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Is There a Longitudinal Effect of Different Types of Digital Technology Use on Preadolescents' Subjective Well-Being?

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Abstract

This study aims to explore the possibility of predicting changes in preadolescents' subjective well-being (SWB) indicators, namely life satisfaction (LS), positive (PA) and negative affect (NA), based on how often they engage in different activities using digital technology (DT). Exploratory, it examines whether gender and age moderate links between DT usage and well-being. The study is conducted using self-report measures at two time points, with one year apart. Participants were 1379 elementary school pupils from Croatia (48% were boys), aged from 8 to 13 (M = 11.03, SD = 1.14) at the first time point. LS was assessed using BMSLSS (Seligson et al., 2003). PA and NA were assessed using PANAS-C scale (Ebesutani et al., 2012). Finally, participants indicated how often they engage in different activities using digital technology: use of social media (using social networks, texting with friends, posting online), playing video games, and watching TV. Only social media use predicted a small decrease in LS one year later. Different types of DT use did not predict changes in PA. These models were the same for boys and girls, and for younger and older preadolescents. Changes in NA were not related to any of the DT predictors. However, differential effects were observed for boys and girls with playing video games emerging as a positive predictor of NA for girls only. All observed effects were very small. These findings point to the importance of evaluating individual contribution of different activities that preadolescents engage in with the use of digital technology to their SWB.

Keywords: well-being, digital technology, adolescents, positive and negative affect, longitudinal design

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Introduction

The widespread use of digital technology (DT) present in recent decades presents an additional load on adolescents' transition from childhood into adulthood. Studies show that children and youth use DT more frequently and at younger age than previous generations (Ofcom, 2021). As for the effect of such use on preadolescent's well-being, the studies are still inconclusive. While some studies report a negative relationship between screen time and well-being in adolescents (e.g., Boniel-Nissim et al., 2015; McDool et al., 2020; Przybylski & Weinstein, 2017), other studies indicate that there is no strong link between these constructs (e.g., Kardefelt-Winther et al., 2020; Orben & Przybylski, 2019; Przybylski & Weinstein, 2017).

In a recent review of studies on DT use and well-being of adolescents, Dienlin and Johannes (2022) argue that it is not screen time, but different activities that adolescents engage in while using DT that can have different effects on their well-being. Also, in terms of well-being markers, various studies focus on different aspects of well-being. Based on Ryan and Deci's (2001) argument that well-being is basically positive mental health, Dienlin and Johannes (2022) argue that since positive mental health comprises of eudaimonic well-being, i.e., life satisfaction (LS), which is more stable over time, and hedonic well-being, i.e., positive (PA) and negative affect (NA), which is subject to more fluctuations, the effects of DT use are to be stronger on short-term markers of well-being, such as PA and NA, when compared to long-term measures such as LS.

While there is a considerable number of studies on DT use and well-being in adolescents, studies focusing on children in middle childhood and early adolescence, are very scarce. One reason for this might be that it is difficult to access their use of DT. Unlike younger children, preadolescents have their own devices, and they often use them independently, so parental reports of children's use are less valid than in younger age groups. At the same time, due to their cognitive immaturity, children are still not very proficient in giving time estimates of their DT use, so the scales used for their self-reports need to be adjusted to their developmental level.

Literature Review

Regarding specific on-line activities, some researchers point to an increasing concern pertaining to the potential impact of social media use on the well-being. Studies with early adolescents in this area are very scarce, probably because children are not allowed to use social networks sites before specific age. However, since the definition of social media includes not only social networks, such as Facebook or Instagram, but also other types of media that are used for communication with friends and family members, such as Viber or WhatsApp, and a broad range of communication channels (Verduyn et al., 2017) it is important to study the potential effect of social media in early adolescents as well. Meanwhile, as for studies with adolescents, while there is a great number of cross-sectional studies, longitudinal studies are again scarce. Cross-sectional studies offer inconsistent findings, and in a review of studies on DT use and well-being, Orben (2020) concludes that while there is a negative association between social media use and well-being in adolescents, this association is weak and the direction between the variables is still unclear. In a longitudinal study with older adolescent Facebook users, Kross et al. (2013) showed that Facebook use predicts negative shifts in LS two weeks later and that more frequent use of Facebook at one point negatively predicts how people feel at the next measurement point in a single day. In a 5-wave measurement study with adolescents aged 10 to 15 years, Booker et al. (2018) showed that higher social media use at age 10 is associated with a later decline in well-being, but only for female participants. On the other hand, Orben et al. (2019) showed that social media use is not, in and of itself, a strong predictor of LS in adolescents. Similarly, Schemer et al., (2021) found that the use of social networking sites is not substantially related to well-being, and Keresteš and Štulhofer (2020) didn't find a longitudinal association between social media use and LS in one year period, but they did find a significant negative association between the use of social networks and LS only at baseline for female adolescents.

Another activity that adolescents engage in through use of DT, that has been extensively studied in relation to well-being, is gaming. Studies on the effect of gaming on adolescents' well-being are still inconclusive, with some studies linking higher levels of gaming to various health problems such as depression (Lemona et al., 2011) or lower academic achievement (Ramírez et al., 2021), but at the same time, other studies failed to find a negative association between gaming and negative outcomes (e.g., Ferguson et al., 2013; Vuorre et al., 2022). However, the extensive research on gaming has resulted in Gaming Disorder being included in the fifth edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) (American Psychiatric Association, 2013) as a condition requiring further study, as well as in the International Classification of Diseases 11th Revision (ICD-11) (World Health Organization, 2022). Despite this inclusion, some authors argue that high engagement in gaming should be distinguished from addiction (e.g., Charlton & Danforth, 2007). Indeed, studies reported different findings for gaming addiction and time spent gaming and its association to well-being, with the former being related to depression, lower academic achievement, and conduct problems, but the latter not (Brunborg et al., 2013, 2014). In a longitudinal study with adolescents aged 12 to 15 years, Van Den Eijnden et al. (2018) found that, while disordered use of games had a negative effect on life satisfaction and their perceived social competence, heavy use of games predicted positive effects on their perceived social competence.

Finally, one type of DT use that has been extensively researched over the years, regarding the effects on well-being of children and adolescents, is watching television. Despite the wide array of concerns regarding watching television, empirical support for these concerns has been inconsistent. Television viewing is often considered as passive use of digital media and as such it was found to have the most detrimental, although small effect on children's socio-emotional outcomes, when compared to other types of use, such as social, interactive, educational, or other, in children aged 10 to 11 (Sanders et al., 2019). Padilla-Moledo et al. (2015) found a negative association between watching television for more than two hours and LS in children and adolescents.

Apart from studies focusing on one type of DT use, there are some longitudinal studies that differentiated between activities with DT and well-being of adolescents and found evidence of different effects. Khan and Burton (2021) found that while playing games was inversely associated with psychological well-being of both male and female adolescents, watching television was inversely associated with psychological well-being only in female adolescents. In a study with younger children aged 2 to 6, Hinkley et al. (2014) found that television viewing was more consistently associated with negative well-being outcomes than gaming. Schemer et al. (2021) found that while there is no substantial relationship between the use of social networking sites and well-being, television viewing is negatively related to life satisfaction.

Current Study

Based on the reviewed literature it is fair to say that, while there are concerns about the negative effects of DT use on well-being of children and adolescents, the evidence of such effects is far from conclusive, and there is a significant research gap concerning early adolescents. To provide the stakeholders with more credible data about the possible links between these activities and well-being, further research, using longitudinal studies with preadolescents is needed.

This study aims to explore the possibility of predicting changes in preadolescents' subjective well-being (SWB) indicators, namely LS, PA, and NA, based on how often they engage in different activities using DT, namely playing video games, watching television, and using social media. Studies with adolescents offer inconclusive findings regarding the effect of different activities with DT and well-being. This study focuses on even younger and therefore more vulnerable participants who are just entering the phase of significant cognitive development, especially in domains of emotion regulation, planning and response inhibition, that occurs in the following years (Andrews et al., 2020). Also, considering they are probably only starting to use social media and are less experienced with such use compared to adolescents, we expect to find a small negative effect of social media use on well-being. Studies show that possible reasons for negative associations between social media use and well-being might be found in social comparison (Wirtz et al., 2021), greater chance of experiencing cyberbullying (Margolis & Amanbekova, 2023) or becoming exposed to inappropriate content (Stasi, 2019).

Studies also show inconsistent findings regarding gaming and television viewing effect on well-being in adolescents. However, considering that, due to their age, early adolescents are starting to use DT more independently and without adult supervision compared to younger children, we expect a small negative effect of these activities on their well-being.

Age and gender are included as covariates in all the models as they are both related to SWB (Savahl et al., 2021). Some studies also found stronger links between heavy DT use and low psychological well-being for girls (Keresteš & Štulhofer, 2020; Twenge & Martin, 2020), and age differences were observed with respect to how adolescents use social media (Madden et al., 2013). Therefore, the study aims to explore whether these models function the same for both girls and boys and younger and older children.

Materials and Methods

Participants

Participants were 1379 elementary school pupils (48% were boys), aged 8 to 13 (M = 11.03, SD = 1.14) at the first time point. They attended third (n = 352, 25.5%), fourth (n = 378, 27.4%), fifth (n = 353, 25.6%) or sixth grade (n = 296, 21.5%) in two counties in Croatia (Osijek-Baranja and Varaždin county). Regarding the socioeconomic status (SES) of the participants, 8% of the sample is experiencing financial hardship, according to their mothers' self-assessed SES and 28.7% of the sample is earning less than 400 EUR per household member.

Procedure

Data presented in this article are a part of a larger longitudinal study "Well-being of children in family context (CHILD-WELL)", funded by the Croatian Science Foundation, conducted in two research waves (T1 and T2). Study was approved by the Ethical board of the authors' institution, as well as Croatian Ministry of Science and Education. Parents of children attending third, fourth, fifth and sixth grade of 15 elementary schools were informed about the purpose of the research and were invited to participate in the study. The response rate of consent for participation was 44.47%. After the parents signed the consent form, the children were approached in school during regular classes by trained researchers or school psychologists. After giving their personal consent to participate, they filled out the prepared questionnaires. Group administration of the questionnaires lasted about 45 minutes (T1). The same questionnaire was administered in the same way approximately one year later (T2).

Measures

Activities Using Digital Technology (DT)

The participants were asked to rate the frequency of engaging in different activities using DT: (1) "playing games or using applications for fun on a tablet, smartphone or a computer", (2) "watching TV", (3) "using social media (Facebook, Instagram, TikTok etc.)", (4) "writing to their friends using Viber, WhatsApp, chat, messages, etc". and (5) "posting photos, videos or texts on the Internet". To provide answers they used a four-point scale: 1 = *almost never*, 2 = *rarely*, 3 = *few times a week*, 4 = *almost every day*. An exploratory factor analysis with five items was performed and yielded two factors which together explained 55% of the variance. The items (3) using social networks (Facebook, Instagram, TikTok etc.), (4) writing to their friends using Viber, WhatsApp, chat, messages, etc., and (5) posting photos, videos or texts on the Internet loaded on the same factor. The one-factor solution for the three items explained 50.69% of the variance and the three items were later used as indicators of a latent factor in all three main models. Unlike some studies that focus on social media use and differentiate between different types of such use (e.g., Frison & Eggermont, 2015), the goal of this study was to capture different dimensions of social media use in preadolescents to obtain a more comprising measure of such use. Similar approach was used in other studies on internet use (e.g., Strong et al., 2018). Although the items (1) "playing games or using applications for fun on a tablet, smartphone or a computer" and (2) "watching TV" loaded on the same factor, a decision was made to use the two items as two separate, manifest variables. One reason is their relatively low correlation (r = .14, p < .01), and the other is the content of the items. They refer to two distinct and different digital activities which have been extensively researched in various contexts (e.g., video games/gaming in context of behavioural addiction or TV in context of early child development). The purpose of this research is to test their unique contribution to explaining changes in children's SWB.

Life Satisfaction (LS)

Children's LS was assessed by the Brief Multidimensional Student's Life Satisfaction Scale (Seligson et al., 2003). Using a seven-point Likert-type response scale, ranging from *very dissatisfied* to *very satisfied* participants assessed how satisfied they were with five different life domains: their family life, their friends, their school experiences, themselves, the place where they live. Apart from individual satisfaction rates regarding each specific domain, the items can be averaged together resulting in a total score, which represents overall LS.

Positive and Negative Affect (PA and NA)

Positive affect (PA) and negative affect (NA) were assessed using the PANAS-C scale (Ebesutani et al., 2012). Using a 5–point scale (1 = *not at all or very slightly*, 5 = *extremely*), children were asked to rate 10 adjectives of varying positive (e.g., joyful) and negative (e.g., scared) mood states based on how often they have felt that way in the past few weeks. Five items for PA were averaged into a total score and five items for NA were averaged into a total score, with higher scores indicating higher PA and NA.

Results

All analyses were conducted in R software with the *lavaan* package (Rosseel, 2012). All main data analysis procedures belong to structural equation modelling (SEM). First, three separate models were made, one for each of the child's SWB measures (LS – Figure 1, PA – Figure 2, NA – Figure 3). SWB measures were modeled as latent factors, as well as social media use. All models were tested with a maximum likelihood robust estimator. Model fit was evaluated based on the following criteria: comparative fit index (CFI) > .90, Tucker-Lewis indeks (TLI) > .90, root mean square error of approximation (RMSEA) < .08, and and standardized root mean square residual (SRMR) < .08. In each model, dependent variable (SWB measure) is from the second study wave, while all the predictors belong to the first study wave. Descriptive statistics (mean, *SD*, and Cronbach alpha values) for the study variables are shown in Table 1.

Table 1

Descriptive Statistics for Manifest Variables and the Test of Difference Between Two Time Points

	Min	Max	*M*	*SD*	Cronbach's alpha	*t*	*p*
LS (t1)	2.00	7.00	6.13	0.80	.69	11.02	<.001
LS (t2)	1.20	7.00	5.89	0.92	.75		
PA (t1)	1.00	5.00	4.17	0.70	.80	5.05	<.001
PA (t2)	1.00	5.00	4.06	0.74	.84		
NA (t1)	1.00	5.00	1.85	0.72	.73	-1.65	.099
NA (t2)	1.00	5.00	1.89	0.70	.73		
Social media	1.00	4.00	2.60	0.71	.51		
Video games	1.00	4.00	3.26	0.87			
TV	1.00	4.00	3.12	0.98			
Age	8.63	13.64	11.03	1.14			

Note. t1 – first time point; t2 – second time point. LS – life satisfaction. PA – positive affect. NA – negative affect.

In each of the three models, dependent variable from the first study wave was included as a predictor, as well as the age and gender of the participants. A longitudinal invariance test was performed to assess the stability of the measurement structure across time 1 and time 2. This analysis aimed to determine whether the same latent constructs were measured in a comparable manner at both time points and showed longitudinal invariances for all the included SWB measures (results are in the Appendix, Table A1). All three models were tested with respect to two age and gender groups – a multigroup analysis was made.

Correlations among the study variables (manifest and latent) are shown in Table 2. The highest correlations in the matrix refer to correlations between SWB measures (t1 and t2), the highest one is between LS and PA at both time points (r = .80/.79, p < .01). The predictors (video games, social media, TV) are differently correlated with the SWB measures. On average, social media has the highest correlations with SWB measures, while playing video games has the lowest. Moreover, the three DT predictors have different relations among each other – social media use is moderately correlated with playing video games (r = .25, p < .01), but is not significantly correlated to watching TV. Playing video games has a weak, but positive correlation with watching TV (r = .14, p < .01). Control variables, age, and gender showed an expected pattern of correlations with SWB measures – older age and female gender are typically related to lower levels of well-being (less LS and PA, more NA).

Table 2

Correlations Among Latent and Manifest Variables in the Study

	Video games	TV	Social media	LS t1	PA t1	NA t1	LS t2	PA t2	NA t2	Age
TV	**.14**	-								
Social media	**.25**	-.05	-							
LS t1	**-.10**	**.21**	**-.22**	-						
PA t1	-.03	**.14**	**-.15**	**.80**	-					
NA t1	.06	-.08*	**.20**	**-.55**	**-.50**	-				
LS t2	**-.08**	**.18**	**-.25**	**.72**	**.59**	**-.44**	-			
PA t2	-.03	**.10**	**-.13**	**.53**	**.59**	**-.37**	**.79**	-		
NA t2	.01	**-.09**	**.19**	**-.52**	**-.42**	**.55**	**-.67**	**-.62**	-	
Age	-.04	**-.19**	**-.29**	**-.25**	**-.21**	.00	**-.25**	**-.23**	**.17**	-
Gender [a]	**-.19**	**-.02**	**.10**	**-.09**	-.06*	**.09**	**-.14**	**-.13**	**.20**	-.03

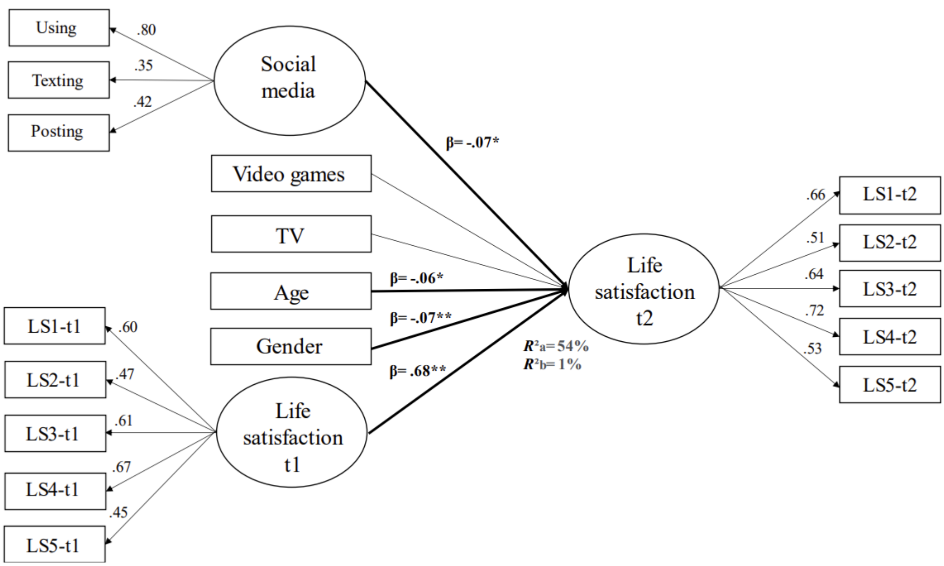
Note. t1 – first time point; t2 – second time point. LS – life satisfaction. PA – positive affect. NA – negative affect. [a] male gender is coded as 1, and female gender is coded as 2.
Bold: correlations significant at $p \leq .01$. $^*p \leq .05$.

Life Satisfaction (LS)

A model with LS (second wave) as the dependent latent variable was specified. Correlations were allowed for the same LS items from the first and second wave. Also, correlations among predictors (social media use, playing video games, watching TV, LS from the first wave) were allowed. This model showed adequate fit indices: $\chi^2(97) = 267.000$, $p < .01$, CFI = .955, TLI = .936, RMSEA = .04, SRMR = .03. In this model, LS is best predicted by the same variable from the previous research wave ($\beta = .68$, $p < .001$). Regarding the predictors related to DT, social media use has emerged as a negative predictor of changes in LS ($\beta = -.07$, $p = .003$). Higher age ($\beta = -.06$, $p = .02$) and female gender ($\beta = -.07$, $p = .004$) are also related to lower levels of LS (t2).

Figure 1

The Structural Model with Social Media, Video Games, TV, Age, Gender, and Life Satisfaction at Baseline as Predictors of Changes in Life Satisfaction



Note. Standardized parameters are shown; bold paths are significant; all predictor intercorrelations are estimated but are not shown in the figure; R^2a – for all predictors, R^2b – social media, video games and TV only.
$^*p < .05$. $^{**}p < .01$.

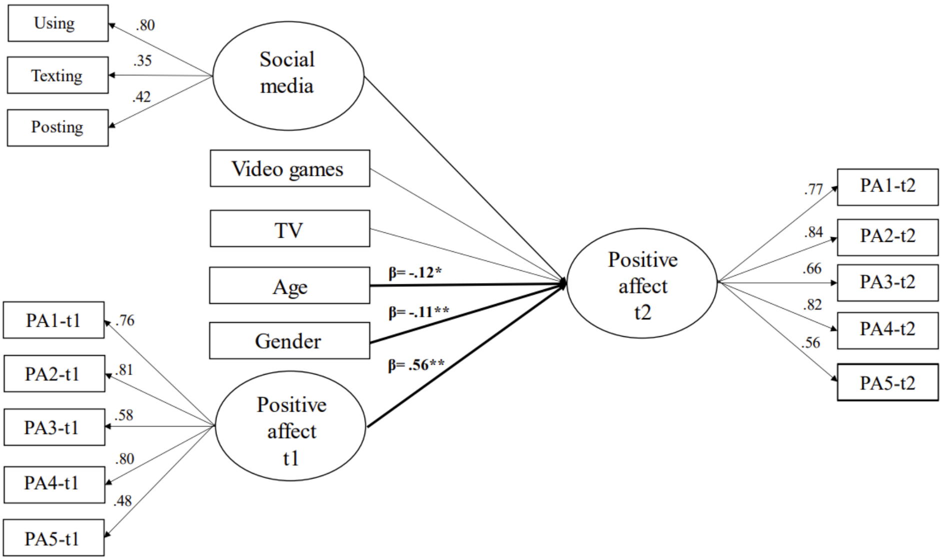
Positive Affect (PA)

A model with PA (second wave) as a dependent latent variable was specified. Correlations were allowed for the same PA items from the first and second wave, as well as the correlations among the predictors. This model showed good fit indices: $\chi^2(97) = 287.297$, $p < .01$, CFI = .968, TLI = .954, RMSEA = .04, SRMR = .03.

Similarly to the previous model, PA is best predicted by the same variable from a previous research wave (β = .60, $p < .001$), while higher age (β = -.12, $p < .001$), and female gender (β = -.11, $p < .001$) are related to lower levels of PA (t2). None of the DT predictors have met the typical significance criteria.

Figure 2

The Structural Model with Social Media, Video Games, TV, Age, Gender, and Positive Affect at Baseline as Predictors of Changes in Positive Affect



Note. Standardized parameters are shown; bold paths are significant; all predictor intercorrelations are estimated but are not shown in the figure.
$^{*}p < .05$. $^{**}p < .01$.

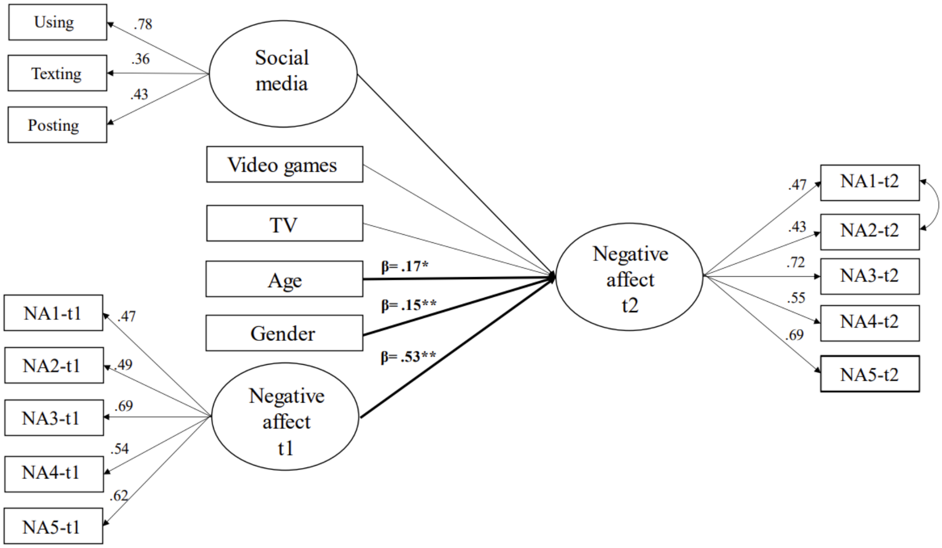
Negative Affect (NA)

A model with NA (second wave) as the dependent latent variable was specified. Correlations were allowed for the same NA items from the first and second wave, as well as the correlations among all predictors. Item residual correlations were allowed for items *afraid* and *scared* for NA. This model showed adequate fit indices: $\chi^2(95) = 342.339$, $p < .01$, CFI =.938, TLI = .911, RMSEA = .05, SRMR = .04. Without the allowed correlation, fit indices were not satisfactory: $\chi^2(97) = 899.648$, $p < .01$, CFI =.809, TLI = .733, RMSEA = .08, SRMR = .06.

NA is best predicted by the same variable from the previous research wave (β = .53, $p < .001$). Higher age (β = .17, $p < .001$) and female gender (β = .15, $p < .001$) are related to higher levels of NA (t2). None of the DT predictors has met the conventional significance criteria.

Figure 3

The Structural Model with Social Media, Video Games, TV, Age, Gender, and Negative Affect at Baseline as Predictors of Changes in Negative Affect



Note. Standardized parameters are shown; bold paths are significant; all predictor intercorrelations are estimated but are not shown in the figure.
$^{*}p < .05$. $^{**}p < .01$.

Since there are some gender and age differences in the usage of different digital media and its links with well-being in prior studies (Madden et al., 2013; Twenge & Martin, 2020), we have also examined whether gender or age group moderate links between digital media use and SWB. Moderation was examined by employing the multigroup method. For gender groups three different models were specified with different SWB measures as dependent variables. Predictors were SWB at baseline, social media use, watching TV, playing video games, and age measured as a continuous variable. In terms of age group models, we have divided our sample into lower (third and fourth grade, age 9-10 at baseline) and higher grade (fifth and sixth grade, age 11-12 at baseline) groups. These models also had different SWB measures as dependent variables. Predictors were SWB at baseline, social media use, watching TV, playing video games, and gender.

Before testing the equivalence of regression paths for different groups, we explored longitudinal multigroup measurement invariance for all our models. Specifically, we examined whether metric invariance holds, which would allow for comparison of regression paths across groups. A configural model was specified first, and in the next step, we constrained loadings of all latent variables to be equal across groups and time (for variables that are measured twice). The difference between configural and metric model was tested via the difference in CFI (Little, 2013). If the change in CFI is .01 or less, then invariance holds (Cheung & Rensvold;

2002; Little, 2013). After a demonstration of metric invariance, regression paths were constrained to be equal across gender or age groups. The equivalence of regression paths was then tested with the scaled difference in the chi-square test by comparing the constrained model with the model where regression paths are all free.

Results of equivalence testing are shown in Table 3 and Table 4. For age groups, there were no observed differences in any of the tested models. This means that digital activities had similar links with LS, PA, and NA affect for younger and older children.

For gender, all models were equivalent for LS and PA. For NA, the model with all regression paths constrained across gender significantly differed from the model with all free paths. Further exploration of these differences showed that playing video games and watching TV had different predictive paths across genders. For girls, there was a significant positive link ($\beta = .10$, $p = .023$) between playing video games and increase in NA. For boys, this link was not significant ($\beta = -.11$, $p = .052$). Next, regression paths for watching TV were not significant in either group, but observed links were opposite in sign, and thus moderation is detected. For girls, there was an insignificant negative effect ($\beta = -.07$, $p = .073$), and for boys, there was an insignificant positive link ($\beta = .06$, $p = .158$) between watching TV and changes in NA.

The final results obtained in multigroup analyses are shown in Appendix (Tables A1 – A7).

Table 3

Comparisons of Different Models Across Two Age Groups

Age groups	*df*	χ^2	r-CFI	r-RMSEA	SRMR	ΔCFI	$\Delta\chi^2$
LS model							
Configural	174	299.880***	.963	.035	.040		
Metric	188	311.254***	.962	.034	.042	-.001	-
All regression paths equal	193	317.165***	.962	.034	.043	-	$p > .05$
PA model							
Configural	174	347.975***	.968	.040	.037		
Metric	188	357.418***	.969	.038	.038	.001	-
All regression paths equal	193	357.854***	.969	.037	.039	-	$p > .05$
NA model							
Configural	170	379.150***	.946	.045	.045		
Metric	184	405.570***	.941	.045	.049	-.005	
All regression paths equal	189	415.580***	.940	.045	.050	-	$p > .05$

Note. LS – life satisfaction. PA – positive affect. NA – negative affect. R-CFI – robust CFI. R-RMSEA – robust RMSEA.
$^{***}p < .001$.

Table 4

Comparisons of Different Models Across Gender

Gender	*df*	χ^2	r-CFI	r-RMSEA	SRMR	ΔCFI	$\Delta\chi^2$
LS model							
Configural	174	305.575***	.965	.036	.040		
Metric	188	321.732***	.963	.035	.043	-.002	
All regression paths equal	193	332.477***	.961	.035	.045	-	$p > .05$
PA model							
Configural	174	316.942***	.975	.037	.036		
Metric	188	333.907***	.974	.036	.038	-.001	
All regression paths equal	193	343.337***	.973	.036	.043	-	$p > .05$
NA model							
Configural	170	354.619***	.952	.042	.046		
Metric	184	373.031***	.950	.042	.048	-.002	
All regression paths equal	189	388.406***	.947	.042	.049	-	$p < .01$
Three regression paths equal[a]	187	374.518***	.950	.041	.048	-	$p > .05$

Note. LS – life satisfaction. PA – positive affect. NA – negative affect. R-CFI – robust CFI. R-RMSEA – robust RMSEA. [a] regression paths for TV and video games are free across gender; this model is compared with Metric model where all regression paths are free.
$^{***}p < .001$.

Sensitivity Analyses

To test whether our modelling choice influenced our results, we decided to check our results by using hierarchical regression modelling with manifest variables. There were no significant differences in interpretation of results.

Discussion

To explore the possibility of predicting changes in preadolescents' SWB based on how often they engage in different activities using digital technology (DT), we tested three models with three different subjective well-being measures (SWB) as criteria variables.

When it comes to specific digital activities that predict changes in well-being, our results show that only social media use predicts a small decrease in life satisfaction (LS) one year later. Some previous studies support these findings. Kross et al. (2013) showed that Facebook use predicts negative shifts in LS, and other studies also showed that social media use can be liked to a later decrease in well-being (Booker et al., 2018). As mentioned earlier, some studies failed to find a longitudinal association between social media use and LS (Keresteš & Štulhofer, 2020; Orben et al., 2019). It is important to note that the participants in our study are slightly younger than in those studies. In fact, they are mostly of age when social media networks are legally forbidden, yet some children in the sample visit these sites. Younger children might not be using social media for as long as older children, and this might be seen as a protective factor. As a result, the influence of this kind of use might not still be evident. On the other hand, younger children are more vulnerable to the effect of these sites, and it is therefore not surprising that there is a detected drop in their LS related to social media use. The latent variable in our study called social media use, included not only use of Facebook, Instagram, TikTok and other social networks, but also texting with friends and posting online. To get a clearer picture of the relationship between social media and well-being, some researchers distinguish between passive and active use of social media or social networks (Selfhout et al., 2009; Verduyn et al., 2017). It seems that studies on passive use of Facebook and well-being offer mixed results, but active use is more often related to positive effects on well-being (Verduyn et al., 2017).

The aim of this study was to differentiate between different types of activities, but only to a certain level. DT has extensively developed and expanded over a short period of time which made capturing the nuances in different types of DT usage very difficult. Even when focusing on a single activity (e.g., watching television), a researcher's task is to capture both the frequency/duration of use and consumed content, as well. In this example, watching television may include learning how to cook by watching cooking shows, as well as watching age-inappropriate content. The problem with capturing the content of DT activities is relevant for all three predictors in this study: playing video games (e.g., violent vs. non-violent games), watching TV (e.g., documentaries vs. reality TV), and, obviously, social media use (e.g., posting one's own landscape photography vs. mindless scrolling). This study did not employ a more detailed investigation into the differences between specific types of social media use because it aimed to observe if there were noticeable differences in effects of more general digital activities on children's well-being. However, future studies should consider differentiating between different social media networks and types of use.

While there was a small but significant effect of social media use on the more stable well-being measure (LS) in one year time, we found no effect of different activities with DT for short-term well-being markers, i.e., positive affect (PA) and negative affect (NA) in the whole sample. This might seem contrary to Dienlin and Johannes' (2022) argument that the effects of DT use are to be stronger and more detectable on short-term than long-term markers of well-being. But PA and NA measures provide estimates of emotional states in the past two weeks, and while the use of DT one year ago did not show a significant relation to these measures, this does not necessary mean that the use of DT for different activities in a more recent timeframe does not have an effect on short-term well-being markers.

The results from this study show that age and gender are related to changes in all SWB measures, with female gender and older age predicting lower LS, less PA, and more NA in a one-year period. Gender differences in LS have been extensively studied over the years, but the findings are still inconsistent. While some studies report no gender differences (Casas et al., 2007; Chui & Wong, 2016; Huebner et al., 2006), a recent meta-analysis of 46 empirical studies with children and adolescents revealed a slight difference in favour of male children and adolescents (Chen et al., 2020). Some authors argue that such differences cannot be observed before the age of 12 (Esteban-Gonzalo et al., 2020), but our findings contradict this showing that female gender significantly predicts lower LS in age younger than 12. In fact, Newland et al. (2018) also showed that female gender, as well as older age, are predictors of decrease in LS in children aged 9 to 14. As for age differences, like Newland et al. (2018), other studies also show that LS decreases with age in period of adolescence (Casas et al., 2007). Our results show that this decrease is evident in other well-being measures as well, besides LS, i.e., PA and NA, and that these changes are evident at age 8 to 13.

After exploring the possibility of predicting SWB based on different types of DT use, we were interested to see if the model would provide the same fit for girls and boys separately, as well as younger and older children. The results showed that the models yielded no differences in relation to two age groups for any of the SWB measures, and no differences between genders for LS and PA. The only exception appeared when predicting changes in NA, where for girls, playing video games predicted more NA one year later. Khan et al. (2023) showed that electronic gaming for more than four hours a day was associated with 69% higher odds for low life satisfaction in girls and 42% in boys (Khan et al., 2023). The significant positive link between playing video games and increases in NA for girls is also in line with other studies that found girls to be more vulnerable to different digital media activities (Svensson et al., 2022). This study shows that at the age of 8 to 13, girls are potentially somewhat more sensitive to the negative effects of gaming than boys. As possible explanation, some studies imply that girls are at greater risk for negative effects of digital media use because of different motivations for such use compared to that of boys, but these findings are mostly regarding social media (Barker, 2009). Vuorre et al. (2022) showed that intrinsic motivation for playing video games had a positive effect on both affect and LS, while extrinsic motivation had a negative effect on both well-being measures (Vuorre et al., 2022). Similarly, Johannes et al. (2021) found a positive association between game playing and well-being and highlighted the benefits of gaming as a leisure activity, arguing that individuals might be motivated to play to support their well-being. Therefore, the information on the type of games and motivation for their use could provide better insight into the different effects of gaming on boys and girls.

Limitations of the Study

When taking into consideration that in the first model, DT predictors explained only 1% of the variance in LS, the given findings point to the possibility that DT activities and SWB measured one year later are not significantly or are only weakly related. This might be because of self-report measures that were used in the study. Indeed, while many researchers currently exploring the effects of DT use on various aspects of psychological functioning have found null results (Ophir et al., 2021), some argue that the "tools" for capturing these relations are not fine-tuned or precise enough to capture the relationship. Some authors called for complete abandonment of self-report measures in this case (Kaye et al., 2020), while others reported a discrepancy between self-reported and objective DT usage data (Parry et al., 2021). Also, due to the age of study participants, the scale with possible answers regarding time spent in different activities with DT had to be very simple and avoid using more exact time intervals, which can be considered as an additional study limitation. Even if the limitations of measuring DT use were not as pronounced, it needs to be considered that other predictors besides DT influence changes in SWB more significantly. Furthermore, longitudinal studies with larger timespan between two measurement points should shed light on this field of research. Researchers could also employ cross-lagged methodology to test the possibility of SWB determining DT consumption. Lower levels of LS, inadequate social support or heightened NA could lead to maladaptive DT use such as mindless scrolling, escapism, etc.

Conclusions

Results from this study show that in children aged 8 to 13, the use of social media is on average a significant, but weak predictor of decreases in LS measured one year later. Other DT activities, such as playing video games and watching television, did not affect any of the SWB measures. For two age groups, there were no observed differences in any of the tested models. For gender, models were equivalent for LS and PA. For NA, the model with all regression paths constrained across gender significantly differed from the model with all free paths. Playing video games positively predicted small increases in NA for girls only. Although all observed effects were very small, these findings point to the importance of evaluating the individual contribution of different activities that preadolescents engage in with the use of DT to different aspects of their SWB.

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Appendix

Table A1

Results of Measurement Invariance for Three Latent Outcomes (LS, PA, NA)

	MLR χ2	*df*	CFI	TLI	SRMR	RMSEA	ΔCFI	Δ*df*	Sig.
LS-configural	58.739	29	.988	.982	.024	.032	.001	4	.18
LS-metric	64.715	33	.987	.983	.027	.032			
PA-configural	101.160	29	.984	.976	.024	.042	.001	4	.64
PA-metric	103.931	33	.985	.979	.025	.044			
NA-configural	114.699	25	.969	.944	.045	.058	0	4	.48
NA-metric	116.846	29	.969	.952	.046	.053			

Note. LS – life satisfaction. PA – positive affect. NA – negative affect.

Table A2

Digital Activities as Predictors of Life Satisfaction at the Second Wave for Younger and Older Children (all Regression Paths are Equal Between the Two Groups)

	Younger			Older		
	b	β	*p*	*b*	β	*p*
LS (t1)	0.801	.643	0	0.801	.710	0
Social media	-0.108	-.087	.020	-0.108	-.068	.020
Video games	-0.021	-.014	.625	-0.021	-.013	.625
TV	0.042	.031	.276	0.042	.029	.276
Gender	-0.192	-.077	.006	-0.192	-.065	.006

Note. LS – life satisfaction.

Table A3

Digital Activities as Predictors of Life Satisfaction at the Second Wave for Boys and Girls (all Regression Paths are Equal Between the Two Groups)

	Boys			Girls		
	b	β	*p*	*b*	β	*p*
LS (t1)	0.805	.682	0	0.805	.694	0
Social media	-0.093	-.079	.034	-0.093	-.065	.034
Video games	-0.016	-.011	.672	-0.016	-.011	.672
TV	0.028	.023	.434	0.028	.021	.434
Age	-0.065	-.063	.034	-0.065	-.054	.034

Note. LS – life satisfaction.

Table A4

Digital Activities as Predictors of Positive Affect at The Second Wave for Younger and Older Children (all Regression Paths are Equal Between the Two Groups)

	Younger			Older		
	b	β	*p*	*b*	β	*p*
PA (t1)	0.597	.563	0	0.597	.561	0
Social media	-0.006	-.006	.871	-0.006	-.005	.871
Video games	-0.044	-.035	.223	-0.044	-.033	.223
TV	0.008	.007	.790	0.008	.007	.790
Gender	-0.232	-.109	0	-0.232	-.094	0

Note. PA – positive affect.

Table A5

Digital Activities as Predictors of Positive Affect at the Second Wave for Boys and Girls (all Regression Paths are Equal Between the Two Groups)

	Boys			Girls		
	b	β	*p*	*b*	β	*p*
PA (t1)	0.586	.565	0	0.586	.549	0
Social media	-0.002	-.002	.965	-0.002	-.001	.965
Video games	-0.044	-.033	.195	-0.044	-.037	.195
TV	-0.001	-.001	.981	-0.001	-.001	.981
Age	-0.110	-.122	0	-0.11	-.112	0

Note. PA – positive affect.

Table A6

Digital Activities as Predictors of Negative Affect at The Second Wave for Younger and Older Children (all Regression Paths are Equal Between the Two Groups)

	Younger			Older		
	b	β	*p*	*b*	β	*p*
NA (t1)	0.548	.517	0	0.548	.573	0
Social media	0.037	.035	.406	0.037	.033	.406
Video games	0.014	.011	.754	0.014	.012	.754
TV	-0.025	-.022	.424	-0.025	-.025	.424
Gender	0.306	.145	0	0.306	.147	0

Note. NA – negative affect.

Table A7

Digital Activities as Predictors of Negative Affect at the Second Wave for Boys and Girls (Regression Paths for Video Games and TV are Free Between the Groups)

	Boys			Girls		
	b	β	*p*	*b*	β	*p*
NA (t1)	0.544	.565	0	0.544	.528	0
Social media	0.030	.031	.514	0.030	.025	.514
Video games	-0.134	-.107	.052	0.117	.100	.023
TV	0.063	.062	.158	-0.076	-.070	.073
Age	0.152	.182	0	0.152	.157	0

Note. NA – negative affect.