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FULL-LENGTH REPORT

What makes children aged 10 to 13 engage in problematic smartphone use? A longitudinal study of changing patterns considering individual, parental, and school factors

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ABSTRACT

Background and aims: The current research aimed to discover classification concerning problematic smartphone use in children. Furthermore, to investigate their longitudinal trajectories, as well as to discover the connection concerning problematic smartphone usage by individual, parental, and school factors. *Methods:* A total of 2,399 South Korean children who were in the 4th grade (female 1,206 (50.3%), age 10–13 years) at baseline. Latent class growth analysis was utilized to discover typologies in problematic smartphone use and their longitudinal trajectories. Multinomial logistic regression analysis was used to find various associations among problematic smartphone use and individual, parental, as well as school factors. *Results:* The results identified three distinct trajectories of problematic smartphone use: (1) a high-level group (7.7%), (2) a mid-increasing group (62.5%), and (3) a low-increasing group (29.8%). The increasing group showed the highest level of problematic smartphone use. Gender, self-esteem, social withdrawal, exercise, parental inconsistency, monthly income, and teacher support were significant predictors. *Discussion and Conclusions:* The findings suggest that there are distinct developmental trajectories concerning problematic smartphone usage of childhood. The results show that the early discovery of children in danger of problematic smartphone use and targeted interventions aimed at reducing parental inconsistency and social withdrawal, improving self-esteem, exercise, and teacher support may be effective strategies for preventing problematic smartphone usage during childhood.

KEYWORDS

problematic smartphone use, trajectories, latent class growth analysis, childhood

INTRODUCTION

Children's problematic smartphone use (PSU) is becoming a worldwide issue. The spread of smartphone is increasing and mobile application technology's development in education, entertainment is used for various purposes. Children are spending more time on their smartphone. Bae (2017)'s research stated that within Asian countries, over 80% of individuals above 12 years have been found to use smartphones. According to the Pew Research Center (2019), Korea is famous for the highest usage of smartphones reaching approximately 95% of the population. Furthermore, a media panel survey stated that, the age at which smartphones are used is gradually getting younger. In South Korea, the rate for the possession of smartphone among elementary school students steadily increased from approximately 50% in 2015 to 81.2% in 2019 (Choi, Jeon, Oh, & Hong, 2020). Additionally, a recent study showed that more than 95% of students in South Korea own smartphones (Hong, Yeom, & Lim, 2021). As smartphone penetration increases, PSU rates are also increasing. In 2020, compared to

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2018, PSU increased by approximately 19% among adolescents, which was greater than the average rise of 13% within high school students (Ministry of Gender Equality and Family, 2020). Furthermore, a national survey conducted in 2018 stated that Korean adolescents' prevalence of PSU was 29.3% which is the highest in all the age groups (Ministry of Science and ICT, 2019). Increase of smartphone usage and PSU must be considered as they give a potentially negative influence on children's growth in various areas. According to various studies, PSU effects children to have negative consequences such as sleep difficulty, academic issues, decreased physical activity, and psychological issues such as depression as well as anxiety (Elhai, Dvorak, Levine, & Hall, 2017; Samaha & Hawi, 2016). Furthermore, behavioral problems such as aggression and impulsivity may be caused by excessive smartphone use (Lee et al., 2018).

In this study, the authors propose using the term 'PSU' to describe behaviors that may not reach the same level of impairment as addiction, but involve excessive use. Excessive usage is frequently assessed by measuring the duration and frequency of smartphone usage, as explored by Bae (2017) and similar studies. Problematic use is distinguished by uncontrolled behaviors leading to adverse outcomes in daily life, as indicated by Billieux et al. (2015). The terms 'PSU' and 'smartphone addiction' have alternating usage at times, contingent upon how researchers perceive the fundamental concepts (Ellis, 2019; Flayelle, Schimmenti, Starcevic, & Billieux, 2022; Panova & Carbonell, 2018). Delving into behavior patterns considered indicative of addiction, Yen et al. (2009) ardently advocates for the term 'smartphone addiction.' On the other hand, Elhai et al. (2017) and Panova and Carbonell (2018) comment on less clarity concerning addiction criteria and argue for the use of 'PSU' instead. In this study, 'PSU' is used. This is because 'PSU' provides a more flexible framework for discussing related issues.

Accordingly, many studies have been conducted on PSU. Specifically, Herrero, Torres, Vivas, and Urueña (2019), Lai et al. (2022) confirmed how PSU changes over time. In particular, Lai et al. (2022) confirmed the change trajectory targeting adolescents between the ages of 10 and 18. As a result, it was confirmed that the PSU increased over time. These studies have important significance in that they identify characteristics over time that cannot be confirmed in cross-sectional analysis. However, these studies have the limitation of assuming that the population is 'one' and missing the fact that there may be various sub-potential groups. Parent, Bond, Wu, and Shapka (2022) overcame the limitation of assuming only one population and performed a latent class analysis to identify various potential groups. However, although this study is meaningful in that it identified various potential groups, it has limitations in that it failed to consider changes over time by analyzing only one point in time. In other words, existing studies have limitations in that they either conducted a longitudinal analysis without identifying various potential groups, or conducted a cross-sectional analysis although they identified various potential groups.

Building upon the significance and limitations of these prior studies, this research aims to identify developmental patterns in children's PSU and examine the predictive factors associated with these patterns. In contrast to prior research, our study employs a latent class growth model to simultaneously explore how developmental trajectories of PSU vary over time and to uncover a range of latent classes associated with these trajectories. This approach aims to address the gaps left by previous research by examining both unexplored developmental trajectories and latent subpopulations in PSU simultaneously.

Based on Ecological Systems Theory (Bronfenbrenner, 1977), this study seeks to examine individual factors and environmental factors (family, school) related to children's PSU. Ecological Systems Theory (Bronfenbrenner, 1977) is a theory that explains that an individual's psychosocial development must consider not only the individual's internal factors but also various surrounding environmental factors. Therefore, it is a good grounding theory for comprehensively considering various factors that can affect children's PSU level. Based on Ecological Systems Theory, this study divided predictive factors into individual factors, parental factors, and school factors.

Individual factors include gender, self-esteem, social withdrawal, and exercise. Regarding gender, various studies have confirmed the relationship between gender and PSU. In some studies, women were found to have a higher risk of PSU than men (Demirci, Akgönül, & Akpinar, 2015; Gutiérrez, de Fonseca, & Rubio, 2016), but in other studies, on the contrary, men were found to have a higher risk of PSU than women (Gentina & Rowe, 2020). Another study found no relationship between the two (Chen et al., 2017). As a result, it is essential to determine the connection of gender and PSU. Self-esteem is also an important predictive factor. According to a study by Bae and Nam (2023), it was confirmed that adolescents' self-esteem and PSU have a negative relationship with each other. Similarly, a study by Li, Liu, and Dong (2019) found that low self-esteem increased the danger of PSU in adolescents. Social withdrawal is also associated with PSU. According to a study by Lim (2022), PSU was found to moderate the connection of social withdrawal and peer relationships. Physical activity level has also been shown to be related to PSU (Oh & Park, 2022), and excessive smartphone use has also shown connection to physical health issues like vision impairment as well as neck pain (Hanphitakphong, Thawinchai, & Poomsalood, 2021).

Relationships with parents have an important relationship with PSU. Qiu, Li, Luo, Li, and Nie (2022) analyzed the longitudinal relations between the parent-child relationship and PSU. As a result, the parent-child relationship was positively related to the child's life satisfaction and showed a negative relationship with the level of PSU. Another study confirmed that the household income was positively related to the PSU (Long et al., 2016). Relationships with teachers and peers at school are also significantly related to PSU. According to various studies, it has been confirmed that positive connections with peers and teachers exhibit a negative association with PSU (Ouyang et al., 2020; Zhen, Liu, Hong, & Zhou, 2019; Zhou et al., 2022).

METHODS

Participants

This study was primarily based on the 2018 Korean Children and Youth Panel Survey (2018 KCYPS), graciously provided by the National Youth Policy Institute (NYPI). The information obtained from this survey furnishes an extensive view of the development and experiences of children and adolescents in the various settings of their families, schools, peer groups, and communities. A stratified multi-stage cluster sampling method was utilized to pick a representative sample of fourth-grade elementary and first-grade middle school students in 2018, who were then followed through multiple consecutive cycles. Schools were selected proportionally to the number of students in 17 cities and provinces nationwide, and each school surveyed students from one class.

The initial step involved allocating a minimum sample of two schools from each of the 17 regions. Then, the sample size for each school was calculated proportionally based on the number of students, following a probability proportional to size sampling method. IRB approval was confirmed by the NYPI, then the selected schools were contacted to verify the children and adolescents' consent for the survey participation. The study employed tablet PCs for data collection. Interviewers carried out in-person interviews with both adolescents as well as the guardians during home visits. Each student, along with their parent or primary guardian, provided a written agreement concerning participation of the research. The KCYPS survey was carried out annually from August to November.

For the evaluation of elementary school students (4th–7th grade) and their parents, data from the 1st time point (2018) to the 4th time point (2021) was utilized. A total of 2,607 individuals were surveyed in the baseline panel. For this study, we excluded those who did not respond to the PSU questions in the first year, resulting in a final study population of 2,399 individuals (female 1,206 (50.3%), age 10–13 years). The attrition rate (2019∼2021) was 6.5% (surveyed 2,437), 7.5% (surveyed 2,411), 12.7% (surveyed 2,275).

Measures

Dependent variable: problematic smartphone use. The reference tool utilized in the current research was the Smartphone Addiction Proneness Scale (SAPS) by Kim, Lee, Lee, Nam, and Chung (2014), according to the Korean Children and Adolescents Panel Survey. The scale which consists 15 items measured by the 4-point Likert scale ranging from 1 (strongly disagree) to 4 (strongly agree). A higher score means a higher PSU. This scale revealed good reliability and construct validity in the Korean adolescent samples (Jeong, Kim, Ryu, & Lee, 2022), and the Cronbach's α for PSU was 0.881 in 2018, 0.875 in 2019, 0.888 in 2020, and 0.850 in 2021 in this study.

Individual factors: gender, self-esteem, social withdrawal, exercise time. Regarding individual factors, male was coded as '1' and female as '0' for the gender variable. Self-esteem was assessed using a scale by Rosenberg's (1965) self-esteem scale consisting of 10 items measured on a 4-point Likert scale ranging from 1 (not at all true) to 4 (very true). In some items, reverse coding was applied, also, a higher score indicated greater self-esteem. The Cronbach's α for self-esteem was 0.836. A revised and expanded version of Kim and Kim (1998)'s social withdrawal scale was utilized. The scale composes of a sum of five items. Responses are measured by the 4-point Likert scale ranging from 1 (not at all) to 4 (strongly agree). A greater score shows a greater level of social withdrawal. This scale indicates good reliability in the Korean adolescent samples (Kim, Han, Park, & Kang, 2020), and the Cronbach's α was 0.860. The questionnaire asked about the amount of exercise in the past week based on the time spent sweating during exercise. Reactions were verified by a 5-point scale ranging from 0 (no exercise) to 4 (4 or more hours).

Parental factors: household income, parenting style (warmth, rejection, inconsistency). The monthly household income was measured from 1 (No income) to 12 (More than 8000 USD), and the greater the score, the greater the average monthly household income. Parenting style was found using Kim and Lee's (2017) parenting style scale, with the "warmth" factor representing positive parenting style (four items), and the "rejection" (four items) and "inconsistency" (four items) factor representing negative parenting style. Each question was measured on a 4-point Likert scale ranging from 1 (not at all) to 4 (very much). The greater the score indicating the greater the warmth, rejection, and inconsistent parenting style. This scale revealed good reliability in the Korean adolescent samples (Kim, Kang, & Lee, 2020), and the Cronbach's α of this study was 0.910 for warmth, 0.633 for rejection, and 0.753 for inconsistency. Although this value is slightly lower compared to the other subscales, it falls within an acceptable range and is compatible with findings from preceding research (Kim, Kang, & Lee, 2020) employing similar measures. Among the parental factors, children responded to parental parenting styles (warmth, rejection, inconsistency), while parents responded to income.

School factors: peer relationship, student-teacher relationship. A 13-item scale by Bae, Hong, and Hyun (2015) was utilized to discover peer relationship quality among adolescents using a 4-point Likert scale ranging from 1 (not at all) to 4 (very much), with negative items reverse-coded. A higher score indicates a better peer relationship. This scale has shown good reliability in the Korean adolescent samples (Lim, 2023), and the Cronbach's α was 0.808. Additionally, a 14-item tool by Kim and Kim (2009) was utilized to find the student-teacher relationship using the same Likert scale.

The greater the score indicating a better teacher relationship. This scale reveals good reliability in the Korean adolescent samples (Kim, Lee, & Park, 2022), and the Cronbach's α was 0.905.

Procedures

The current research utilized the latent class growth analysis (LCGA) to discover longitudinal trajectory patterns of PSU from 4th to 7th grade. The number of latent classes are confirmed by information indices, classification quality, and model comparison tests (Nylund, Asparouhov, & Muthén, 2007). Akaike information criterion (AIC), Bayesian information criterion (BIC), and sample size-adjusted BIC (SSA-BIC) are commonly used indices, and a smaller value means a better model (Muthén & Shedden, 1999). The Entropy index is a measure of classification quality, ranging from 0 to 1, and a higher value means a better group classification (Clark, 2010). The Lo-Mendell-Rubin adjusted likelihood ratio test (LMR-LRT) and parametric bootstrapped likelihood ratio test (BLRT) are utilized for model comparison. If the p value is not significant, the k-1 latent group number model is judged to be appropriate. The minimum proportion of each latent class varies from scholar to scholar; some argue that it should be at least 5% (Jung & Wickrama, 2008), while others consider it acceptable if it is only 1% or more (Nooner et al., 2010).

A logistic regression analysis was performed applying the r3step method suggested by Asparouhov and Muthén (2014). The r3step method conducts analysis by considering errors due to the influence of predictive factors when classifying latent groups. To compare the mean differences of key variables across latent class, the BCH method was used. The Mplus 8.7 program was used to perform the analysis. When assessing the relationship between latent class and predictors, predictors measured at the 1st time point were employed.

Ethics

The research process was conducted referring to the Declaration of Helsinki. Ethics consent was given by the Author's Institutional Review Board. All members provided informed consent.

RESULTS

Classification of latent groups according to changes in PSU

Before identifying the number of unobservable groups based on the changes in PSU, we conducted a chi-square difference test on a linear change model and a quadratic curve model for the entire group. Latent growth curve models have been employed for examination of both linear change as well as quadratic curve model. The null hypothesis was rejected, showing that the quadratic curve model was more suitable compared to the linear model. Consequently, we decided to use the quadratic curve model to classify the latent groups, as presented in Table 1.

A LCGA was conducted to identify the number of latent classes that exists within change trajectory of PSU. The results of comparing the models can be seen in Table 2.

As the number of latent classes heightened by one, both the AIC and BIC values decreased, and the LMR-LRT test was significant as well. However, in the case of class 4, the proportion of the sample in terms of the minimum case numbers was small at 4.9% (Jung & Wickrama, 2008) and the LMRT p-value was not significant. After a comprehensive consideration of various indices and interpretability, the optimal model was determined to be the three-class model, which had an appropriate distribution of case numbers. The average latent class probabilities of the three classes were 0.781, 0.849 and 0.850, respectively.

Next, the results of estimating the average of the primary value, linear rate of change, and second rate of change for every latent class of the three-class model are shown in Table 3, and the changes in PSU for the derived groups are depicted in Fig. 1.

The initial value of PSU for the whole sample (n = 2,399) was 1.799 ($p < 0.001$), the linear rate of change was 0.251 ($p < 0.001$), and the second rate of change −0.048 ($p > 0.001$). Whole sample exhibited moderate level of PSU initially, followed by a linear increase in PSU. However, this increase gradually slowed over time.

Table 1. The results of the chi-square difference test

Model	x^2	df	CFI	IFI	RMSEA
Linear model	211.128	5	0.864	0.864	0.131
Quadratic curve model	16.001	1	0.990	0.990	0.079
Testing for differences in models	195.127	4 ($p < 0.001$)	0.126	0.126	0.052

Table 2. Comparison of fit indices for latent class growth models with 1–4 classes for problematic smartphone use

Variable	Class 1	Class 2	Class 3	Class 4
AIC	12,730.413	11,562.408	11,342.626	11,295.267
BIC	12,770.893	11,626.019	11,429.368	11,405.140
SSA-BIC	12,748.652	11,591.069	11,381.710	11,344.773
LMRT p value	–	0.0000	0.0393	0.3491
BLRT p value		0.0000	0.0000	0.0000
Entropy	–	0.619	0.667	0.637
class1	2,399 (100.0%)	1,007 (42.0%)	184 (7.7%)	678 (28.3%)
class2		1,392 (58.0%)	1,499 (62.5%)	171 (7.1%)
class3			716 (29.8%)	118 (4.9%)
class4				1,432 (59.7%)

Table 3. Classification of individuals based on their most likely latent class pattern

Mean	Whole group		Class 1 (High-level) $N = 184$		Class 2 (Mid-increasing) $N = 1{,}499$		Class 3 (Low-increasing) $N = 716$	
	estimate	S.E.	estimate	S.E.	estimate	S.E.	estimate	S.E.
Initial value	1.799***	0.010	2.485***	0.239	1.835***	0.043	1.521***	0.029
Linear slope	0.251***	0.013	0.230	0.176	0.375***	0.040	0.030***	0.027
Quadratic slope	−0.048***	0.004	−0.069	0.036	−0.079***	0.013	0.016*	0.007

Note. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

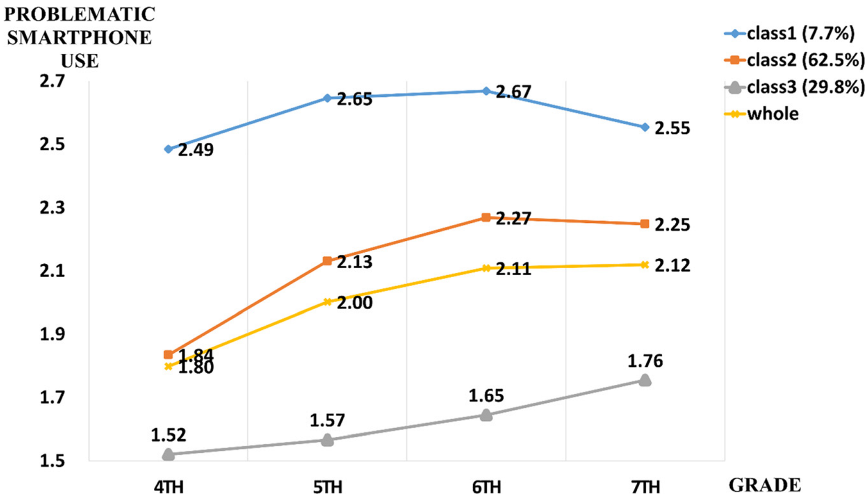

Fig. 1. Whole group and class specific trajectories of problematic smartphone use

Class 1 comprised 7.7% of the sample ($n = 184$). The initial value of PSU for class 1 was 2.485 ($p < 0.001$), the linear rate of change was 0.230 ($p > 0.05$), and the second rate of change −0.069 ($p > 0.05$). Class 1 exhibited the highest level of PSU among the three groups in the fourth grade and maintained it thereafter. Therefore, it was named the “high level group.” Class 2 comprised 62.5% of the sample ($n = 1{,}499$). The initial value of PSU for class 2 was 1.835 ($p < 0.001$), the linear rate of change was 0.375 ($p < 0.001$), and the second rate of change −0.079 ($p < 0.001$). Class 2 exhibited a moderate level of PSU initially, followed by a linear increase in PSU. However, this increase gradually slowed over time. Therefore, it was named the “mid-increasing group.” Class 3 comprised 29.8% of the sample ($n = 716$). The initial value of PSU for class 3 was 1.521 ($p < 0.001$), the linear rate of change was 0.030 ($p < 0.001$), and the second rate of change 0.016 ($p < 0.05$). Class 3 displayed the lowest initial PSU level, followed by a linear increase in PSU. Interestingly, this increase accelerated over time. Therefore, it was named the “low-increasing group.”

Descriptive statistical results of key variables

Table 4 displays the correlation coefficients for the key variables. The sociodemographic characteristics of the study participants and descriptive statistics for each latent class group’s key variables are presented in Table 5 (first year point data) and Table 6 (fourth year point data). Furthermore, to test for differences in the mean values of key variables among each latent class, BCH methods analysis was conducted. As a result, most variables showed significant differences between the classes.

Factors affecting latent classes of PSU

Table 7 presents the results of logistic regression analysis using r3step, which shows the probabilities of belonging to each class based on the predictive factors. First, when comparing the high-level group (class 1), which had the highest level of PSU, with the mid-increasing group (class 2), individuals with higher income, lower social withdrawal, and lower parental inconsistency were inclined to be part of the mid-increasing PSU group than the high-level PSU group. Second, when comparing the high-level group (class 1) and low-increasing group (class 3), female, individuals with high self-esteem, exercise for ‘one hour, two hours, three hours, and four hours or more’ compared to not exercising at all, higher income, higher teacher support, lower social withdrawal, and lower parental inconsistency were inclined to be part of the low-increasing group than the high-level group. Lastly, when comparing the mid-increasing group (class 2) and low-increasing group (class 3), female, individuals with high self-esteem, exercise for ‘1 hour’ and ‘4 hours or more’ compared to not exercising at all, higher teacher support, and lower parental inconsistency were inclined to be part of the low-increasing group than the mid-increasing group.

Table 4. Correlation coefficient analysis among variables at first wave

	G	SE	SW	EX	WA	RJ	INS	INC	PE	TE	PSU1	PSU2	PSU3	PSU4
G	1	0.052*	−0.076**	0.295**	0.006	−0.021	−0.015	−0.051**	−0.138**	−0.058**	0.084**	0.042*	0.012	0.010
SE		1	−0.408**	0.156**	0.496**	−0.494**	−0.409**	0.090**	0.447**	0.381**	−0.347**	−0.222**	−0.212**	−0.159**
SW			1	−0.154**	−0.220**	0.252**	0.239**	−0.100**	−0.311**	−0.226**	0.267**	0.144**	0.146**	0.126**
EX				1	0.072**	−0.068**	−0.078**	0.070**	0.125**	0.081**	−0.096**	−0.088**	−0.097**	−0.074**
WA					1	−0.512**	−0.387**	0.097**	0.364**	0.381**	−0.249**	−0.146**	−0.124**	−0.074**
RJ						1	0.462**	−0.102**	−0.310**	−0.226**	0.241**	0.144**	0.134**	0.110**
INS							1	−0.062**	−0.286**	−0.265**	0.298**	0.178**	0.151**	0.144**
INC								1	0.100**	0.120**	−0.157**	−0.075**	−0.047*	−0.070**
PE									1	0.422**	−0.245**	−0.156**	−0.145**	−0.120**
TE										1	−0.245**	−0.185**	−0.174**	−0.126**
PSU1											1	0.409**	0.312**	0.231**
PSU2												1	0.449**	0.342**
PSU3													1	0.488**
PSU4														1
Mean	–	3.21	2.03	3.50	3.58	1.63	1.89	6.55	3.07	2.99	1.81	1.98	2.13	2.11
SD	–	0.48	0.74	1.41	0.53	0.53	0.62	2.22	0.42	0.49	0.51	0.49	0.53	0.45
Range	–	1–4	1–4	0–4	1–4	1–4	1–4	1–12	1.38–4	1–4	1–4	1–3.67	1–3.87	1–4
Skewness	–	−0.607	0.315	−0.314	−1.224	0.843	0.384	0.610	−0.108	−0.314	0.558	0.204	0.094	0.077
Kurtosis	–	0.211	−0.635	−1.339	1.293	0.952	−0.124	0.215	0.047	0.681	0.250	−0.338	−0.533	−0.019

Note. G = gender, SE = self-esteem, SW = social withdrawal, EX = exercise time, WA = parent warmth, RJ = parent rejection, INS = parent inconsistency, INC = income, PE = peer relationship, TE = teacher relationship, PSU = problematic smartphone use, SD = standard deviation. For continuous variables, Pearson's correlation coefficient was employed, while for ordinal variables, Spearman's rank order correlation coefficient was utilized. Regarding gender, 'male' was coded as '1,' and 'female' as '0.' Exercise time was coded as follows: 0 (no exercise), 1 (1 h), 2 (2 h), 3 (3 h), and 4 (4 or more hours).

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 5. Descriptive statistics of problematic smartphone use by latent classes at first wave (N = 2,399)

Variable		Class 1 (High-level) N = 184		Class 2 (Mid-increasing) N = 1,499		Class 3 (Low-increasing) N = 716		Overall Chi square test	Post-hoc pairwise comparisons		Effect size (*partial eta squared*)
		M	*SE*	*M*	*SE*	*M*	*SE*		*Groups*	*Chi-Square*	
Individual factor	Gender (*n*, *%*) male	97 (52.7%)		758 (50.6%)		338 (47.2%)		2.907			
	female	87 (47.3%)		741 (49.4%)		378 (52.8%)					
	Self-esteem	2.826	0.043	3.170	0.016	3.415	0.020	201.794***	C1 vs. C2	49.414***	0.073
									C1 vs. C3	162.869***	
									C2 vs. C3	75.700***	
	Social withdrawal	2.565	0.069	2.046	0.024	1.828	0.034	101.641***	C1 vs. C2	43.777***	0.041
									C1 vs. C3	95.704***	
									C2 vs. C3	22.088***	
	Exercise	2.947	0.145	3.463	0.046	3.750	0.061	33.556***	C1 vs. C2	9.844**	0.014
									C1 vs. C3	27.033***	
									C2 vs. C3	11.172**	
Parental factor	Warmth	3.311	0.052	3.548	0.018	3.730	0.022	78.991***	C1 vs. C2	15.714***	0.030
									C1 vs. C3	56.684***	
									C2 vs. C3	33.193***	
	Rejection	1.976	0.056	1.650	0.017	1.481	0.022	88.390***	C1 vs. C2	27.079***	0.038
									C1 vs. C3	70.914***	
									C2 vs. C3	28.562***	
	Inconsistency	2.335	0.056	1.935	0.020	1.668	0.027	142.696***	C1 vs. C2	39.149***	0.054
									C1 vs. C3	120.054***	
									C2 vs. C3	50.185***	
	Income	5.674	0.194	6.494	0.073	6.933	0.101	37.549***	C1 vs. C2	13.239***	0.014
									C1 vs. C3	34.455***	
									C2 vs. C3	9.902**	
School factor	Peer support	2.785	0.036	3.047	0.013	3.184	0.020	105.286***	C1 vs. C2	40.477***	0.039
									C1 vs. C3	99.600***	
									C2 vs. C3	26.243***	
	Teacher support	2.744	0.047	2.939	0.016	3.167	0.022	102.313***	C1 vs. C2	13.370***	0.042
									C1 vs. C3	68.845***	
									C2 vs. C3	55.296***	

Note. M = mean, SE = standard error. In this table, for between-group mean comparisons, we used the BCH procedure.
*p < 0.05, **p < 0.01, ***p < 0.001.

DISCUSSION

Patterns of PSU trajectories

As a result of the study, three PSU change trajectory types were identified: a high-level group (7.7%), a mid-increasing group (62.5%), and a low-increasing group (29.8%). The finding is compatible with those of Parent et al. (2022), whom identified three latent groups of PSU, this is a similar result, but at the same time, it is a new result that was not confirmed in previous studies. In the study by Parent et al. (2022), three latent classes were identified: the ‘connected class,’ the ‘problematic class,’ and the ‘distracted class.’ Previous studies have identified various subtypes of PSU. However, the current study is different from existing studies in that it not only identified various subtypes of PSU, but also confirmed longitudinal changes in these subtypes. For example, in previous studies, individuals belonging to the ‘connected class’ are a class classified at a certain point in time, but if these characteristics change over time, they may be classified into a different latent class in a longitudinal study. Additionally, according to Ecological Systems Theory, an individual’s psychosocial and behavioral aspects are influenced by interactions with the surrounding environment. Since the environment, such as technological changes and social norms, can change over time, this longitudinal research is very important. It highlights the importance of considering both the temporal aspects and the broader context when studying behaviors like PSU.

In summary, the findings of this research may serve as important evidence to develop mid- to long-term intervention strategies related to children’s PSU. First, the high-level group shows consistently high PSU characteristics over time. It can be seen that mid- to long-term interventions such as counseling and cognitive behavioral therapy may be necessary for these groups. Second, the mid-increasing group is the group with the highest proportion, and early intervention related to PSU is important. In particular, it is thought

Table 6. Descriptive statistics of problematic smartphone use by latent classes at fourth wave (N = 2,090)

Variable			Class 1 (High-level) N = 163		Class 2 (Mid-increasing) N = 1,282		Class 3 (Low-increasing) N = 645		Chi square test or F/Welch	Post-hoc pairwise comparisons (*Bonferroni*)		Effect size (*partial eta squared*)
			M	*SD*	*M*	*SD*	*M*	*SD*		*Groups*	*MD*	
Individual factor	Gender (*n, %*)	Male	82 (50.3%)		650 (50.7%)		307 (47.6%)		1.680			
		Female	81 (49.7%)		632 (49.3%)		338 (52.4%)					
	Self-esteem		2.77	0.44	2.88	0.42	3.10	0.49	62.992^{***}	C1 vs. C2	-0.1182^{*}	0.057
										C1 vs. C3	-0.3313^{*}	
										C2 vs. C3	-0.2130^{*}	
	Social withdrawal		2.40	0.74	2.10	0.66	1.98	0.77	24.039^{***}	C1 vs. C2	0.2995^{*}	0.023
										C1 vs. C3	0.4198^{*}	
										C2 vs. C3	0.1203^{*}	
	Exercise		2.34	1.31	2.53	1.33	2.85	1.38	16.142^{***}	C1 vs. C2	-0.1914	0.015
										C1 vs. C3	-0.5153^{*}	
										C2 vs. C3	-0.3239^{*}	
Parental factor	Warmth		3.16	0.53	3.18	0.57	3.43	0.58	43.725^{***}	C1 vs. C2	-0.0267	0.040
										C1 vs. C3	-0.2746^{*}	
										C2 vs. C3	-0.2479^{*}	
	Rejection		2.06	0.67	1.97	0.64	1.69	0.63	47.143^{***}	C1 vs. C2	0.0959	0.043
										C1 vs. C3	0.3753^{*}	
										C2 vs. C3	0.2794^{*}	
	Inconsistency		2.28	0.61	2.17	0.57	1.97	0.67	30.261^{***}	C1 vs. C2	0.1035	0.028
										C1 vs. C3	0.3067^{*}	
										C2 vs. C3	0.2032^{*}	
	Income		6.39	2.06	6.90	1.99	7.33	2.14	17.507^{***}	C1 vs. C2	-0.5041^{*}	0.017
										C1 vs. C3	-0.9422^{*}	
										C2 vs. C3	-0.4382^{*}	
School factor	Peer support		2.90	0.37	3.03	0.39	3.18	0.43	48.537^{***}	C1 vs. C2	-0.1287^{*}	0.044
										C1 vs. C3	-0.2858^{*}	
										C2 vs. C3	-0.1571^{*}	
	Teacher support		2.68	0.46	2.75	0.44	2.93	0.50	38.564^{***}	C1 vs. C2	-0.0778	0.036
										C1 vs. C3	-0.2564^{*}	
										C2 vs. C3	-0.1786^{*}	

Note. M = mean, SD = standard deviation. In this table, for between-group mean comparisons, we used ANOVA procedure based on the latent groups classified at the first wave as the reference point.
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

that the risk of PSU will be lowered if education on healthy smartphone use is provided to both children and parents and if they are involved in alternative events. Lastly, the fact that the low-increasing group also has a low PSU level at the initial point, but shows a continuous increasing trend must be considered. Therefore, preventive intervention is needed to prevent PSU in the future by intervening on social withdrawal or low self-esteem related to this group.

Predictors regarding patterns of PSU trajectories

The findings of this research propose that several individual factors are associated with a less likelihood of belonging to a group with increased levels of PSU during childhood. Specifically, being female, having higher self-esteem, spending more time exercising, and experiencing less social withdrawal had lower possibility in high-level group. These findings are compatible with or support past research discoveries (Chiang, Chang, Lee, & Hsu, 2019; Demirci et al., 2015; Gutiérrez et al., 2016; Lee et al., 2018; Lee & Kim, 2018; Lim, 2022). These results carry significant implications for mental health professionals, educators, and parents who care for children and teenagers. Strategies to promote self-esteem, encourage physical activity, and address social withdrawal could be useful in preventing or reducing PSU in childhood. Also, we found a higher likelihood of PSU among adolescent male compared to female. This result suggests that male may be more vulnerable to developing PSU. In this regard, several scholars have confirmed that women mainly use smartphones for social relationships, while men mainly use smartphones for fun, games, and gambling. In other words, the purpose of using a smartphone may differ depending on gender, and this difference may cause a difference in PSU (Frangos, Fragkos, & Kiohos, 2010; Gentina & Rowe, 2020; Van Deursen, Bolle, Hegner, & Kommers, 2015).

Table 7. Results of the r3step analysis on the relationship between PSU trajectory patterns and predictors

Variable		Dependent variable: Problematic smartphone use														
		C2: Mid-increasing group vs. C1: High-level group (Ref)					C3: Low-increasing group vs. C1: High-level group (Ref)					C3: Low-increasing group vs. C2: Mid-increasing group (Ref)				
		B	*S.E.*	*OR*	*CI (95%)*		*B*	*S.E.*	*OR*	*CI (95%)*		*B*	*S.E.*	*OR*	*CI (95%)*	
Individual factor	Male (ref: female)	−0.228	0.247	0.796	0.490	1.292	−0.615*	0.255	0.541	0.328	0.891	−0.387*	0.149	0.679	0.507	0.910
	Self-esteem	0.509	0.320	1.663	0.888	3.115	1.429***	0.337	4.176	2.158	8.080	0.921***	0.216	2.511	1.643	3.836
	Social withdrawal	−0.607***	0.170	0.545	0.391	0.760	−0.667***	0.177	0.513	0.363	0.726	−0.060	0.110	0.941	0.759	1.167
	Exercise (Ref: 0 h) 1 h	0.388	0.389	1.474	0.688	3.157	0.982*	0.438	2.671	1.133	6.298	0.594*	0.323	1.812	0.961	3.415
	2 h	0.586	0.444	1.796	0.752	4.292	1.314**	0.485	3.722	1.439	9.630	0.728	0.332	2.072	1.080	3.974
	3 h	0.859	0.499	2.361	0.889	6.276	1.403**	0.534	4.068	1.429	11.582	0.544**	0.341	1.723	0.883	3.362
	≥4 h	0.736	0.403	2.087	0.948	4.597	1.684***	0.446	5.385	2.245	12.916	0.948	0.314	2.580	1.394	4.775
Parental factor	Warmth	−0.162	0.226	0.851	0.546	1.326	−0.210	0.255	0.811	0.491	1.337	−0.048	0.195	0.953	0.651	1.396
	Rejection	−0.138	0.270	0.871	0.513	1.479	−0.252	0.277	0.777	0.451	1.338	−0.114	0.170	0.892	0.639	1.246
	Inconsistency	−0.682**	0.231	0.506	0.321	0.796	−1.117***	0.239	0.327	0.205	0.522	−0.435**	0.135	0.647	0.496	0.844
	Income	0.167**	0.060	1.182	1.051	1.329	0.220***	0.061	1.246	1.106	1.404	0.053	0.031	1.055	0.992	1.121
School factor	Peer support	0.432	0.287	1.541	0.878	2.705	0.338	0.310	1.403	0.764	2.575	−0.094	0.210	0.910	0.603	1.374
	Teacher support	0.118	0.244	1.125	0.698	1.814	0.770**	0.266	2.160	1.283	3.638	0.652***	0.179	1.920	1.351	2.730

Note. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

The parental factors play an important role. Specifically, previous research has shown that children whose parents have inconsistent parenting styles and lower monthly incomes are more likely to fall into the category of high-increasing PSU. These recent findings support the previous research (Brown, Campbell, & Ling, 2011; Kim, Kang, & Lee, 2020) and highlight the significance of parental environments in the development of children's PSU. Children's use of smartphones may increase as a way to relieve stress due to unfavorable environments due to low income and parents' inconsistent parenting methods, which can ultimately lead to PSU. Therefore, intervention related to parents' parenting attitude and economic situation is important. For example, if negative parenting by parents is confirmed, relevant education and counseling is provided, and in cases of economic poverty, children are provided with a variety of support.

Lastly, this study confirmed that positive relationships with teachers were an important protective factor in preventing PSU. This can be seen as being compatible to the findings of Shi et al. (2022), who found that teachers' positive support for children was negatively related to PSU. This means that positive interactions with teachers can strengthen children's sense of belonging and academic motivation, which can ultimately prevent PSU. In conclusion, teacher support can be a valuable tool in preventing PSU in children during their school years. By fostering a positive and supportive classroom environment, teachers can help children develop better social skills, academic performance, and a reduced need for escapism through smartphone use.

CONCLUSIONS

The current research goals were to verify various latent classes of children's PSU change trajectories and identify predictive factors associated with these latent classes. As a result, three change trajectories were identified: high-level, mid-increasing, and low-increasing. The high-level type showed a high PSU that persisted over time, the mid-increasing type showed a PSU gradually increasing over time, and the low-increasing type showed a gradual increase in PSU over time. However, it was still at a low level. Additionally, it was confirmed that gender, self-esteem, social withdrawal, exercise, parental parenting style, and teacher-student relationship were significantly related to this type of longitudinal change in PSU. These findings have the advantage of providing mid- to long-term evidence for children's PSU intervention by confirming the type of longitudinal change in PSU that was not confirmed in existing studies. Despite the contributions and implications of this study, several limitations should be considered. First, the applicability of the findings might be restricted to the specific demographic of South Korean children. This study acknowledges that not using the clustering option could potentially have an impact on the usual mistakes and significance levels of the statistical findings. Also, it is possible that individuals with more severe PSU may have had a higher dropout rate from the sample over time. Second, the study relied on self-report measures to assess PSU and associated factors. Information gathered through self-reporting can be influenced by certain biases like the desire to present oneself favorably or inaccuracies in recollection, that may influence the precision and trustworthiness of the data collected. Third, it is essential to note that, despite the utilization of a longitudinal design, we cannot establish causal relationships between variables. Also, it is worth noting that there may be other potentially relevant individual, parental, or school factors excluded in the current research which could influence the understanding of the dynamics of PSU as well as its developmental trajectories.

Future research might consider incorporating these additional factors such as media exposure, technological environment, academic stress, and mental health factors for a more comprehensive analysis. Nevertheless, the importance of this study lies in its contribution to the understanding of the developmental course of PSU in children. By identifying different trajectories of PSU, this research may notify the advancement of targeted involvement that may prevent and reduce PSU in children.

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