
	Rarely	0.0510	0.2658	**0.3357**	0.1850			
Obtain information of interest	Never	**0.6340**	0.2365	0.0759	0.3825			
	Sometimes	0.1081	**0.3244**	0.3683	0.2400	71.0043	3.8e-16	0.2669
	Frequently	0.0223	0.1898	**0.4052**	0.1450			

Table 2 continued

		Introvert (Cluster 2)	Versatile (Cluster 1)	Expert communicator (Cluster 3)	Total	Wald	p	R^2
Download applications	Never	**0.9224**	**0.5207**	0.2191	0.6525	63.1480	1.9e-14	0.2795
	Rarely	0.0724	0.2995	**0.2934**	0.2050			
Download games	Never	**0.9184**	**0.7565**	**0.5056**	0.7950	32.5943	8.4e-8	0.1237
Look for friends	Sometimes	**0.4169**	**0.5632**	**0.5166**	0.4975			
Look for a job	Never	**0.8458**	**0.7172**	**0.4271**	0.7375	33.3858	5.6e-8	0.1106
Communicate news they believe to be of interest to all	Never	**0.9390**	**0.5451**	0.2552	0.6750	45.6990	1.2e-10	0.2667
	Sometimes	0.0036	0.1447	**0.3089**	0.1050			
Share state of mind	Never	**0.9399**	**0.4802**	0.0819	0.6250	74.0028	8.5e-17	0.4158
	Sometimes	0.0032	0.1805	**0.4256**	0.1350			
Share links of interesting webs	Never	**0.8641**	**0.4331**	0.0478	0.5675	71.5871	2.9e-16	0.3915
	Sometimes	0.0197	0.2544	**0.6085**	0.1975			
Communicate ideas/reflections	Never	**0.8711**	0.3136	0.0363	0.5125	79.0189	6.9e-18	0.4444
	Rarely	0.1185	**0.3685**	0.1676	0.2425			
	Sometimes	0.0102	0.2747	**0.4917**	0.1900			
Inform about what they are doing at the time of writing	Never	**0.7675**	0.2692	0.0257	0.4475	88.9274	4.9e-20	0.4026
	Sometimes	0.0505	**0.3614**	**0.4678**	0.2450			
Inform about brands or products they use	Never	**0.9677**	**0.6565**	0.2808	0.7425	54.8617	1.2e-12	0.2783
	Sometimes	0.0013	0.1038	**0.3340**	0.0875			
Comment on advertisements and publicity	Never	**0.9996**	**0.8189**	0.3899	0.8450	30.7418	2.1e-7	0.2794
	Rarely	0.0004	0.1696	**0.4152**	0.1275			

Note: **Boldface** indicates the most important relatively by segments.

Table 3. *Profile of Latent Segments (Covariates)*

Descriptive criteria	Categories	Introvert (Cluster 2)	Versatile (Cluster 1)	Expert communicator (Cluster 3)	Total	χ^2	p
Gender	Male	0.4673	0.4260	0.3102	0.4300	2.904	0.234
	Female	**0.5327**	**0.5740**	**0.6898**	0.5700		
Age[a]	Less than 25	0.1597	0.1826	**0.3325**	0.1900	121.049	0.308
	From 25 to 32	0.1972	**0.2749**	0.1834	0.2325		
	Over 51	**0.2758**	0.1554	0.0875	0.1975		
Frequency of participation in SNSs[a]	Less than once a week	**0.4528**	0.0583	0.0462	0.3400	114.011	0.000
	Several times a week	0.1625	**0.3194**	0.2123	0.2425		
Time SNSs used weekly[a]	Less than 1 hour	**0.7458**	0.3718	0.1156	0.4975	143.351	0.000
	Between 1 and 5 hours	0.2482	**0.5303**	**0.4529**	0.4050		
	Private	**0.5042**	**0.4250**	**0.4893**	0.4650		
Number of contacts	From 10 to 50	**0.3400**	0.2568	0.2243	0.2875	25.276	0.000
	From 51 to 100	0.2164	0.2937	0.2338	0.2550		
	More than 100	0.1973	**0.3109**	**0.4756**	0.2825		
Nature of contacts[b]	People known outside Internet	**0.7590**	**0.9178**	**0.8319**	0.8425	17.358	0.000
	People known before but now have contact only through Internet	**0.6203**	**0.7162**	**0.7465**	0.6800	5.420	0.067
Number of SNSs used	2	**0.5734**	**0.4626**	**0.4770**	0.5100	24.306	0.018

Table 3 continued

Descriptive criteria	Categories	Introvert (Cluster 2)	Versatile (Cluster 1)	Expert communicator (Cluster 3)	Total	χ^2	p
Motives for using SNSs	Entertainment	0.3601	**0.5837**	**0.6833**	0.5025	23.019	0.000
	Professional interest	0.1627	0.1744	**0.3114**	0.1850	5.914	0.052
	Was invited	0.4614	**0.5069**	**0.5019**	0.4875	0.810	0.667
	Novelty/because it is the trend	0.1742	0.2859	**0.3993**	0.2525	11.194	0.004
	Maintain contact with friends and acquaintances	0.4956	**0.7076**	**0.8410**	0.6350	24.454	0.000
	Because friends use SNSs	0.1591	0.3544	**0.5880**	0.3000	35.620	0.000
	Keep informed about events, e.g., parties	0.0272	0.0598	**0.2698**	0.0700	33.340	0.000
	Keep informed of comments on new products of interest	0.0354	0.0854	**0.1101**	0.0675	5.016	0.081
	Make new friends	0.0466	0.1757	**0.4435**	0.1525	45.910	0.000
	Make contacts/relationships on a professional level	0.1365	0.1634	**0.2987**	0.1675	6.244	0.044
	Know better, or have a closer relationship with, persons with whom do not have a direct relationship	0.0600	0.1137	**0.2113**	0.1025	8.675	0.013
	Look for partner/dating	0.0281	0.0488	**0.0690**	0.0425	1.482	0.477

Notes: [a] These intervals were estimated using the Latent GOLD statistical program, as the variables introduced were numeric; [b] Only positive values (yes response) are reflected in the Table.

Introvert users have contacts whom they know outside the Internet and with whom they have maintained previous contact offline. The majority use two SNSs, which they use mainly because they were previously invited to contact friends or acquaintances.

Versatile User

This is the largest group (Cluster 1), representing 47.38% of SNSs users. The majority of these users share or upload photos, send private messages, look for friends, and update their profiles. Less frequently, they make comments on what their contacts do or say, inform others about what they are doing at the time of the online session, look for information about topics of interest, and send public messages. On the other hand, most users in this group rarely communicate ideas or reflections, or comment on friends' photos. This group comprises predominantly females aged between 25 and 32. They participate several times a week in SNSs sessions, between one and five hours per week. The highest proportion of users has a private profile, with more than 100 contacts whom they have met offline and with whom they may or may not have other types of contact at that time. They have, on average, accounts in two SNSs that they have joined mainly to maintain contact with friends and acquaintances (70.76%), for entertainment (58.37%), and because they were invited (50.69%).

Expert Communicator User

This is the smallest group (Cluster 3), representing 11.31% of SNSs users, but it is also the most active. The most outstanding feature is that the users are more likely to perform different activities frequently, specifically sharing photos, sending private messages, and obtaining information of interest. Most of these users occasionally share links to interesting websites, update their profiles, and comment on friends' photos. Less frequently, they share ideas or reflections, comment on what their contacts do or say, inform about what they are doing at that time, share their state of mind, send public messages, browse across SNSs, examine user profiles, inform others about brands or products they use, and communicate news they believe to be of interest to others. In addition, the highest proportion of users rarely comments on advertisements and publicity, label friends in pictures, and download applications. This group comprises predominantly females aged under 25. They are the most participative users in these websites, taking part at least once a day and for more than one hour per week, and are users of two SNSs with private profiles. They have a much higher number of contacts than the other groups (usually more than 50), mainly with people they know offline. They use SNSs to maintain contact with friends and acquaintances for entertainment, because their friends use SNSs, and because they were invited. Regarding the motives for using SNSs, this group encompasses the greatest number of individuals. They use these websites to make new friends (44.35%), because of the novelty (39.93%), because of professional interest (31.14%), to make contacts or establish relationships on a professional level (29.87%), to keep informed about events such as parties (26.98%), to get to know better or develop a closer relationship with persons with whom they do not have a direct relationship (21.13%), to keep informed of comments on new products of interest (11.01%), and to look for a partner (6.90%).

Discussion

We have argued that SNSs present businesses with new opportunities for reaching an ever-increasing online customer population. However, the motives and benefits of participating in the use of SNSs are mainly of a sociological and psychological nature for users. SNSs enable users to fulfill various needs such as communicating, interacting, exchanging information, establishing new relationships, strengthening existing relationships, and engaging in transactions (Boyd & Ellison, 2008; Kwon & Wen, 2010).

The main objective in this study was to identify market segments among SNSs users in The Netherlands. Application of latent segmentation methodology resulted in three groups of whom introvert and versatile users were not active in creating commercial comments, such as product reviews or comments on products or brands. Expert communicator group users only were actively engaged in marketing-related activities, such as the posting of product reviews.

It is interesting to note that the majority of users in every segment are females and that the segments identify clear demographic and behavioral user profiles. The sample is representative of the Dutch population concerning gender, age, and area of residence. In addition, a demographic analysis of SNSs users in Europe, developed by comScore (2011), revealed that more women were engaged in SNSs than men.

The findings indicate that each group uses different SNSs at different frequencies. It is important to point out that a minority of SNSs users carry out marketing-related activities such as commenting on advertisements or gathering information on brands or products they use. The majority use them mainly as sources of information and as communication channels. Because of the growing adoption of SNSs by users (e.g., Forrester Research Report), the increase of the value of online social networks as part of business strategy (e.g., Constantinides & Fountain, 2008; Kaplan & Haenlein, 2010; Mangold & Faulds, 2009), and according to the results obtained in this research, SNSs could be used as communication channels by businesses for reaching their customers by way of providing product information and information related to customer service issues (Constantinides & Fountain, 2008). The information gained through these channels will be appreciated by the customers if it is based on their specific needs and if it is not experienced as advertising or push communication. Engagement with the customer and response to specific and expressed customer needs is therefore the basis for building and maintaining relationships with customers who are actively using SNSs (Kaplan & Haenlein, 2010). To carry this out, companies should create a new position of community manager, specifically dedicated to the maintenance of a company presence in the different SNSs, and they should also adopt new tools to monitor conversations about their products and brands.

Our results indicate that the expert communicator user group presents the most interesting possibility as a potential source of market information and for engagement as a brand ambassador. Businesses should attempt to increase the number of engaged customers and create brand advocates by better understanding the needs and motives of their customers, and engaging them in open dialogue. Businesses should also develop online content adapted to potential and profitable customers by the users.

Companies can obtain a large amount of information about and feedback from their customers regarding their habits, personalities, and lifestyles, from the voluntary uploading by users on SNSs. This information allows refined market segmentation depending on the industry involved. An analysis of user behavior can also provide an early warning of unknown product problems. Therefore, businesses can use SNSs as a source of customer voice. They can obtain, at very low cost, direct and valuable market information that is necessary for decision-making and for control of opinions and complaints about the organization, and also for providing suggestions about new products or services.

The main limitation in this study is that a sample of only one country (The Netherlands) was used. A wider sample could be used in a future study. In particular, the sample should represent a greater diversity of nationalities to form a more comprehensive understanding of SNSs users in Europe, and to observe the differences and similarities between the different nationalities. We also recommend the inclusion of psychosocial variables such as trust, satisfaction, perceived risk, perceived benefits, and ease of use, to examine their effect on the use of SNSs. This research would contribute to the development and empirical analysis of a causal model, thus providing a more accurate insight into the relationships between the variables, and may be able to be used to predict the use of SNSs. The model could also be used to design an experimental study, in which user behavior during SNS browsing is analyzed.

References

Alarcón-del-Amo, M. C., Lorenzo-Romero, C., & Gomez-Borja, M. A. (2011). Classifying and profiling social networking site users: A latent segmentation approach. *CyberPsychology, Behavior, and Social Networking*, *14*, 547-553.

Barker, V. (2009). Older adolescents' motivations for social network site use: The influence of gender, group identity, and collective self-esteem. *CyberPsychology & Behavior*, *12*, 209-213. **http://doi.org/gzm**

Bernoff, J. (2010). Introducing the new social technographics®. *Forrester Research Report*. Accessed at **http://www.forrester.com/rb/Research/introducing_new_social_technographics%26%23174%3B/q/id/56291/t/2**

Boyd, D. M., & Ellison, N. B. (2008). Social network sites: Definition, history, and scholarship. *Journal of Computer-Mediated Communication*, *13*, 210-230. **http://doi.org/gzn**

comScore. (2011). The 2010 Europe digital year in review. Accessed at **http://www.comscore.com/esl/Press_Events/Presentations_Whitepapers/2011/2010_Europe_Digital_Year_in_Review**

Constantinides, E., Alarcón-del-Amo, M. C., & Lorenzo-Romero, C. (2010). Profiles of social networking site users in The Netherlands. *Proceedings of the 8th High Technology Small Firms Conference*. Accessed at **http://www.utwente.nl/nikos/events/htsf/2010/htsfpapers/constantinides.pdf**

Constantinides, E., & Fountain S. (2008). Web 2.0: Conceptual foundations and marketing issues. *Journal of Direct Data and Digital Marketing Practice*, *9*, 231-244. **http://doi.org/gzp**

Dillon, W. R., & Kumar, A. (1994). Latent structure and other mixture models in marketing: An integrative survey and overview. In R. P. Bagozzi (Ed.), *Advanced methods of marketing research* (pp. 295-351). Cambridge, MA: Blackwell.

Hagenaars, J. A. (1993). *Loglinear models with latent variables*. Newbury Park, CA: Sage.

Hofstede, G. (1980). *Culture's consequences: International differences in work-related values*. Beverly Hills, CA: Sage.

Joiner, R., Gavin, J., Duffield, J., Brosnan, M., Crook, C., Durndell, A., … Lovatt, P. (2005). Gender, Internet identification, and Internet anxiety: Correlates of Internet use. *CyberPsychology & Behavior*, *8*, 371-378. **http://doi.org/gzq**

Kaplan, A., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of social media. *Business Horizons*, *53*, 59-68. **http://doi.org/gzr**

Kwon, O., & Wen, Y. (2010). An empirical study of the factors affecting social network service use. *Computers in Human Behavior*, *26*, 254-263. **http://doi.org/gzs**

Li, C. (2007). Social Technographics®: Mapping participation in activities forms the foundation of a social strategy. *Forrester Research Report*. Accessed at **http://www.scob.alaska.edu/afef/mapping_participation_in_activit.htm**

Magnuson, M. J., & Dundes, L. (2008). Gender differences in "social portraits" reflected in MySpace profiles. *CyberPsychology & Behavior*, *11*, 239-241. **http://doi.org/gzt**

Mangold, W. G., & Faulds, D. J. (2009). Social media: the new hybrid element of the promotion mix. *Business Horizons*, *52*, 357-365. **http://doi.org/gzv**

Park, N., Kee, K. F., & Valenzuela, S. (2009). Being immersed in social networking environment: Facebook groups, uses and gratifications, and social outcomes. *CyberPsychology & Behavior*, *12*, 729-733. **http://doi.org/gzw**

Pelling, E. L., & White, K. M. (2009). The theory of planned behavior applied to young people's use of social networking web sites. *CyberPsychology & Behavior*, *12*, 755-759. **http://doi.org/gzx**

Pi, S.-M., Liao, H.-L., Liu S.-H., & Hsieh, C.-Y. (2010). The effects of user perception of value on use of blog services. *Social Behavior and Personality: An international journal*, *38*, 1029-1040. **http://doi.org/gzz**

Schepers, J., & Wetzels, M. (2007). A meta-analysis of the technology acceptance model: Investigating subjective norm and moderation effects. *Information & Management*, *44*, 90-103. **http://doi.org/gz2**

Vermunt, J. K., & Magidson, J. (2005). *Latent GOLD 4.0 user's guide*. Belmont, MA: Statistical Innovations.