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ORIGINAL ARTICLE

A Latent Profile Analysis for the Study of Multiple Screen Addiction, Mobile Social Gaming Addiction, General Mattering, and Family Sense of Belonging in University Students

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Abstract
During the COVID-19 period, individuals who physically isolated themselves from the social environment increased their screen time compared to before, and the time spent in the family environment increased. Increasing screen time is considered a factor that increases addiction. In this context, the purpose of this study was to examine the profiles of university students according to multiple screen addiction, mobile social online gaming addiction, and general mattering. The participants of this study are 588 university students. Personal information form and four different scales were used in the study. The latent profile analysis was used to analyze the data. As a result of the research, four different sets of participants were formed. The variables excessive behavior, compulsive behavior, and loss of control increase the likelihood that students will be clustered in the average profile. It was observed that all variables except gender and age increased the probability of clustering in the medium multiple screen addiction low gamers profile. It was observed that excessive behavior, compulsive behavior, and loss of control variables increased the probability of clustering in the high multiple screen addiction high gamers profile. As a stronger predictor than other profiles, it was determined that the probability of students performing high multiple screen addiction high gameplay activities was approximately 3 times more than the students in profile 1.

Keyword Mobile Social Online Gaming Addiction · Multiple Screen Addiction · General Mattering · Family Sense of Belonging · University Students

There is access to information and communication technology (ICT) tools such as phones, tablets, computers, and TVs, which are connected and continuous, anytime and anywhere. This usually means that there is simultaneous access to one or several devices at any given time. In some way, we lead a life dependent on the screens of these devices (Lin et al., 2020). This continuous association brings with it negative uses that include excessive, obsessive, and repetitive behavioral patterns (such as checking the phone screen frequently

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during the day). This can cause behavioral disorders caused by the problematic use of these devices, such as internet addiction, social media use disorder, smartphone addiction, and multiple screen addiction (MSA). In this study, multiple screen addiction, which is one of the problematic behaviors, was emphasized.

It can be said that the significant isolation of people from their physical social environment during the COVID-19 epidemic caused the increase in screen time of individuals compared to before. In addition, the fact that the activities carried out at almost all levels of working life and education processes, especially at the university level, are carried out over the internet with ICT tools (Pokhrel & Chhetri, 2021; Sultana et al., 2021) is one of the factors of this increase. The increase in screen time increases the probability of facing problems in the context of socio-emotional and mental well-being (Public Health England, 2013; Yang et al., 2013). It is thought that negative changes in screen time and usage habits increase the development and prevalence of MSA. In various studies, it is emphasized that there are dramatic increases in screen time during the COVID-19 epidemic period (Sarıtepeci, 2021; Sultana et al., 2021; Wong et al., 2021). In support of this, it was reported in the We Are Social (2021) that daily internet usage is 6H 54 M and daily time spent watching TV 3H 24 M for the 16–64 age group. The continuation of the increase in media consumption after COVID-19 is a possibility (Wong et al., 2021) that has the potential to trigger MSA or make it a deeper problem. One of the most important risk groups related to this situation is university students. Although face-to-face education has been returned at other education levels, almost all of the learning-teaching activities at the university level have been and continue to be carried out online. At the university level, where social interaction is prominent, the fact that students' interactions are so restricted is an important source of stress. To overcome this stress, besides learning-teaching activities, it causes more orientation to digital environments for entertainment and interaction purposes (Khalili-Mahani et al., 2019). Chaturvedi et al. (2021) found that 64% of the participants in the 18–22 age range during the COVID-19 period turned to digital activities (listening to music, online gaming, web series, social media, online surfing, etc.). It is thought that this orientation to screens to avoid stress may lead to excessive screen time and the development of MSA over time. Sarıtepeci (2021) in a study examining the MSA level of university students reported that half of the participants were at risk of screen addiction, considering the polythetic criteria.

Increases in screen time with social isolation, social media usage, internet browsing, and watching activities and behaviors such as digital game playing behaviors increase. 92.0% of women and 95.4% of men play digital games among internet users between the ages of 16–24, which includes the majority of university students (We Are Social, 2021). One of the main sources of excessive screen time in this age group is digital game playing and mobile online game playing behaviors that have become widespread recently. In addition, the situation of playing mobile games and spending more time in games has emerged during the COVID-19 period (Amin et al., 2022; Narusk, 2020). Another reason for the dramatic increase in the time devoted to mobile social online games is that games have now become a social interaction tool with many social features (Louie, 2021). The titles that stand out in the well-attended report on mobile gaming in the COVID-19 period presented by Google Play (2020) support these findings: "(1) More play and longer sessions, (2) social gaming has increased, (3) one-third have spent more time for playing, and (4) new gamer plan to continue the playing." It can be said that this situation increases the risks of individuals developing mobile social online gaming addiction (MSOGA).

Family sense of belonging and general mattering are thought to be some of the main variables that may affect MSA and MSOGA levels, where individuals under the age of

20 who experience social isolation during the COVID-19 period and make up a significant portion of the participants have been subjected to more severe restrictions than other age groups for a long time. It was emphasized in various studies that deterioration in family sense of belonging and family function is associated with problematic technology use (Gökçearslan et al., 2021; Li et al., 2014; Park et al., 2008). It is estimated that the fact that individuals in this age group have to spend most of their time in the same social environment with their families during the isolation period will increase the impact of family relations on their behavior. It is also known that individuals with high GM perceptions exhibit relatively less problematic behaviors (Rayle, 2005; Taylor & Turner, 2001). On the other hand, it is thought that the social environment that contributes to the general mattering of individuals will cause them to spend more time in environments such as social media and social games during the isolation period. Accordingly, in this study, the determination of the profiles of university students according to MSA, MSOGA, GM, and Family Sense of Belonging and the similarities and differences between these profiles were examined in terms of different variables.

The Purpose of the Study

The purpose of this study was to examine the profiles of university students according to multiple screen addiction, mobile social online gaming addiction, general mattering, and family sense of belonging. In line with the stated purpose, answers were sought for the following sub-questions:

1. Which profiles can be determined for students in environments based on students' problematic use of digital technologies?
2. To what extent do students' personal characteristics (age, gender, and grade), excessive behavior, compulsive behavior, loss of control, general mattering, and family sense of belonging profile predict their membership?

Conceptual Framework

Theoretical Background

The possibilities offered by new technologies, new features of many applications, social media, and social games support the technology usage density of individuals (Durak, 2019; Durak & Saritepeci, 2019). With the intensive use of new technologies, the problematic situations that have arisen in this regard have been the focus of attention. Stănculescu and Griffiths (2021) and Stănculescu (2022) highlighted the emergence of new psychological disorders, including social media addiction. However, a distinction must be made between use and addiction. According to Griffiths (2010), excessive use should not be equated with problematic use. In this context, there is a need to separate the actual pathological uses and profiles of these users from the frequent and excessive use of digital technologies. More research is needed to expand the understanding of multiple screen addiction profiles and their relative symptoms and psychosocial antecedents. However, there are several theories associated with the research context. For example, Uses and Gratifications Theory (UGT) is a theory which is related to communication and media (Blumler & Katz,

1974) and includes the electronic media consumption such as mobile devices usage. Based on individual differences, the UGT intends to figure out the "why and how" of individuals' communication tools and media use (Rosengren, 1974). In the UGT, the factor direction media preferences, and usages like social media, mobile device may include psychological as well as psychopathological features. Another theory to explain the conceptual framework of electronic media consumption usage is Compensatory Internet Use Theory (CIUT), developed by Kardefelt-Winther (2014). CIUT intends to make sense the internet usage and assumes that individuals spend a great deal of time on internet as a way of easing the life stress and negative situations/feelings. Individuals with a high level of problematic technology usage will provide more satisfaction using their devices and applications. Social cognitive theory presents an optimistic situational picture by stating that individuals can control their actions.

Social Cognitive Theory (SCT) states that human behavior can be explained by the triad of personal factors, behaviors and environment, and their mutual causality. Individual factors, the behavior of the individual, and the environment mutually affect each other's current and future behavior (Bandura, 1982). In this study, individual and family-specific factors were considered as the explanatory factor of multiple screen addiction. SCT indicates that behaviors that result in a positive or rewarding reward are more likely to occur. The use of digital technologies is reinforced by the positive results of the use, such as providing general mattering (Chakraborty et al., 2010).

Multiple Screen Addiction

Screens take place in every moment of daily life, and their usage areas are increasing day by day. In addition to this increased accessibility, the usage areas of these screens that facilitate daily life (banking, e-government, e-mail, etc.) and entertainment (social media, watching TV series-movies, gaming, online shopping, etc.) increase screen time increasing factors. Increasing time spent with screens is considered one of the main signs of psychological addiction (Saral & Priya, 2021). According to Lin et al. (2020), MSA can be expressed as "a continuum of unregulated media behaviors using multiple screen devices, extending from compulsive media consumption to extremely problematic and even pathological behaviors." In summary, it can be defined as excessive, uncontrolled, and obsessive media consumption using devices with MSA screens. MSA is not associated with obsessive use of a tool or service such as internet addiction, problematic social media use, and smartphone addiction (Sarıtepeci, 2021). It is associated with psychological and behavioral withdrawal symptoms that occur when an individual loses access to some or all of the media production/consumption tools (PC, tablet PC, smartphone, smartwatch, TV, etc.) (Yildiz Durak, 2018; Lin et al., 2020; Sarıtepeci, 2021). Technology addictions like MSA have helped people regulate their moods in emergencies such as the COVID-19 pandemic (Servidio et al., 2021). However, the heavy use of digital technologies can cause technology dependencies (Yildiz Durak, 2020). Therefore, the impact of MSA and other types of technology-based addictions has become evident in the COVID-19 crisis.

Mobile Social Online Gaming Addiction

Online games have been described as one of the most addictive activities on the internet since the late 1990s (Young, 1998). Online gaming addiction can be defined as a subcategory of behavioral addiction (e.g., Griffiths (2000). Weinstein (2010) stated that it is the degree to which gaming affects other areas of a player's life independently, regardless of the time spent gaming. Today, the prevalence of mobile devices, narrowing spatial restrictions in internet connection, and high usage rates of social media environments make online games and mobile social games a popular choice for leisure activities (Durak et al., 2022; Yildiz Durak, 2019). According to Chen and Leung (2016) and Pan et al. (2019), social games have become the most popular entertainment tools today.

According to Griffiths et al. (2012), the concept of the game and accordingly the concept of addiction have recently expanded. New gaming environments have more stimulating, wider visual and auditory effects, social communication, and motivational elements that encourage continued use compared to online internet games. This may result in the need for greater concern and attention towards mobile social games.

Multiple Screen and Mobile Social Online Gaming Addiction and Family Sense of Belonging

Internet addiction affects daily routine activities, school performance, and family relationships (Hyun et al., 2015). One of them is communication within the family. Durak and Kaygin (2020) and Yen et al., (2007) emphasized that the basic functioning of the family is associated with internet addiction in teenagers and that family-based preventive intervention, however, shows great promise in the prevention of various addictions. Similarly, Wang and Wang (2013) and Uslu and Durak (2022) considered family factors as key factors of internet addiction and problematic technology usage. Internet addiction is associated with social media use today (Yildiz Durak, 2020). It can be argued that the games on social networking sites also cause this addiction. Social isolation caused by the COVID-19 pandemic is seen as an element that increases internet addiction (Garcia-Priego et al., 2020). In addition, it is thought that this social isolation process has a positive effect on the time spent with the family. In this context, it is thought that the relationship between family belonging and MSA and social game addiction will become more evident. For these reasons, family belonging was seen as a determining variable in the profiles related to MSA and social game addiction.

Multiple Screen and Mobile Social Online Gaming Addiction and General Mattering

General mattering is the perception of the level of belief that individuals are important to others and is one of the most important aspects of wellbeing (Haktanir et al., 2016). Rayle (2005) emphasizes that individuals' self-importance is related to their belief of family members and other important people that they are crucial. When studies on problematic technology use (e.g., Anderson et al., 2017; Cheung et al., 2018) were examined, it was emphasized that psychological factors have significant effects on wellbeing, interpersonal relationships, and perceptions of personal mattering among teenagers. When considered in this context, it is assumed that general mattering will be a determining variable in the profiles related to MSA and social game addiction.

Table 1 Demographic characteristics

Variables	Options	f	%
Gender	Female	409	69.6
	Male	179	30.4
Age	M = 21.35 Sd = 3.416		
Educational grade	Freshman	220	37.4
	Sophomore	181	30.8
	Junior	80	13.6
	Senior	107	18.2
Field	Science and Engineering	108	18.4
	Health Sciences	86	14.6
	Social Sciences	370	62.9
	Sports Sciences	18	3.1

Table 2 ICT usage status

Variables	Minimum	Maximum	Mean	SD
Daily social media usage time (hours) (DSMUT)	0.00	15.00	4.0183	2.51549
Daily online game play time (hours) (DOGPT)	0.00	10.50	1.1233	1.53643
Daily TV viewing time (hours) (DTVT)	0.00	13.00	1.4860	1.57544
Daily computer and tablet usage time (hours) (DCaTUT)	0.00	13.00	2.7600	3.3264
Daily phone usage time (hours) (DPUT)	0.00	17.00	5.7240	3.2769

Methods

Participants

The participants of this study are 588 university students. Data were collected during the 2020–2021 academic year fall semester pandemic period. Information about the participants is presented in Table 1.

According to Table 1, 69.6% of the students participating in the study were female and 30.4% were male. The average age of the students participating in the study is 21.35. Considering the class level of the participants, it is seen that mostly (37.4%) are 1st grade students. According to the distributions considering the fields of education, the majority of the students are in the field of social sciences (62.9%).

According to Table 2, the average daily phone and social media usage times of the participants are 5,7240 and 4,0183 h, respectively. The technological occupation in which the students spend the most time is the "phone," and the technological occupation that the students spend the least time using is "playing."

According to Table 3, compared to pre-COVID-19, the rate of participants stating that their mobile social online game playing time has increased during the pandemic is 38.1%. 13.8% of the participants stated that it increased partially. The rate of participants who think that they spend more time with any screen (TV, computer, smartphone, tablet, etc.) due to the COVID-19 epidemic is 76.5%. 16.0% of the participants stated that it increased partially.

Table 3 ICT usage status change according to COVID-19

	Options	f	%
Do you think you have started to use Mobile Social Online Game Play (Fortnite, PubG, Candy Crush Saga, 101Plus, Head Ball 2, etc.) more due to the COVID-19 outbreak?	No	283	48.1
	Partially	81	13.8
	Yes	224	38.1
Do you think that you spend more time with any screen (TV, Computer, Smartphone, Tablet, etc.) due to the COVID-19 outbreak?	No	44	7.5
	Partially	94	16.0
	Yes	450	76.5

Data Collection Tools

Personal Information Form This form was developed by researchers. In this form, questions about age, gender, university, department, class, technology usage status, and the time spent on various screens before and after COVID-19 were included.

Multiple Screen Addiction Scale This scale was developed by Sarıtepeci (2021). The aim of the scale is to determine the multiple screen addiction levels of university students. The Likert-type scale has 15 items and a 3-factor structure. There are 8 items in the compulsive behavior dimension, 3 items in the loss of control dimension, and 4 items in the excessive screen time dimension. The internal consistency coefficient of the scale was calculated as 0.924.

Mobile Social Online Gaming Addiction Scale This scale was adapted from Young's Internet Addiction Test by Chen and Leung (2016). The purpose of this scale is to measure the degree of addiction to mobile social games. Mobile social online games include games (Fortnite, PubG, Minecraft, etc.) that more than one person can play over the internet (online) with their mobile devices (phone, tablet, etc.). Participants were given two options. The internal consistency coefficient of the scale was calculated as 0.744.

General Mattering Scale This scale was developed by Marcus (1991) and adapted into Turkish by Haktanir et al. (2016). The purpose of the scale is to measure the degree to which individuals believe that they are important to others. This scale, which includes a Likert-type evaluation, consists of five items. The scores that can be obtained from the scale range from 5 to 20. Higher scores indicate a more important perception. The internal consistency coefficient of the scale was calculated as 0.865.

Family Sense of Belonging Scale This scale was developed by Mavili et al. (2014). The purpose of the scale is to determine the belonging of individuals to their families. The internal consistency coefficient of this scale, which includes a Likert-type evaluation, was calculated as 0.898.

Data Collection and Analysis

The data set was obtained through online data collection tools, taking into account a wide representation from all regions of Turkey. Participants participated in the study voluntarily. The duration of the questionnaires is between 20 and 30 min. Latent profile analysis was performed in MPlus 8.0 program to determine the profiles in the data set. Models with one and seven profiles were tried to determine the number of profiles. The Akaike Information Criterion (AIC) (Akaike, 1974), the Bayesian Information Criterion (BIC) (Schwarz, 1978), the sample-size-adjusted BIC (SABIC) (Sclove, 1987) were used to evaluate the goodness-fitness of these models. Low values of these criteria indicate a good fit (Ferguson et al., 2020). In determining the number of profiles, whether the k-profile model fits better than the k-1 profile model was evaluated with the Lo-Mendell-Rubin likelihood ratio test (Lo et al., 2001). The BLRT (bootstrapped likelihood ratio test) was used to select the best fit between the models. In addition, the entropy values of the models were examined. An entropy value above 0.8 indicates a good model fit (Muthén, 2004). Finally, the criterion of the smallest profile not being below 5% of the sample was taken into account (Marsh et al., 2009). After determining the number of profiles, one-way variance analysis (ANOVA) was used to determine whether students' multiple screen addiction, mobile social online gaming addiction, general mattering, family sense of belonging, and various technology usage scores differed between profiles. The determined profiles were considered as polychotomous-dependent variables, and multinomial regression analysis was performed to predict these profiles. The independent variables involved in the prediction of profiles are (a) age, (b) grade, (c) excessive behavior, (d) compulsive behavior, (e), loss of control, (f) general mattering, and (g) family sense of belonging; ANOVA and multinomial regression analyses were performed with SPSS 24.0 package program.

Linear correlation between independent variables required for multinomial logistic regression (for non-categorical data set) was analyzed. After obtaining the calculated values for the averaged variables, correlation values were calculated for the categorical variables. The results are obtained regarding the model summary; Cox & Snell and Nagelkerke fit values are given in Table 10.

Findings

Preliminary Analysis

Confirmatory factor analysis was performed on the variables included in the profiling before the LPA analysis. As a result of confirmatory factor analysis, factor loadings were determined to be significant, and goodness fit indices were found to be sufficient for construct validity [$\chi 2$ (314, $N=588$) = 1145.11, $p<0.000$, RMSEA = 0.067, S-RMR = 0.055, CFI = 0.95, IFI = 0.95, NNFI = 0.94]. For LPA, full information maximum likelihood (FIML) was used as a statistical estimator; since the variables in the data set were continuous, there was no missing data, and the skewness and kurtosis values indicated a normal distribution (see Table 4). Since there was no missing value in the data set, LPA analysis was performed with 588 cases. This sample size meets the recommended number of 500 for LPA (Spurk et al., 2020).

Table 4 Descriptive statistics and Pearson correlations

		M (SD)	Skewness	Kurtosis	[2]	[3]	[4]	[5]
Excessive behavior	**[1]**	**2.814 (1.010)**	1.020	0.081	0.739**	0.515**	0.262**	0.100**
Compulsive behavior	**[2]**	**2.688 (0.974)**	0.259	−0.644	-	0.549**	0.262**	0.112
Loss of control	**[3]**	**1.882 (0.861)**	0.203	−0.877		-	0.284**	0.092**
Mobile social online gaming addiction	**[4]**	**0.196 (0.232)**	1.093	0.844			-	0.035
General mattering	**[5]**	**2.225 (0.758)**	0.329	−0.588				-

Table 4 shows the mean, standard deviation, and correlation coefficients of excessive behavior, compulsive behavior, loss of control, mobile social online gaming addiction, and general mattering variables included in the LPA analysis.

According to Table 4, there are medium to high correlations between multiple screen addiction factors. There is a low level of a positive relationship between multiple screen addiction factors and mobile social gaming addiction. The general mattering is associated with excessive behavior and loss of control at a low level.

Random Starts and Global Maxima

There is usually more than one maximum of probability due to where the software starts estimating and the initial values used in LPA (Berlin et al., 2014). Maximum likelihood estimations for LPA models tend to converge to globally non-maximized cases (Jason et al., 2022). It is recommended to use more than one initial value set to find the global maxima (Berlin et al., 2014). A value of 7000 for random initialization and 200 for optimization is used to reach the global maxima and avoid local solutions (Hipp & Bauer, 2006). Thus, care was taken to ensure that the model estimated using multiple initial values produced the same results. For one-, two-, three-, four-, and five-class models that were tried with different initial values, the software did not produce error output and concluded that the maximum likelihood was replicated. However, the best log-likelihood value for the six-class model was not replicated. As a result of the analysis, it is output that there may be a local maxima problem in the six-class model and the generated *p* value is not trustworthy.

Table 5 Fit indices for different profile models

Model	# of free param-eter	AIC	BIC	SABIC	Log-likeli-hood	Entropy	Smallest profile	LMR p	BLRT
1	10	15,827.79	15,871.56	15,839.81	-	-	-	-	-
2	16	15,278.24	15,348.27	15,297.47	−7903.896	0.777	42.1	.000	.000
3	22	15,083.70	15,179.99	15,110.15	−7623.119	0.803	12.9	.178	.000
4	28	14,978.47	15,101.02	15,012.13	−7519.850	0.860	10.9	.008	.000
5	34	14,879.06	15,027.87	14,919.93	−7461.235	0.869	3.9	.032	.000
6	40	14,805.77	14,980.84	14,853.86	−7405.531	0.891	3.2	.149	.000

Table 6 Profile size in models

	1 Class	2 Classes	3 Classes	4 Classes	5 Classes
Class 1	100%	42.1%	42.9%	37.6%	17.8%
Class 2		57.9%	12.9%	19.0%	35.9%
Class 3			44.2%	32.1%	31.9%
Class 4				11.2%	10.6%
Class 5					3.9%

Table 7 Descriptive statistics of four profiles

	Profile 1: *Non-addiction and non-gamer* 37.6%	Profile 2: *Gamer and non-addiction* 19.0%	Profile 3: *Addiction and non-gamer* 32.1%	Profile 4: *High addiction and gamer* 11.2%
	M (SD)	M(SD)	M(SD)	M(SD)
Mobile social online gaming addiction	0.050 (0.080)	0.464 (0.145)	0.080 (0.107)	0.560 (0.158)
General mattering	2.078 (0.771)	2.237 (0.740)	2.345 (0.746)	2.351 (0.711)
Excessive behavior	2.038 (0.599)	2.564 (0.729)	3.398 (0.762)	4.162 (0.643)
Compulsive behavior	1.803 (0.477)	2.406 (0.562)	3.423 (0.532)	4.022 (0.507)
Loss of control	1.336 (0.444)	1.866 (0.652)	2.192 (0.864)	2.853 (0.944)

Selection of the Number of Profiles

Six models were tested for the selection of the number of profiles. The goodness-fit indices of these models were given in Table 5.

The six-class model was rejected due to problems with the reliability of the generated values because it contains a local maxima problem. BIC, SABIC, and AIC values for the remaining five models were examined. As the number of classes increased, lower BIC, SABIC, and AIC values were achieved. However, more than one fit indices should be examined in model selection. First, BLRT values were evaluated and found to be significant for all models. However, it is stated that the BLRT test should be examined together with non-normal indicators (Morgan et al., 2016). Accordingly, when the LMR values are examined, it is seen that the three-class model is not significant. Another criterion used in the selection of profiles is entropy, which is a measure of the fit of the data to the profiles. The entropy value was found to be 0.860 in the four-class model and 0.869 in the five-class model. These values are higher than the two- and three-class models. Finally, the smallest sample sizes in the models were examined. Profiles containing less than 5% of the sample may be misleading and need to be evaluated for interpretability (Ferguson et al., 2019; Masyn, 2013). Group sizes are given in Table 6.

According to Table 6, in the five-class model, there is a class that contains less than 5% of the sample. Considering that the four-class model has lower BIC, SABIC, and AIC values compared to the two- and three-class models, and its entropy value is higher, it was decided to choose the four-class model.

Description of Latent Profiles

The descriptive statistics of the profiles in the selected model were presented in Table 7. The four profiles that emerged were named as follows: (a) non-addiction and non-gamer, (b) gamer and non-addiction, (c) addiction and non-gamer, and (d) high addiction and gamer. In the first profile, mobile social online gaming addiction (MSOGA), general mattering (GMS), excessive behavior (EB), compulsive behavior (CB), and loss of control (LoC) scores are below the average scores found for the entire sample. The dependency and general mattering scores of the participants in the second profile are the closest groups to the sample mean. Students in profile 3 generally have an addiction and general mattering scores above the sample mean. This situation is an exception only in mobile social online gaming addiction. In this profile, mobile social online addition scores were below the general average. Profile 4 is the group with the highest average scores in addiction and general mattering scores compared to other groups.

In Fig. 1, the four profiles' mobile social online gaming addiction, general mattering, excessive behavior, compulsive behavior, and loss of control scores were shown in comparison. A comparison of profiles according to Z scores is presented in Fig. 2.

Table 8 shows the distribution of the four profiles according to demographic variables.

When the distribution of profiles by gender is examined, it is seen that the percentage of female students in profile 1 is slightly higher than other profiles. When the profiles were evaluated according to the class of the student, it was determined that the first, third, and fourth profiles mostly included first-year students. In profile 2, there are more sophomore students. When the answers given by the students in the profiles to the question about the increase in their gaming behavior after the COVID-19 pandemic were examined, it was seen that 64.7% of the students in the first profile answered no. 71.4% of those in profile 2 answered yes. Accordingly, it can be interpreted that the COVID-19 pandemic did not greatly affect the gaming habits of the participants in the first profile. Profile 2, on the other hand, was more affected by this situation. It was observed that 62.4% of the students in profile 3 reported that the pandemic did not change the frequency of playing games. However, 82.8% of the participants in the fourth profile stated that their frequency of playing online games increased after the pandemic. It was observed that the group in the 4th profile gave the highest rate of answering yes to the question about the increase in multiple screen addiction during the pandemic period (96.9%). This was followed by profile 3 (86.8%) and profile 2 (83.1%), respectively. The group with the lowest yes response is profile 1 (58.3%). It is seen that COVID-19 affects all students in all four profiles, albeit at different levels. On the other hand, it was also noteworthy that there was a distinction between behaviors towards multiple screen addiction and mobile social online gaming.

Examining the Differences Among the Latent Profiles

The differentiation of dependent variables among the implicit profiles was examined by one-way ANOVA. Descriptive statistics and ANOVA results were presented in Table 9.

First, the homogeneity of variance between latent profiles was checked using the Levene test. Profile membership was found to have a significant effect on the dimensions of multiple screen addiction (see Table 9) (excessive behavior $F (3, 587) = 230.155$, $p = 0.000$; compulsive behavior $F (3,587) = 503.188$, $p = 0.000$; loss of control $F (3.587) = 98.469$, $p = 0.000$). Profile membership was also found to have an effect on mobile social online gaming addiction

Table 8 Distribution of the four profiles by demographic variables

		Profile 1 Low ($n = 221$)	Profile 2 Average ($n = 112$)	Profile 3 Medium multi-screen addiction low gamers ($n = 189$)	Profile 4 High ($n = 64$) High multi-screen addiction and high gamers
Gender	Male	63 (28.5%)	40 (35.7%)	57 (30.2%)	19 (29.6%)
	Female	158 (71.4%)	72 (65.3%)	132 (69.8%)	47 (71.2%)
Grade	Freshman	70 (31.6%)	53 (47.3%)	71 (37.6%)	26 (40.6%)
	Sophomore	74 (33.5%)	27 (24.1%)	56 (29.6%)	24 (37.5%)
	Junior	34 (15.4%)	17 (15.2%)	23 (12.2%)	6 (9.4%)
	Senior	43 (19.4%)	15 (13.4%)	39 (20.6%)	10 (15.2%)
Most frequently used apps	Instagram	41	51	23	26
	YouTube	16	26	18	15
	Twitter	18	11	21	8
	Facebook	6	5	6	3
	WhatsApp	121	16	105	12
Mobile social online game play in the COVID-19 outbreak	No	143 (64.7%)	14 (12.5%)	118 (62.4%)	8 (12.5%)
	Partially	33 (14.9%)	18 (16.1%)	25 (13.2)	5 (7.81%)
	Yes	45 (20.4%)	80 (71.4%)	46 (24.3%)	53 (82.8%)
Spend time with any screen in the COVID-19 outbreak	No	33 (14.9%)	3 (2.6%)	8 (4.2%)	0
	Partially	59 (26.7%)	16 (14.3%)	17 (9.0)	2 (3.1%)
	Yes	129 (58.3%)	93 (83.1%)	164 (86.8%)	64 (96.9%)

Table 9 Descriptives and ANOVA results

	Profiles	*N*	Mean	SD	*F*	*p*	Post hoc (Tukey HSD)
Excessive behavior	Profile 1	221	8.1538	2.39959	230.155	0.000	1–2,3,4
	Profile 2	112	10.2589	2.91855			2–1,3,4
	Profile 3	189	13.5926	3.04892			3–1,2,4
	Profile 4	66	16.6515	2.57498			4–1,2,3
Compulsive behavior	Profile 1	221	14.4253	3.82338	503.188	0.000	1–2,3,4
	Profile 2	112	19.25	4.50125			2–1,3,4
	Profile 3	189	27.3915	4.2608			3–1,2,4
	Profile 4	66	32.1818	4.06073			4–1,2,3
Loss of control	Profile 1	221	4.009	1.33482	98.469	0.000	1–2,3,4
	Profile 2	112	5.5982	1.95655			2–1,3,4
	Profile 3	189	6.5767	2.59309			3–1,2,4
	Profile 4	66	8.5606	2.83456			4–1,2,3
Mobile social online gaming addiction	Profile 1	221	0.4072	0.64438	615.726	0.000	1–2,3,4
	Profile 2	112	3.7143	1.16579			2–1,3,4
	Profile 3	189	0.6402	0.86151			3–1,2,4
	Profile 4	66	4.4848	1.26786			4–1,2,3
General Mattering	Profile 1	221	10.3937	3.85578	5.036	0.002	1–3,4
	Profile 2	112	11.1875	3.70423			3–1
	Profile 3	189	11.7249	3.7329			4- 1
	Profile 4	66	11.7576	3.55641			
Family sense of belonging	Profile 1	221	17.3801	5.1204	0.861	0.461	
	Profile 2	112	16.5089	5.37092			
	Profile 3	189	16.7566	5.23023			
	Profile 4	66	17.000	5.00769			
Daily social media usage time (hours)	Profile 1	221	3.4525	2.28806	9.989	0.000	1–3,4
	Profile 2	112	3.9955	2.51974			2- 4
	Profile 3	189	4.2659	2.59136			3–1,4
	Profile 4	66	5.2424	2.5241			4–1,2,3
Daily online game play time (hours)	Profile 1	221	0.8382	1.38954	31.821	0.000	1–2,4
	Profile 2	112	1.9129	1.69449			2–1,3
	Profile 3	189	0.6455	1.12337			3–2,4
	Profile 4	66	2.1061	1.79854			4–1,3
Daily TV viewing time (hours)	Profile 1	221	1.3258	1.38341	2.414	0.066	
	Profile 2	112	1.375	1.25831			
	Profile 3	189	1.7235	1.92943			
	Profile 4	66	1.5303	1.48033			
Daily computer and tablet usage time (hours)	Profile 1	221	2.324	2.7221	2.226	0.084	
	Profile 2	112	3.098	3.2493			
	Profile 3	189	2.907	3.7813			
	Profile 4	66	3.227	3.7858			

Table 9 (continued)

	Profiles	N	Mean	SD	F	p	Post hoc (Tukey HSD)
Daily smartphone usage time (hours)	Profile 1	221	5.000	3.1388	10.153	0.000	1–3,4
	Profile 2	112	5.804	2.9373			2- 4
	Profile 3	189	5.936	3.4393			3–1,4
	Profile 4	66	7.409	3.1426			4–1,2,3

and general mattering (F (3, 587) = 615.726, $p = 0.000$; F (3, 587) = 5.036, $p = 0.002$). In addition, daily social media usage time, online game play, and smartphone usage time (hours) differ according to profile memberships (F (3, 587) = 9.989, $p = 0.000$; F (3, 587) = 31.821, $p = 0.000$; F (3.587) = 10.153, $p = 0.000$). Post hoc comparisons showed that students in high multiple screen addiction high gamers profiles had higher addiction and technology use time scores than students in other profiles.

Predicting Multiple Screen Addiction Profile Memberships

In order to determine which student background variables predict profile membership, multinomial logistic regression analysis was conducted with excessive behavior, compulsive behavior, loss of control, mobile social online gaming addiction general mattering, and family sense of belonging scales and profile membership as the dependent variable. Profile 1 was set as the reference category. The results of the multinomial logistic regression analysis are given in Table 10.

According to Table 10, excessive behavior, compulsive behavior, and loss of control variables show that students increase the probability of clustering in the average profile. A one-unit increase in the excessive behavior variable increases the probability of performing activities in the average profile 1.166 times (OR = 1.166; 95% CI = 1.037–1.311). Compulsive behavior increases this probability by 1,294 times, while loss of control increases it by 1.570 times. It was observed that all variables except gender and age increased the probability of clustering in the medium multiple screen addiction low gamers profile. Excessive behavior, compulsive behavior, and loss of control variables increase the probability of students performing the activities in profile 3 approximately 2 times. In the profile of high multiple screen addiction high gamers, excessive behavior, compulsive behavior, and loss of control variables increased the clustering probability. Excessive behavior, compulsive behavior, and loss of control variables increase the probability of students performing the activities in profile 3 approximately 2 times. As a stronger predictor than other profiles, it was determined that the probability of students performing “high multiple screen addiction high gameplay” activities was approximately 3 times more than the students in profile 1.

Table 10 Multinomial logistic regression results predicting MSA profile membership

	Profile 2						Profile 3						Profile 4					
					95% confidence interval for Exp(B)						95% confidence interval for Exp(B)						95% confidence interval for Exp(B)	
	B	Std. error	Sig	OR	Lower	Upper	B	Std. error	Sig	OR	Lower	Upper	B	Std. error	Sig	OR	Lower	Upper
Gender	−0.221	0.319	0.488	0.801	0.429	1.497	−0.297	0.482	0.538	0.743	0.289	1.911	−0.741	0.605	0.220	0.477	0.146	1.559
Age	−0.048	0.057	0.403	0.953	0.852	1.067	0.104	0.069	0.133	1.110	0.969	1.271	−0.013	0.096	0.890	0.987	0.817	1.192
Grade	−0.288	0.149	0.053	0.750	0.560	1.003	−0.467	0.222	0.035	0.627	0.406	0.969	−0.388	0.279	0.164	0.678	0.393	1.172
Excessive behavior	0.153	0.060	0.010	1.166	1.037	1.311	0.628	0.102	0.000	1.874	1.534	2.290	0.858	0.121	0.000	2.358	1.859	2.990
Compulsive behavior	0.258	0.042	0.000	1.294	1.191	1.406	0.784	0.077	0.000	2.190	1.882	2.548	0.966	0.090	0.000	2.628	2.205	3.133
Loss of control	0.451	0.094	0.000	1.570	1.306	1.888	0.658	0.126	0.000	1.930	1.508	2.470	0.781	0.141	0.000	2.184	1.656	2.879
General mattering	0.048	0.040	0.232	1.049	0.970	1.136	0.133	0.065	0.041	1.142	1.006	1.297	0.149	0.079	0.058	1.161	0.995	1.355
Family sense of belonging	−0.048	0.031	0.120	0.953	0.897	1.013	−0.100	0.049	0.041	0.905	0.823	0.996	−0.080	0.059	0.177	0.923	0.822	1.037

Note. The profile *Profile 1* is the reference group. Pseudo R^2 (Cox & Snell = 0.763) (Nagelkerke = 0.825), (McFadden = 0.557)

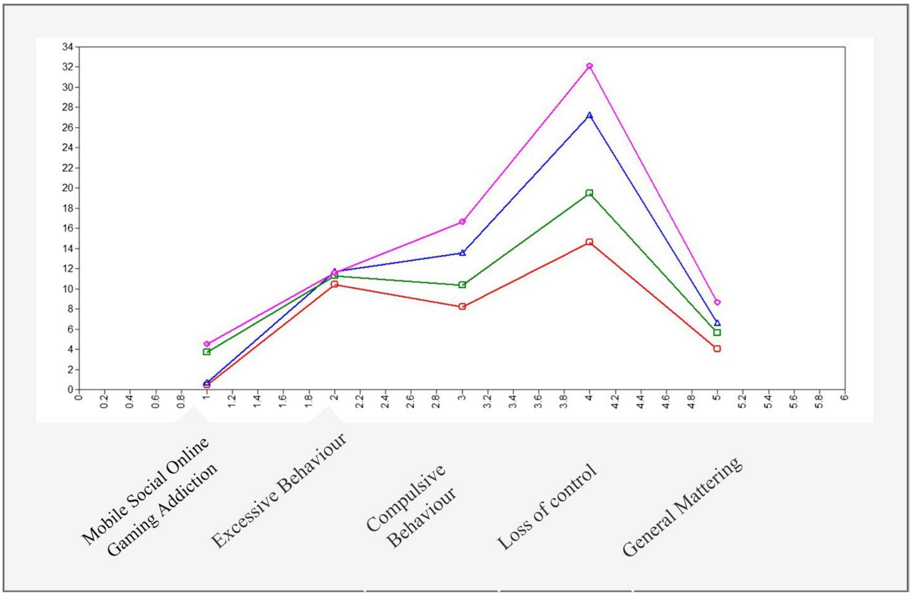

Fig. 1 Comparison of profiles

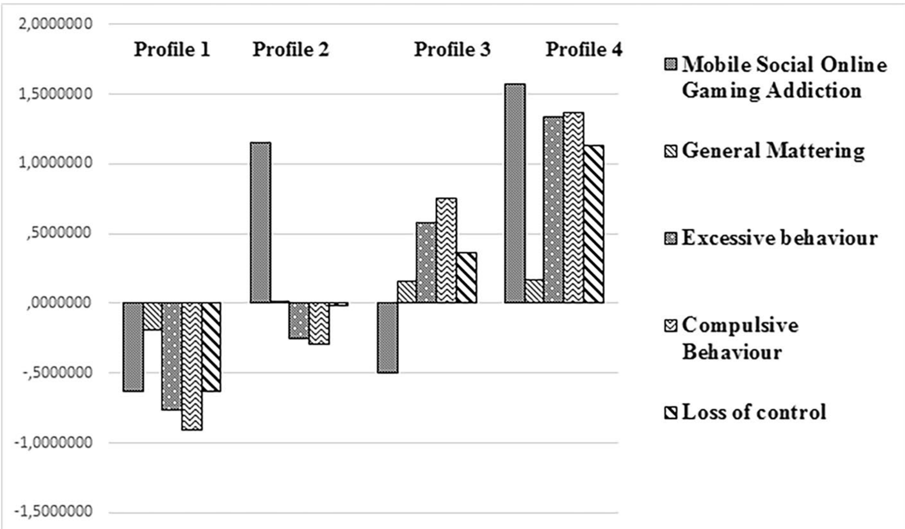

Fig. 2 Student profiles (Z scores) in multiple screen addiction, mobile social online gaming addiction, and general mattering

Discussion and Conclusions

In this study, the profiles of multiple screen addiction, mobile social online gaming addiction, general mattering, and family sense of belonging were examined, and the relationship of these profiles with MSOGA, MSA, GMS, family sense of belonging, technology usage habits, and personal variables was discussed. Four different sets of participants were formed. The first profile ($n = 221$) has the lowest EB, CB, LoC, MSOGA, and GMS values compared to the other profiles. In addition, MSA subscales and MSOGA scores indicate a low level of dependency according to polythetic criteria. Therefore, the first profile was named "non-addiction and non-gamer." In the second cluster ($n = 112$), although it was the closest group to the sample mean in terms of EB, CB, LoC, and GMS values, its MSOGA score was above the mean, and it was named gamer and non-addiction. In the third profile, the situation is opposite to the second profile. The EB, CB, LoC, and GMS values of the participants in this profile were above the sample average, and their MSOGA score was below the average. The average score obtained from the MSA sub-dimensions shows that the participants exhibit addictive behavior according to the polythetic criteria. On the other hand, it is seen that the participants did not develop mobile online game addiction. Therefore, this group is expressed as "addiction and non-gamer." The fourth profile has the highest EB, CB, LoC, MSOGA, and GMS scores compared to the other profiles. While the average scores obtained from the MSA subscales are an indicator of high dependency according to the polythetic criteria, the score obtained from the MSOGA scale indicates above-average dependence. Accordingly, this profile was named as "high addiction and gamer."

When the profiles are examined, the trend between the groups in the addiction and non-gamer clusters differs in terms of MSOGA level. Here, the trend in the MSA sub-dimensions does not show parallelism with the MSOGA level, and multiple screen addiction is related to some or all of these tools or services rather than the uncontrolled use of a tool or service alone (Sarıtepeci, 2021) is relevant.

Problematic Technology Use Latent Profiles: Similarities and Differences

Multiple screen addiction, mobile social online gaming, general mattering, family sense of belonging, and technology usage habits variables were examined to determine the similarities and differences between the four profiles. The most important result of this review is that profile membership has a significant effect on multiple screen addiction (EB, CB, LoC). It was determined that there was a significant difference in MSA scale sub-dimensions among all profiles. Accordingly, it can be said that the MSA level of the participants is a distinctive feature of the profiles.

Profile membership was found to have a significant impact on MSOGA. When the profiles are examined, the MSOGA levels of the "high addiction and gamer" and "gamer and non-addiction" profiles are relatively higher than the other two profiles. Another consequence associated with this finding is the effect of profile membership on daily online game play time. Accordingly, "high addiction and gamer" and "non-addiction and gamer" profiles have daily online game play time significantly higher than the other two profiles. Accordingly, it can be said that the level of addiction affects the duration of gameplay. Lee and Kim (2017) reported in their study that game addicts spend much more time playing computer and mobile games than non-addicts.

Profile membership has an impact on the GM. According to the results of the study, the GM level in the "non-addiction and non-gamer" profile was significantly lower than in the "addiction and non-gamer" and "high addiction and gamer" profiles. On the other hand, individuals with high GM levels are expected to exhibit relatively less problematic behavior (Rayle, 2005; Taylor and Turner, 2001). Here, one of the main reasons for such a different result may be the low GM level in the sample and all profiles. The fact that the participants are teenagers and the close social circle of the teenagers are generally peers can be considered an important factor here. In the framework of general mattering and staying away from school friends who make up their close social circle during the COVID-19 period, they may have tended to maintain their bonds with their friends through media such as social media. Findings of daily social media usage time support this determination.

The impact of profile membership on daily social media usage time is significant. It is seen that there is an increase in daily social media usage from profile 1 to profile 4. This situation is thought to be related to the MSA level, which is one of the basic criteria in profiling. In support of this, in the Digital 2021 Report, while women in the 16–24 age range have daily social media usage time of 3H 14 M, men in the same age group have 2H 39 M (We Are Social, 2021). The findings of this study are above the value stated in this report by daily social media usage time in all profiles. In the high addiction and gamer profile, daily social media usage time is higher (5.24H) compared to other dimensions. This triggers excessive screen time and carries a potential risk of becoming addicted.

It was concluded that there was no significant difference between profiles in terms of daily TV time and daily computer and tablet usage time variables. On the other hand, profile membership effect on daily smartphone usage time is significant. The daily smartphone usage time of the participants in the "high addiction and gamer" profile was higher than the other groups. In addition, the daily smartphone usage time level of the "addiction and non-gamer" profile was found to be significantly higher than the "non-addiction and non-gamer" profile.

Although the level of family sense of belonging did not differ in all 4 profiles, it was relatively higher in the non-addiction and non-gamer profiles compared to the others. It was also reported in the literature that deterioration in the family factor is one of the important predictors or antecedents of problematic technology use (Gökçearslan et al., 2021; Li et al., 2014; Park et al., 2008). Although there is no significant difference, considering the profile characteristics, the fact that family sense of belonging is higher in relatively fewer MSA and MSOGA groups has parallels with the literature. However, the relative decrease in the effect of family relationships on behaviors during adolescence may explain the limited effect of profile membership on the family sense of belonging.

Limitations and Recommendations

Although this study has important contributions to the literature, since the data were collected cross-sectionally, the relationships between the profiles and the variables discussed do not offer causal inferences. Longitudinal studies are needed to examine the profiles created in more detail and to determine the changes in the profiles over time.

This study focused on the important indicators of problematic technology use, which increased with the COVID-19 epidemic among university students who were exposed to long-term social isolation. This affects the generalizability of the results obtained in the study before or after the epidemic. Another limitation in terms of the generalizability of the study is that the participants were not selected randomly.

MSA is one of today's main problematic technology use behaviors. In this study, participant profiles were extracted, and classification was focused on according to MSA and other variables. On the other hand, no inferences are presented in this study in terms of the antecedents or consequences of MSA in terms of the individual's affective and behavioral aspects. It is recommended that future studies focus on the antecedents and consequences of MSA. Finally, the measurements in this study were cross-sectional. It is recommended to conduct studies to replicate the findings of this study at different time points and with different samples.

Data Availability Our data are not yet available online in any institutional database.

Declarations

Ethical Statement The research was conducted in a school in Turkey and approved by the school administration. Participation was voluntary and anonymous. Informed consent was obtained from all participants. All procedures performed in this study involving human participants were in accordance with the ethical standards of the institutional and national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Conflict of Interest The authors declare no competing interests.

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