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The longitudinal associations between mental health indicators and digital media use and physical activity during adolescence: A latent class approach

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ABSTRACT

Introduction: Evidence for the relationship between movement behaviors and mental health among adolescents is inconclusive. We aimed to identify profiles of digital media use (including related bedtime delay) and leisure-time physical activity (LTPA) in adolescence, and to examine whether preadolescent mental health predicted later behavior profiles.

Methods: This study included 1285 participants assessed at 11 years of age, and followed-up four years later. Participants completed the Self-Perception Profile for Children (SPPC), Center for Epidemiological Studies Depression Scale for Children (CES-DC) and Screen for Child Anxiety-Related Emotional Disorders (SCARED) at baseline, and reported digital media use (active and passive use, gaming, and related bedtime delays) and LTPA at follow-up. A latent class approach was employed to identify behavior profiles, membership of which was then predicted with mental health and covariates, including baseline digital media use and LTPA.

Results: We identified four behavior profiles: ***1) high digital media use/moderate LTPA (20% of adolescents; 78% boys), 2) moderate digital media use/high LTPA (31%; 28%), 3) high digital media use/high LTPA (26%; 15%), 4) high passive digital media use and gaming/low LTPA (23%; 89%).*** After adjusting for covariates, higher LTPA and better perception of athletic competence at baseline associated with higher odds of belonging to any other profile than to the unhealthiest profile (4) at follow-up. Symptoms of depression or anxiety did not associate with later behavior profiles.

Conclusions: LTPA and related self-esteem seem to be stronger predictors of future digital media use and LTPA behavior during adolescence than mental health symptoms alone.

1. Introduction

Physical activity and an adequate duration of sleep provide multiple health-related benefits for adolescents, whereas sedentary behaviors (defined as any waking behavior with an energy expenditure of ≤1.5 metabolic equivalents [METs] while in a sitting, reclining, or lying posture (Tremblay et al., 2017) associate with adverse health indicators (J. P. Chaput et al., 2016; J.-P. Chaput et al., 2020). Yet, 81% of adolescents aged 11–17 years are insufficiently physically active (doing less than 60 min of daily physical activity of moderate-to-vigorous intensity or being active for less than 60 min on 5 days per week) globally, with significant differences found across sexes and countries (Guthold, Stevens, Riley, & Bull, 2020). Moreover, time spent using digital media, a common sedentary behavior, has increased and sleep duration has decreased among youth in recent decades (Barnett & Kelly, 2018; J. P.; Chaput et al., 2016). Physical inactivity and sedentary behaviors tend to track from adolescence to adulthood (Biddle, Pearson, Ross, & Braithwaite, 2010; Telama et al., 2014). Among adults, physical inactivity and higher amounts of sedentary behavior associate with an elevated risk of cardiovascular disease, type 2 diabetes and premature mortality (Bull et al., 2020; Lee et al., 2012). Moreover, physical activity associates with improvements in adult mental health and sleep, whereas

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the evidence is limited for sedentary behavior and mental health (Bull et al., 2020). Therefore, investigating the possible factors that increase the risk of physical inactivity and higher amounts of sedentary behavior during the period of adolescence is relevant to promoting long-term healthy behavior patterns and health.

Research on movement behaviors, including physical activity, sedentary behavior, and sleep, has traditionally concentrated on examining individual behaviors and their associations with health-related factors using a variable-oriented approach. Current research, however, is moving towards identifying different combinations of these behaviors, which may have important implications for health already during adolescence (Tremblay & Ross, 2020). Moreover, a person-oriented approach seeks to identify unique latent groups within a population through maximizing between group variation and minimizing within-group variation, and focuses on profiles across characteristics to describe a certain phenomenon (Renninger et al., 2019). Recent studies employing this approach identified several distinct profiles or patterns indicated by sedentary behavior and physical activity (del Pozo-Cruz et al., 2019; Jago et al., 2018; Kim, Umeda, Lochbaum, & Stegemeier, 2016; M.; Liu et al., 2019) and sleep (Brown, Cairney, & Kwan, 2021; Brown, Kwan, Arbour-Nicitopoulos, & Cairney, 2021) among children and youth.

Simultaneously, the prevalence of depressive and anxiety disorders has recently increased among adolescents in many countries (Erskine et al., 2017; Gyllenberg et al., 2018; Keyes, Gary, O'Malley, Hamilton, & Schulenberg, 2019). While symptoms of depression and anxiety are among the key symptoms of mental ill-being, self-esteem, in turn, is considered an important indicator of mental wellbeing among adolescents (Antaramian, Scott Huebner, Hills, & Valois, 2010). According to positive psychology and a dual-factor model, incorporating indicators of both mental ill-being and positive wellbeing are important when examining adolescents' psychological adjustment (Antaramian et al., 2010; Greenspoon & Saklofske, 2001; Seligman & Csikszentmihalyi, 2000).

Achieving higher levels of physical activity, lower levels of sedentary behavior, better sleep quality, adequate sleep duration, and shorter sleep latency associate with better mental health and wellbeing among adolescents (Bell, Audrey, Gunnell, Cooper, & Campbell, 2019; Biddle, Ciaccioni, Thomas, & Vergeer, 2019; Lovato & Gradisar, 2014; O'Callaghan et al., 2021; Rodriguez-Ayllon et al., 2019; Weatherson et al., 2020). Cross-sectional studies often assume movement behaviors represent the causal factor, that is, they affect mental health. However, the association may also be reverse; adolescents with poorer mental health may be less likely to engage in favorable behaviors (Lovato & Gradisar, 2014; Pascoe & Parker, 2019; Puukko, Hietajärvi, Maksniemi, Alho, & Salmela-Aro, 2020; Vella, Swann, Allen, Schweickle, & Magee, 2017). Gunnell et al., for example, examined bidirectional relationships between physical activity, screen time, and symptoms of anxiety and depression over time during adolescence, although not by using a person-oriented approach (Gunnell et al., 2016). They found that greater initial symptoms of depression predicted greater decreases in physical activity, but no other relationship between initial behavior, anxiety, or depression as predictors of change in each other were detected (Gunnell et al., 2016).

Despite widespread public attention to the assumed negative consequences of digital use on mental health, existing research evidence showing associations between higher amounts of digital media use and poorer psychological wellbeing among young people is primarily cross-sectional (Appel, Marker, & Gnambs, 2020; Babic et al., 2017; Odgers & Jensen, 2020; Orben, 2020; Orben & Przybylski, 2019; Tang, Werner-Seidler, Torok, Mackinnon, & Christensen, 2021; Tóth-Király, Morin, Hietajärvi, & Salmela-Aro, 2021). Furthermore, many studies do not differentiate between different types of digital use, such as between active (participatory media use, e.g., chatting, messaging, and liking) and passive use (media consumption, e.g., viewing programs) (Hallgren, Dunstan, & Owen, 2020), although different types of digital media use may be differentially associated with mental health (Tang et al., 2021) and recent studies have questioned the use of total screen time (Hietajärvi, Salmela-Aro, Tuominen, Hakkarainen, & Lonka, 2019; Hietajärvi, Seppä, & Hakkarainen, 2017).

The primary theories concerning how and why digital use and mental health might be related include the Goldilocks hypothesis, which proposes that digital use at moderate levels is not intrinsically harmful and may be advantageous, whereas "overuse" may displace alternate enriching activities and spending time with family and friends (Przybylski & Weinstein, 2017). Moreover, digital use may relate to mental health by displacing physical activity and sleep (Rodriguez-Ayllon et al., 2019; Sampasa-Kanyinga et al., 2020). However, the relationship between different combinations of movement behaviors and mental wellbeing among youth remains relatively unstudied until recently (Gilchrist et al., 2021; Khan & Burton, 2017; Sampasa-Kanyinga et al., 2020). A recent cross-sectional study identified four distinct movement behavior profiles among adolescents and observed that a profile characterized by high amounts of physical activity and low amounts of digital media use was consistently associated with the highest levels of mental wellbeing (Brown, Cairney, & Kwan, 2021). Another study found a similar profile characterized by high levels of physical activity and low amounts of digital media use among adolescents to be associated with lowest depressive symptoms both currently and one year later (Brown, Kwan, et al., 2021). Furthermore, a study using isotemporal substitution analysis showed that replacing 60 minutes of screen time with either moderate-to-vigorous physical activity or sleep associated with better self-esteem and resiliency among adolescents (Brown & Kwan, 2021).

At present, little is still known about how digital media use, physical activity, and sleep behaviors interact among adolescents, or about the determinants of behavior patterns. Additional research integrating multiple types of digital media use with related sleep behaviors and physical activity, and which includes a wide range of mental health indicators with a several year follow-up period is needed. Thus, we aimed to identify behavior profiles indicated by digital media use (including related bedtime delays) and physical activity assessed at 15 years in a large sample of adolescents. In addition, we aimed to examine whether self-esteem, and depressive or anxiety symptoms at 11 years predict these identified behavior profiles four years later.

2. Methods

2.1. Study design and participants

The Finnish Health in Teens study (Fin-HIT) is a prospective cohort study among school-aged adolescents across Finland (Figueiredo et al., 2018). In this analysis, we analyzed data from the Fin-HIT pilot study, which comprised a total of 1599 children and included assessments of mental health symptoms (Figueiredo et al., 2018). Baseline data were collected in 2011, when participants' mean age was 11 years, with follow-up data collected in 2015, when the mean age was 15 years. All children born in Finland between February 26, 2000 and May 6, 2000 and for whom household information was available from the Population Register Center were invited to participate in the Fin-HIT pilot study in 2011. The participation rate was 14% (1599 out of 11282 children). More detailed description of the Fin-HIT cohort appears elsewhere (Figueiredo et al., 2018). All Fin-HIT study procedures adhered to the 1964 Helsinki Declaration and its subsequent amendments or by employing comparable ethical standards. The Coordinating Ethics Committee of the Hospital District of Helsinki and Uusimaa approved the study protocol (169/13/03/00/10). We obtained written informed consent from all children who participated in the study and from one of their guardians.

2.2. Measures

2.2.1. Mental health indicators at 11 years

Self-esteem. We assessed self-esteem using the 24-item Self-Perception Profile for Children (SPPC) (Harter, 1982; Miller, 2000). SPPC consists of four subscales all of which showed satisfactory internal consistency and composite reliability based on the bootstrapped 95% confidence interval (CI) for Cronbach's alpha (α) and MacDonald's omega (ω): *athletic competence* (six items: α 95% CI: 0.64–0.69; ω 95% CI: 0.65–0.70), *scholastic competence* (six items: α 95% CI: 0.69–0.74; ω 95% CI: 0.69–0.74), *self-acceptance* (six items: α 95% CI: 0.82–0.85; ω 95% CI: 0.82–0.85), and *social acceptance* (six items: α 95% CI: 0.69–0.74; ω 95% CI: 0.71–0.75). Higher mean composite scores indicate a stronger self-esteem on the corresponding component.

Depressive symptoms. We used the 20-item Center for Epidemiological Studies Depression Scale for Children (CES-DC) to assess the frequency of depressive symptoms during the last week (Weissman, Orvaschel, & Padian, 1980). CES-DC has exhibited a solid internal consistency in previous studies (Stockings et al., 2015; Weissman et al., 1980) as well as in the current study (α 95% CI: 0.91–0.93; ω 95% CI: 0.92–0.93). A higher mean composite score indicates greater depressive symptoms.

Anxiety symptoms. We assessed children's anxiety symptoms during the last three months using 16 items from the Screen for Child Anxiety-Related Emotional Disorders (SCARED) (child-reported version) (Birmaher et al., 1997). SCARED has shown excellent internal consistency and a good test–retest reliability (Birmaher et al., 1997; Runyon, Chesnut, & Burley, 2018). SCARED includes subscales for *social anxiety* (seven items: α 95% CI: 0.84–0.86; ω 95% CI: 0.84–0.86) and *generalized anxiety* (nine items: α 95% CI: 0.92–0.93; ω 95% CI: 0.92–0.93). Higher mean composite scores indicate a higher anxiety level.

2.2.2. Digital media use and physical activity at 11 years and at 15 years

We assessed digital media use and physical activity outside school hours using a web-based questionnaire. The digital media use questions were adopted from the World Health Organization (WHO)'s Health Behavior in School-aged Children (HBSC) study (WHO, 2006). WHO HBSC questions have shown a fair to substantial test–retest reliability depending on the criteria used (Bobakova et al., 2014; Y. Liu et al., 2010; Vereecken, 2001).

Passive and active media use, and gaming. We assessed passive media use (i.e., media consumption) through the following questions: "How many hours a day during your free time do you normally watch TV, videos, or DVDs? By TV, we mean programs that can be watched on TV as well as on a computer." In addition, we asked about active media use (i.e., participatory media use). This differed between baseline and follow-up so that at baseline the question included gaming: "How many hours a day during your free time do you normally use a computer, e.g. spend time on the Internet, chat or play computer or TV games sitting down (e.g. PlayStation, Xbox)?, whereas at follow-up gaming was not included with the following phrasing: "How many hours a day during your free time do you normally use a computer, tablet (e.g., iPad), or smart mobile phone for purposes other than games? For example, we mean for homework, emailing, tweeting, Facebook, chatting, or surfing the internet." Instead, gaming was assessed separately with a third question at follow-up, "How many hours a day during your free time do you normally play computer games or console games (e.g., PlayStation, Xbox, GameCube, etc.)? Do not count any so-called movement games (e.g., Move or Wii)." Adolescents answered each question separately for weekdays and for weekends or days off by choosing between nine response options, ranging from "not at all" to "around seven or more hours a day". For follow-up, we recoded each item to capture categories derived from earlier research examining the low-moderate and "too high" cut-offs of "screen time" in relation to observed effects in well-being, referred to as the Goldilocks hypothesis of media use (Przybylski, Orben, & Weinstein, 2020; Przybylski & Weinstein, 2017): 1) not at all; 2) moderate (<2 hours with expected positive outcomes); 3) elevated (2–5 hours before which negative outcomes can be observed); and 4) excessive (>5 hours which expected to associate with psychological ill-being). For baseline, we calculated overall self-reported daily screen time by summing up reported scores, with weekday scores weighted by 5 and weekend scores weighted by 2.

Bedtime delay. At follow up, participants also reported the time at which they stopped using digital devices each evening as an indicator of bedtime delay by answering the following questions: "When do you normally stop using a computer, tablet, phone, game console, or other electronic device if you go to school on the following day?" and "… on weekends or days off, when you do not go to school on the following day?" The 15 response options ranged from "9.00 p.m. or earlier" to "4.00 a.m. or later". We categorized responses to indicate bedtimes that would enable children to get the recommended amounts of sleep, i.e. 8–10 hours per 24 hours for adolescents aged 13–18 years (Paruthi et al., 2016), assuming that they need to wake up for school at least on weekdays: 1) no delay (before 10 p.m.); 2) slightly delayed (10–11 p.m.); 3) delayed (11 p.m. to midnight); and 4) very delayed (after midnight).

Leisure-time physical activity (LTPA). At baseline, participants reported the weekly duration of physical activity outside school hours by answering the following question in the questionnaire: "How many hours a week you normally exercise or do sports during your free time? Include all the exercise you do in a club or team and any exercise you do by yourself, with family or friends". The ten response options ranged from "not at all" to "10 hours or more per week". We scaled the weekly LTPA duration to represent daily LTPA at baseline.

At follow-up, the participants reported the frequency of physical activity by answering the following question: "How often do you normally exercise or do sports during your free time? Include all the exercise you do in a club or team and any exercise you do by yourself, with family or friends". The ten response options ranged from "never" to "seven times a week or more often". In addition, the average duration of each exercise session was assessed with the question, "On average, how long do you exercise or do sports each time during your free time?", with four response options: "less than 20 minutes", "20–40 minutes", "40–60 minutes", and "more than 60 minutes". The following question addressed the average intensity of exercise: "How intensively do you normally exercise or do sports during your free time?". The three response options were as follows: "I do not get out of breath", "I get a little bit out of breath (I can talk without panting)", and "I get out of breath a lot (I cannot talk without panting)".

For follow-up, we calculated the MET (hours/week) index (one MET refers to the resting metabolic rate while sitting) for LTPA by multiplying the frequency, mean duration, and mean intensity similar to previous studies (Pahkala et al., 2013; Raitakari et al., 1996). Coefficient values for the weekly frequency of activity were 0 (no LTPA), 0.25 (less than once a month), 0.5 (1–3 times per month), 1 (once a week), 2 (twice a week), and so on. Coefficient values for the average duration of each session were 0.17 (less than 20 minutes), 0.5 (20–40 minutes), 0.83 (40–60 minutes), and 1.33 (more than 60 minutes). We chose coefficient value 4 to correspond with light activity (I do not get out of breath), 6 with moderate activity (I get a little bit out of breath), and 10 with vigorous activity (I get out of breath a lot) in order to estimate the average metabolic cost of that intensity level (Ainsworth et al., 2011). The range of the MET index was 0–93 h/week. We categorized LTPA into 1) very low (<7.5 MET hours/week), 2) low (≥7.5–20 MET hours/week), 3) moderate (≥21–42 MET hours/week), and 4) high (>42 MET hours/week). The categorization was based on the physical activity guidelines for adolescents. Thus, ≥21 MET hours/week corresponds to meeting the recommendation of at least an average of 60 minutes/day of moderate-to-vigorous intensity physical activity across the week (J.-P. Chaput et al., 2020; Lee, Djoussé, Sesso, Wang, & Buring, 2010).

2.2.3. Background characteristics

We verified information on participants' birthdays and sex with the National Population Information System at the Population Register Center (Figueiredo et al., 2018). The sample was sex-balanced, consisting of 51.5% girls. We used maternal occupation at the time of the child's birth, which was collected from the Finnish Institute for Health and Welfare's Medical Birth Register (THL, 2022), as an indicator of maternal socioeconomic status (SES). We categorized SES into higher (upper-level employees and lower-level employees) and lower (manual workers, students, self-employed persons, stay-at-home mothers, unemployed persons and pensioners) level. In addition, parents reported their highest education qualification at baseline: the majority were educated beyond the secondary education level, with participants whose parents had no degree underrepresented when compared to the general Finnish population (SVT, 2021). However, the education qualification was missing for 8% of participants, which, if indicative of no degree, would correct the distribution, becoming more representative of Finland in general. We categorized parental education into higher (university or university of applied sciences) and lower (high school, vocational school or comprehensive school) education. At baseline and follow-up, families received instructions on how to measure the weight and height of adolescents, and we calculated an age- and sex-specific BMI z-score (BMIz) according to the International Obesity Task Force reference values (Cole & Lobstein, 2012). BMI based on self-reported measurements did not significantly differ when compared to standardized measurements at school (Sarkkola et al., 2016).

2.3. Statistical methods

Missing data and attrition. Altogether, 7.99% of the data was missing from the raw items in our sample, showing a pattern or completely missing at random ($\chi^2(13880) = 4463$, $p = 1$). Out of 1288 participants at baseline, 814 continued to the follow-up. Based on the attrition analysis (linear models with missing data at Time 2 predicted using predictor variable values from Time 1), it seems that participants whose parents had higher educational level (college or university) were less likely to drop-out of the study than participants whose parents had lower educational level. All data were multiply imputed.

Preliminary analyses. First, we conducted preliminary analyses and examined the amount and pattern of the missing data; the dataset was then multiply imputed 20 times. We further examined the distributions, correlations (Additional file 1) and reliabilities (when applicable, from observed data) of the variables to ensure data integrity and that our data satisfied the required statistical assumptions.

Latent class analysis to identify profiles of digital media use and physical activity. Based on simulations and the characteristics of our model (LCA with categorical indicators and multiply imputed data), we decided to utilize the pooled Bayesian Information Criterion (BIC) to initially inform the number of classes (Masyn, 2013; Morovati, 2014; Nylund, Asparouhov, & Muthén, 2007; Yang, 2006). In addition, we computed Bayes factors and likelihood increment percentage based on the pooled BIC (Grimm, Houpt, & Rodgers, 2021; Masyn, 2013). Lower values for BIC point towards a better fit to the data, The Bayes factor can be used to compare two competing models (k+1). The likelihood increment percentage and it's per parameter version (LIPpp) provides information on the likelihood improvement by each additional parameter – when this improvement is low, a more parsimonious model is preferred. Furthermore, to limit the computational time and to avoid capitalizing on chance over too many statistical tests, we decided on class enumeration through a two-fold process (Asparouhov & Muthén, 2012; Nylund et al., 2007). First, we examined the range of plausible solutions with BIC and LIPpp by increasing the number of classes until the lowest value in BIC or an elbow point in either BIC or LIPpp (Masyn, 2013; Nylund et al., 2007) was identified. Second, we tested between competing neighboring models using BF. In addition, we relied on an entropy value as an indicator of the classification quality, with entropy >0.8 indicative of a clear classification of participants in their most likely classes.

However, simulation studies have shown that none of the indices alone can reliably detect the proper solution across all combinations of, for instance, model specification, sample size, or number of indicators (Masyn, 2013; Morovati, 2014) and little is known of pooled fit indices performance with multiply imputed data. Thus, given the known discrepancies between statistical information criteria across situations, we relied heavily on the interpretability of the additional classes in terms of usefulness and their revealing of qualitative differences in the shape of the profiles instead of mere differences (Masyn, 2013; Morovati, 2014).

Differences in means between the identified profiles in background characteristics, and baseline digital media use and LTPA, and follow-up BMIz were examined using Wald test.

Latent class predictors. Covariates (maternal SES, parental education, and baseline BMIz, passive and active digital media use and LTPA) and baseline mental health indicators were treated as class predictors of the identified digital media use and LTPA class profiles. After selecting the final latent class model, we specified three models for class membership prediction using the manual Bolck-Croon-Hagenaars (BCH) functionality (Asparouhov & Muthén, 2020), essentially creating a hierarchical multinomial logistic regression model while taking into account the classification uncertainty. Model 1 comprised of sex, maternal SES and parental education. In Model 2, baseline variables BMIz, passive digital media use, active digital media use, and LTPA were added as additional predictors. In Model 3, mental health indicators assessed at baseline were further added as predictors. The profiles that we considered as unhealthiest (class 4) and healthiest (class 2) profiles of digital media use and physical activity behaviors were used as reference groups. Due to concerns of multicollinearity among the mental health indicators, simplified models for each mental health predictor were further estimated. Finally, explorative analyses were conducted to visually examine the means and mean differences of the baseline variables by each latent class using the manual BCH and z-tests for comparing pairwise mean differences.

Statistical analyses were conducted with the softwares R 4.1.2 (R Core Team, 2021), Rstudio 2021.09.1 (RStudio Team, 2020), and Mplus 8.6 (Muthén & Muthén, 1998-2021).

3. Results

3.1. Participant characteristics

In total, 1599 preadolescents participated in the Fin-HIT pilot study, for whom 1288 data were available on the mental health indicators at baseline, and 815 who also participated at follow-up. The mean age of participants was 11.23 years (SD ± 0.11) at baseline and 15.46 years (SD ± 0.10) at follow-up. The mean follow-up time was 4.23 years (SD ± 0.13). Table 1 summarizes the background characteristics, and baseline digital media use, LTPA and mental health indicators of participants, while Table 2 shows the categories of digital media use and LTPA at follow-up. For example, the proportions of adolescents who at follow-up engaged in excessive amounts of media use (>5 hours/day) on weekdays and on weekends were 4% and 15% for passive media consumption, 11% and 20% for active media participation, and 2% and 11% for gaming, respectively. In addition, only 3% reported a very delayed bedtime (after midnight) because of digital use on weekdays, which increased to 33% on weekends. Altogether 37% of adolescents engaged in very low or low levels of LTPA at follow-up.

3.2. Correlations between variables

Additional file 1 presents the full correlation matrix of baseline and follow-up variables. The following baseline variables correlated with each other (r < 0.1). Greater symptoms of depression and general anxiety correlated with higher amounts of passive (r = 0.17; r = 0.12) and

Table 1
Characteristics and mental health indicators of participants (multiply imputed values for the full sample, n = 1288).

Characteristic	Mean (SD), or %
Baseline	
Age (in years)	11.23 (0.11)
Body mass index z-score	0.31 (0.98)
Sex	
Girl	51.5%
Boy	48.5%
Maternal socioeconomic status	
Higher level	71.8%
Lower level	28.2%
Parental educational level	
University or University of Applied Sciences	46.0%
High school, vocational school or comprehensive school	54.0%
Depressive symptoms (CES-DC score)	1.46 (0.38)
Anxiety symptoms (SCARED scores)	
Social anxiety	1.81 (0.48)
Generalized anxiety	1.55 (0.45)
Self-esteem (SPPC scores)	
Athletic competence	2.15 (0.36)
Scholastic competence	2.35 (0.35)
Self-acceptance	2.54 (0.38)
Social acceptance	2.33 (0.36)
Passive digital media use (hours/day)	1.94 (1.14)
Active digital media use (hours/day)	1.45 (1.12)
Leisure-time physical activity (hours/day)	0.95 (0.38)
Follow-up	
Age (in years)	15.46 (0.10)
Body mass index z-score	0.40 (0.92)
Sex	
Girl	51.6%
Boy	48.4%

Abbreviations: *CES-DC,* Center for Epidemiological Studies Depression Scale for Children (20 items); *SCARED,* Screen for Child Anxiety-Related Emotional Disorders (child-reported version, 16 items); *SD,* standard deviation; *SPPC,* Self-perception Profile for Children (24 items).

active (r = 0.22; r = 0.11) digital media use, whereas greater symptoms of social anxiety correlated with lower amount of LTPA (r = −0.12). Perceptions of better athletic competence and self-acceptance correlated with lower BMIz (r = −0.18; r = −0.13), less passive (r = −0.15; r = −0.17) and active (r = −0.14; r = −0.18) media use, and higher amount of LTPA (r = 0.32; r = 0.13). Perception of better scholastic competence correlated with less passive (r = −0.16) and active (r = −0.20) media use. Perception of better social acceptance correlated with lower amounts of passive (r = −0.12) and active (r = −0.12) digital media use and with higher amount of LTPA (r = 0.20). Moreover, symptoms of depression correlated positively with social anxiety (r = 0.23) and general anxiety (r = 0.38) and negatively with the dimensions of self-esteem (athletic competence, r = −0.24; scholastic competence, r = −0.34; self-acceptance, r = −0.52; social acceptance, r = −0.38).

3.3. Profiles of digital media use and physical activity at follow-up

Class enumeration. The lowest pooled BIC was achieved at six classes (see Additional file 2). Similarly, Bayes Factor showed support up to six classes. However, LIPpp started to flatten and showed low improvement (0.3) with the addition of five or more classes. The elbow plot indicated that the BIC values flattened after fourth class, and the confidence intervals of the pooled BIC values overlapped, indicating that extracting more than four profiles could entail overfitting. The entropy value was high (>0.85) for all considered solutions. Based on the substantive information provided by the classes, the final four-class solution (Fig. 1) provided all of the qualitatively different classes and >10% of participants were likely to belong even to the smallest class, whereas fifth and sixth classes started to repeat the class-structure without meaningful differences in profile shape.

Fig. 1 (and Additional file 3) shows the identified four class profiles,

Table 2
Digital media use and physical activity at follow-up (multiply imputed values for the full sample, n = 1288).

	%
Digital media use on weekdays	
Passive media use (n = 789)	
None	5%
Moderate (<2 hours/day)	44.6%
Elevated (2–5 hours/day)	46.9%
Excessive (>5 hours/day)	3.5%
Active media use (n = 813)	
None	2.3%
Moderate (<2 hours/day)	41.9%
Elevated (2–5 hours/day)	45.2%
Excessive (>5 hours/day)	10.6%
Gaming (n = 813)	
None	56.7%
Moderate (<2 hours/day)	20.5%
Elevated (2–5 hours/day)	20.5%
Excessive (>5 hours/day)	2.4%
Bedtime delay (n = 814)	
No delay (before 10 p.m.)	43.1%
Slightly delayed (10–11 p.m.)	42.1%
Delayed (11 p.m. to midnight)	21.3%
Very delayed (after midnight)	2.5%
Digital media use on weekends or days off	
Passive media use (n = 798)	
None	1.4%
Moderate (<2 hours/day)	18.6%
Elevated (2–5 hours/day)	65%
Excessive (>5 hours/day)	14.9%
Active media use (n = 813)	
None	2.0%
Moderate (<2 hours/day)	30.2%
Elevated (2–5 hours/day)	48.4%
Excessive (>5 hours/day)	19.5%
Gaming (n = 813)	
None	47.9%
Moderate (<2 hours/day)	16.6%
Elevated (2–5 hours/day)	24.5%
Excessive (>5 hours/day)	11.0%
Bedtime delay (n = 813)	
No delay (before 10 p.m.)	11.9%
Slightly delayed (10–11 p.m.)	24.0%
Delayed (11 p.m. to midnight)	31.4%
Very delayed (after midnight)	32.7%
Leisure time physical activity (n = 799)	
Very low (<7.5 MET hours/week)	12.6%
Low (≥7.5–20 MET hours/week)	24.2%
Moderate (≥21–42 MET hours/week)	31.9%
High (>42 MET hours/week)	31.3%

Abbreviations: *MET,* metabolic equivalent.

which we labeled as follows:

Class 1 (n~255/20% of participants; 78% boys): high digital media use/moderate LTPA. This profile was characterized by elevated passive and active digital media use throughout the week. In addition, adolescents belonging to this profile showed moderate gaming on weekdays but elevated on weekends. They reported slightly delayed bedtime on weekdays and very delayed bedtime on weekends, and moderate LTPA.

Class 2 (n~399/31% of participants; 28% boys): moderate digital media use/high LTPA. This profile showed moderate passive and active media use on weekdays and elevated only on weekends. Adolescents belonging to this profile reported no gaming, and no bedtime delay on weekdays, and only slightly delayed bedtime on weekends. Their LTPA was high.

Class 3 (n~336/26% of participants; 15% boys): high digital media use/high LTPA. Adolescents in this profile reported elevated passive media consumption throughout the week, and elevated active media participation on weekdays and excessive on weekends. They showed no gaming throughout the week, and had only slightly delayed bedtime on weekdays but very delayed bedtime on weekends. They

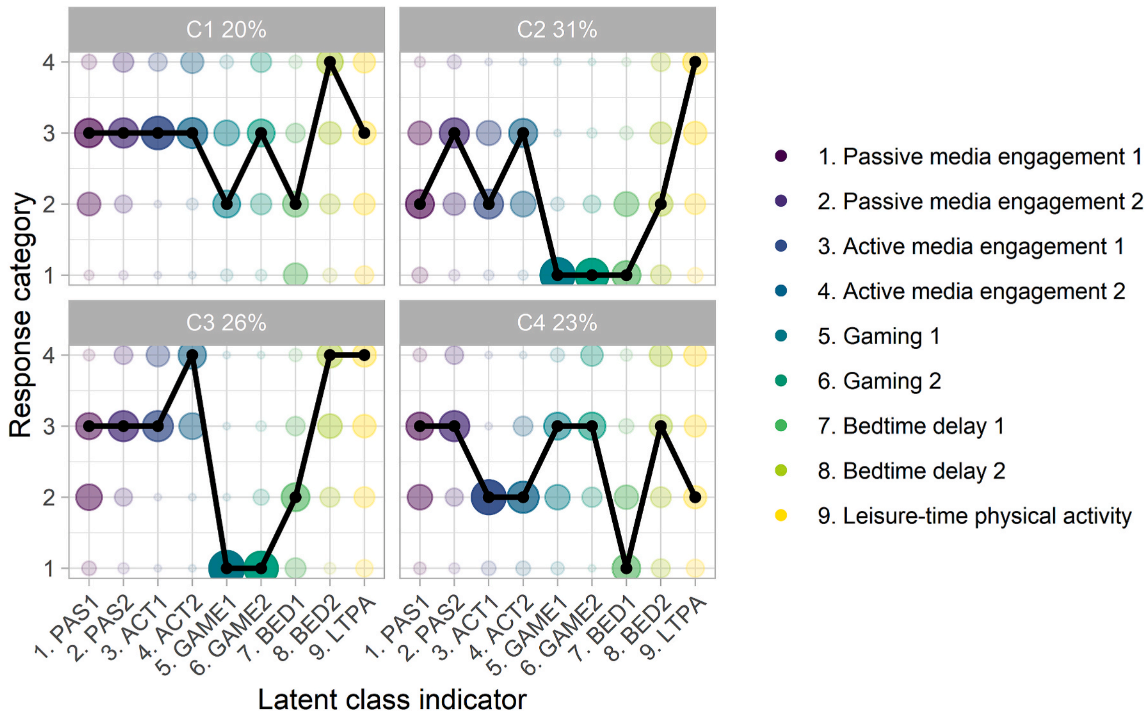

Fig. 1. Four identified classes (C1–C4) indicated by digital media use and leisure time physical activity at 15 years old (follow-up). Most likely response option (mode) plotted with black over the observed response distribution by most likely class. Variable names: 1 = on weekdays, 2 = on weekends or days off. Response categories: for digital media use (variables 1–4): 1 = not at all, 2 = moderate (<2 hours/day), 3 = elevated (2–5 hours/day), and 4 = excessive (>5 hours/day); for bedtime delay: 1 = no delay (before 10 p.m.), 2 = slightly delayed (10–11 p.m.), 3 = delayed (11 p.m. to midnight), and 4 = very delayed (after midnight); and for leisure-time physical activity variable: 1 = very low (<7.5 MET hours/week), 2 = low (≥7.5–20 MET hours/week), 3 = moderate (≥21–42 MET hours/week), and 4 = high (>42 MET hours/week).

reported high LTPA.

Class 4 (n~298/23% of participants; 89% boys): high passive digital media use and gaming/low LTPA. This profile showed elevated passive media consumption and gaming throughout the week, but moderate active media participation throughout the week. They reported no bedtime delay on weekdays but delayed bedtime on weekends. Their LTPA was the lowest.

Among the four identified profiles, we consider class 2 as "the healthiest" behavior profile with moderate overall digital media use and high LTPA. Conversely, we consider class 4 as "the unhealthiest" profile with high passive media consumption and gaming, bedtime delay on weekends, and lowest LTPA.

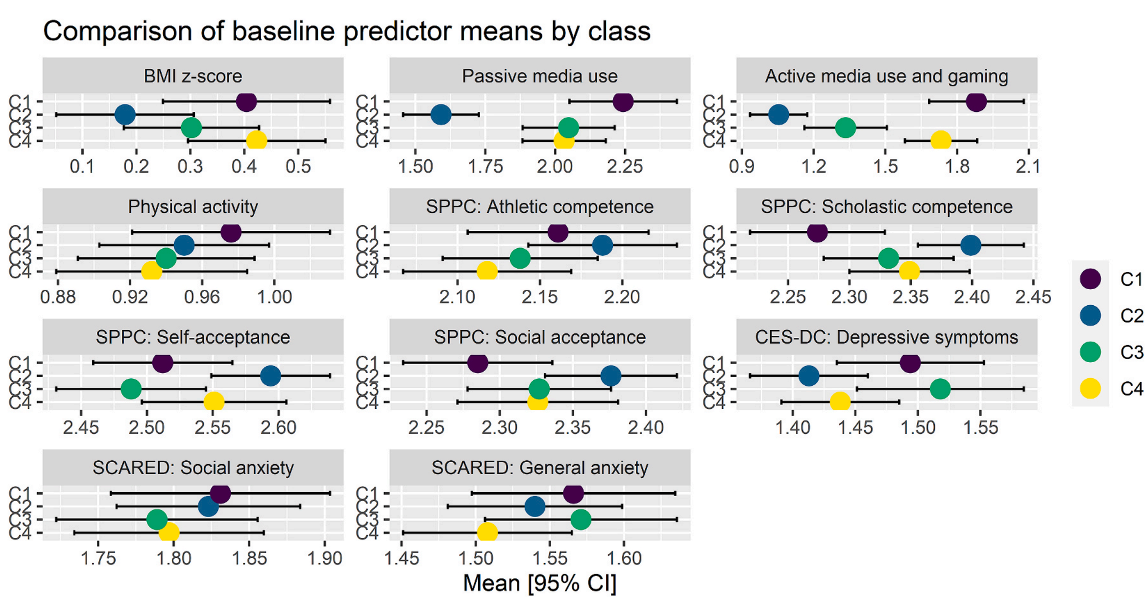

Fig. 2. Means with 95% confidence intervals for baseline body mass index z-score, digital media use, physical activity and mental health indicators by the class profiles indicated by follow-up digital media use and physical activity (C1–C4). Abbreviations: *CES-DC*, Center for Epidemiological Studies Depression Scale for Children (20 items); *SCARED*, Screen for Child Anxiety-Related Emotional Disorders (child-reported version, 16 items); *SD*, standard deviation; *SPPC*, Self-Perception Profile for Children (24 items).

3.4. Explorative examination of digital media use and physical activity profiles

Explorative examination of the variable means by the follow-up digital media use and LTPA profiles indicates that the groups differed in some key indicators already at baseline (Fig. 2). More precisely, class 4 (*high passive digital media use and gaming/low LTPA)* had higher baseline BMIz compared to class 2 *(moderate digital media use/high LTPA)* (p = 0.011). Class 2 engaged in higher amounts of passive digital media use compared to all other classes (p < 0.001 for all), whereas classes 1 *(high digital media use/moderate LTPA)* and 4 (*high passive digital media use and gaming/low LTPA)* engaged in higher amounts of active digital media use compared to classes 2 and 3 *(high digital media use/high LTPA)* (p < 0.001 for all), and class 3 compared to class 2 (p = 0.023). Class 2 experienced better scholastic competence (p < 0.001) and better social acceptance (p = 0.013) compared to class 1 *(high digital media use/moderate LTPA)*. Class 2 also experienced better self-acceptance (p = 0.010) but more depressive symptoms compared to class 3 (p = 0.021). Furthermore, the four classes differed in follow-up BMIz (see Additional file 6). The mean follow-up BMIz was lowest in class 2 (*moderate digital media use/high LTPA)*.

3.5. Covariates as predictors of digital media use and physical activity profiles

Fig. 3 shows the probability of class membership predicted by sex, maternal SES, parental educational level, baseline BMI z-score, and baseline passive and active digital media use and LTPA, when all in the same model (Model 2) (see Additional files 4 and 5 for all parameters). The healthiest (class 2) and unhealthiest (class 4) behavior profiles were used as reference groups. Boys were more likely to be in class 4 (*high passive digital media use and gaming/low LTPA)* compared to all other classes, and in all other classes than in class 2 *(moderate digital media use high LTPA)*. Moreover, higher amount of LTPA at baseline associated with higher odds of belonging to any other class compared to class 4. Moreover, lower digital media use at baseline associated with higher odds of belonging to class 2 or 3 (*high digital media use/high LTPA)* compared to class 4. Higher passive digital media use associated with higher odds of belonging to classes 1 (*high digital media use/moderate LTPA)* or 3 compared to class 2*,* and higher active media use and gaming associated with higher odds of belonging to class 4 compared to class 2.

3.6. Baseline mental health indicators as predictors of digital media use and physical activity profiles

Fig. 4 summarizes the adjusted (for sex, maternal SES, parental educational level, and baseline BMIz, passive and active digital media use and LTPA) associations of self-esteem and symptoms of depression and anxiety at the age of 11 years with the digital media use and LTPA behavior profiles at the age of 15 years (probability of class memberships) (see Additional files 4 and 5 for parameters).

Self-esteem. Perception of better athletic competence at baseline associated with increased odds of belonging to all other classes compared to class 4 (*high passive digital media use and gaming/low LTPA)* at follow-up. Perceptions of scholastic competence, or social or self-acceptance did not associate with later behavior profiles after controlling for baseline covariates.

Symptoms of depression and anxiety. Experiencing symptoms of depression or anxiety at baseline did not associate with the digital media use and LTPA profiles four years later after controlling for baseline covariates, including digital media use and LTPA.

The post-hoc models indicated that the effects concerning athletic competence were also significant with the exception that in the simplified model there were no difference between class 1 (*high digital media use/moderate LTPA)* and class 4 (*high passive digital media use and gaming/low LTPA)*. In addition, the post-hoc models indicated that poorer perception of scholastic competence and social acceptance in preadolescence would be associated with belonging to class 1 compared to class 2 *(moderate digital media use/high LTPA)* in adolescence, although these effects were not significant in the full model. Due to the gendered nature of the profiles the interaction of sex with each of the mental health indicators were tested with product terms, but none were significant, indicating that sex did not moderate the relationships.

4. Discussion

Our study was the first to examine whether mental health indicators in preadolescence predict future behavior profiles indicated by different types of digital media use, related bedtime delay, and LTPA in adolescence. We identified four different behavior profiles in adolescence (at 15 years of age); One third (31%) of adolescents belonged to the profile considered the healthiest and characterized by *moderate digital media use and high LTPA*, while 23% belonged to the unhealthiest behavior profile characterized by *high passive digital media use and gaming, and low LTPA*. In addition, 20% of participants belonged to a profile showing *high digital media use and moderate LTPA*, and 26% belonged to a profile

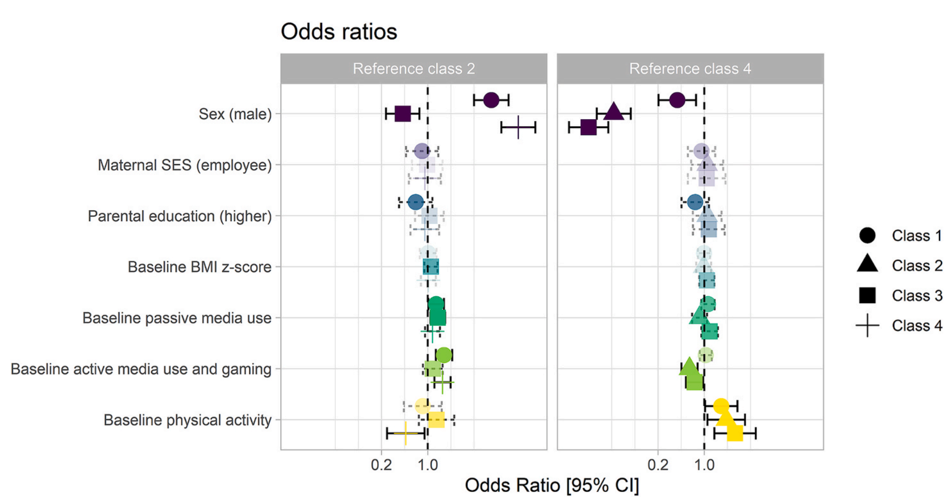

Fig. 3. Odds ratios and 95% confidence intervals (CI) for sex, maternal socioeconomic status (SES), parental education, and baseline body mass index (BMI) z-score, passive and active digital media use and leisure-time physical activity (all in same model) as predictors of class membership (C1–C4) at follow-up. X-axis on logarithmic scale, dashed error bar indicates a non-significant odds ratio (confidence interval contains 1).

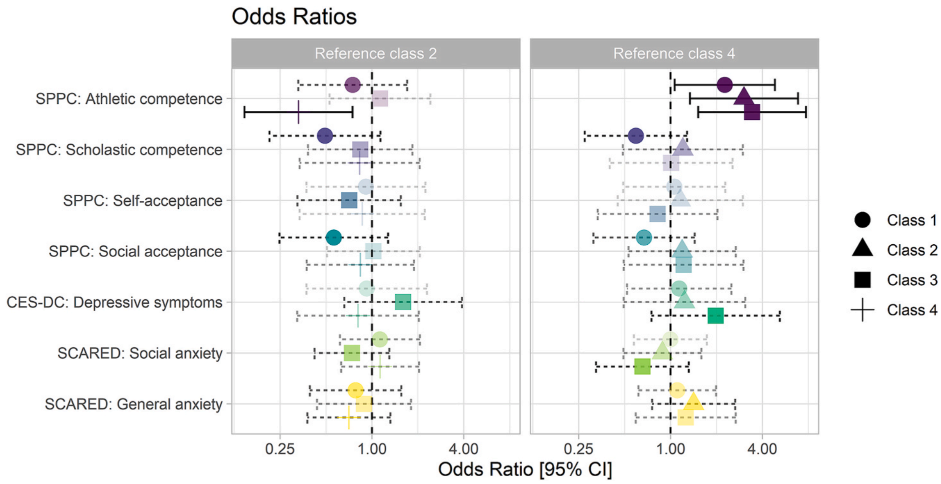

Fig. 4. Odds ratios and 95% confidence intervals (CI) for mental health indicators at 11 years as predictors of class membership (C1–C4) at 15 years. X-axis on logarithmic scale, dashed error bar indicates a non-significant odds ratio (confidence interval contains 1). Adjusted for sex, maternal SES, parental educational level, and baseline covariates: body mass index z-score, passive and active digital media use and physical activity. Abbreviations: *CES-DC*, Center for Epidemiological Studies Depression Scale for Children (20 items); *SCARED*, Screen for Child Anxiety-Related Emotional Disorders (child-reported version, 16 items); *SD*, standard deviation; *SES*, socioeconomic status; *SPPC*, Self-Perception Profile for Children (24 items).

showing *high digital media use and high LTPA*. Moreover, higher amount of LTPA and better perception of athletic competence at the age of 11 years predicted belonging to all other digital media use and LTPA behavior profiles than to the unhealthiest one four years later. Symptoms of depression or anxiety did not predict later behavior profiles.

The four class profiles identified as well as our correlational analysis on baseline variables indicate that lower levels of LTPA and bedtime delay often occur alongside with elevated or excessive amounts of overall digital media use. However, even within the profiles characterized by high digital media use, a proportion of adolescents engaged in high levels of LTPA. It may be that some adolescents with high LTPA engage in high amounts of sport-related digital media use. More importantly, high amounts of digital media use do not necessarily displace LTPA but rather activities involving lighter intensity physical activity, such as walking and hanging out with friends, which were not captured by the LTPA measure we used. Moreover, our explorative crude examinations showed that adolescents belonging to the unhealthiest follow-up behavior profile characterized by *high passive digital media use and gaming/low LTPA* had higher BMI at baseline compared to the healthiest behavior profile. In addition, follow-up BMI was lowest in the healthies profile, which in general showed moderate digital media use and high LTPA. These results are in accordance with our previous findings showing that higher amounts of total screen time and lower amounts of LTPA associate with higher weight among Fin-HIT adolescents (Engberg, Figueiredo, Rounge, Weiderpass & Viljakainen, 2019, 2019; Engberg, Leppänen, Sarkkola, & Viljakainen, 2021).

A major strength to our study is its prospective study design, which enables examining the longitudinal relationships between mental health indicators and behavior profiles. However, the assessment methods of digital media use and LTPA differed between baseline and follow-up, and thus, we were unable to examine the actual change in those behaviors. We were, however, able to use the amounts of active and passive digital media use and LTPA at baseline as covariates/class predictors in our analyses. When all covariates were in the same model, the follow-up behavior profiles differed by baseline behaviors: LTPA, active digital media use and gaming, and passive digital media use, and by sex. More precisely, boys were most likely to belong to the unhealthiest profile (*high passive digital media use and gaming/low LTPA)*. In contrast to our finding, other studies showed that North American and Canadian adolescent girls were more likely than boys to belong to unhealthier behavior profiles characterized by low physical activity and high overall daily screen time (Brown, Cairney, & Kwan, 2021; Brown, Kwan, et al., 2021). This discrepancy between the previous and our results may be partly explained by the profile indicators used. In our study, digital media use was measured in more detail by separating active and passive media use and gaming, whereas the other two studies used total screen time, and assessed physical activity with different questions than we did. Gaming is more prominent digital media activity and more likely develops into problematic gaming among boys than among girls (Stevens, Dorstyn, Delfabbro, & King, 2021).

We showed that higher amount of LTPA at baseline predicted belonging to any other profile than to the unhealthiest profile at follow-up, whereas higher amounts of active media use and gaming predicted belonging to the unhealthiest profile compared to the healthiest profile. Another longitudinal study also used the latent class analysis and identified five classes of accelerometer-measured physical activity and sedentary behavior at the age of 6, and six classes at the age of 9 (Jago et al., 2018). They showed that five classes exhibited similar general behavior patterns at both time points, which is line with our findings and with previous studies (Biddle et al., 2010) suggesting that these behaviors are relatively stable over time. The transition between classes was associated with sex, screen viewing, participation in out-of-school activities, and BMI (Jago et al., 2018). Similarly to our findings, the classes they identified indicate differences in adolescents' behaviors between weekdays and weekends.

We examined both mental ill-being (symptoms of depression and anxiety) and psychological assets (self-esteem), providing a more comprehensive picture of adolescents' mental adjustment (Antaramian et al., 2010; Greenspoon & Saklofske, 2001). Two very recent studies used the person-centered approach to identify distinct movement behavior profiles among 16-year-old adolescents, and examined its relationship with mental wellbeing or depressive symptoms (Brown, Cairney, & Kwan, 2021; Brown, Kwan, et al., 2021). In accordance with our findings, both prior studies identified four distinct profiles which differed by sex. Furthermore, one of these studies detected that U.S. adolescents belonging to the profile characterized by low physical activity and high screen time were more likely to have a lower household income (Brown, Kwan, et al., 2021). Sleep duration among each of the profiles was similar in both prior studies. A profile characterized by high amounts of physical activity and low amounts of digital media use associated with the most favorable scores for flourishing, self-esteem and resiliency and with lowest depressive symptoms, for which the trend was evident also one year after (Brown, Cairney, & Kwan, 2021; Brown, Kwan, et al., 2021). We detected similar cross-sectional crude associations of digital media use and physical activity with mental health indicators in our study, but the longitudinal associations were different, showing that perception of poor athletic competence reported in pre-adolescence predicted belonging to a future behavior profile characterized by elevated passive digital media use and gaming and low LTPA. After adjusting for confounding factors, including baseline digital media use and LTPA, symptoms of depression or anxiety did not predict later behavior profiles in our study. Unlike the two prior studies, we included different types of digital media use as well as bedtime delay related to digital media use in addition to physical activity when identifying behavior patterns.

We assessed mental health indicators only at baseline, and therefore, were unable to examine bidirectional associations between these indicators and digital media use and physical activity behaviors. However, one previous longitudinal study found bidirectional relationships between mental health indicators and sports participation among adolescents (Vella et al., 2017). Another recent longitudinal study identified three joint longitudinal parent-reported physical activity/screen time trajectories among children aged 0 to 9 using growth mixture modeling. Unlike we, they were able to examine the actual changes in behavior, and observed that children who progressively increased their physical activity and maintained low screen time levels experienced the best health-related quality of life and socio-emotional outcomes, while those who maintained low physical activity levels and increases in screen time experienced the worst (del Pozo-Cruz et al., 2019). Moreover, another study found that symptoms of depression, but not anxiety, at 14 years old predicted greater decreases in physical activity, but not vice versa. Neither depressive nor anxiety symptoms associated with changes in screen time (Gunnell et al., 2016), which is in line with our results showing that symptoms of depression and anxiety did not predict later behavior profiles. The above-mentioned studies examined total screen time and did not differentiate between the types of digital media use as we did. In another recent longitudinal study, depressive symptoms predicted small increases in active social media use during both early and late adolescence, whereas no evidence of the reverse relationship was found (Puukko et al., 2020).

The three digital media use profiles with the highest amounts of digital media use we identified were further characterized by delayed or vey delayed bedtime because of digital media use on weekends, but only slightly delayed or not at all delayed bedtime on weekdays. The discrepancy between sleep times on weekdays and weekends can cause individuals to feel "jet lagged" or fatigue (the social jet lag) with harmful health consequences (Touitou, Touitou, & Reinberg, 2016). The use of digital media and related overexposure to artificial light particularly at night may affect circadian physiology and serve as a major contributor to adolescents' decreased sleep duration and quality (Okoli, Hanlon, & Brady, 2021; Touitou et al., 2016), while poor sleep quality may increase problems with functioning at school (May, Bauer, Seibert, Jaurequi, & Fincham, 2020). Previous studies on the relationship between digital media use and delayed bedtime among adolescents have shown inconsistent results, some suggesting that the association is weak (Orben & Przybylski, 2020) and others that the associations vary according to adolescents' age or developmental phase (Maksniemi et al., 2022).

As previously mentioned, we found that higher amount of LTPA and better perception of athletic competence predicted healthier digital media use and LTPA behavior. The relationship between self-esteem and sedentary or digital media behaviors has not been extensively studied, with evidence showing mostly null or negative cross-sectional associations (Rodriguez-Ayllon et al., 2019). Moreover, prior studies indicate associations between higher levels of physical activity and better self-esteem among adolescents, although these findings are somewhat contradictory and mostly derived from cross-sectional studies (Eime, Young, Harvey, Charity, & Payne, 2013; Rodriguez-Ayllon et al., 2019). The association between digital media use or physical activity and athletic self-esteem may be bidirectional in nature. For example, young people with greater psychosocial assets such as better self-esteem may be more likely to participate in organized sports, which, in turn, may serve to further facilitate the development of psychosocial assets. Our results regarding physical activity and related self-esteem being strong predictors of later movement behaviors are in line with previous studies showing that physical activity behavior seem to track throughout the years (Telama et al., 2014). Therefore, our findings highlight the importance of promoting physical activity among youth.

The limitations of our study include our reliance on self-reported digital media use and LTPA, and not using more objective and device-based measurement methods, such as log data and an accelerometer. Despite these limitations related to possible under- or overreporting (Parry et al., 2021), self-report tools provide solid estimates of context-specific sedentary behavior, such as digital media use (Lubans et al., 2011). In addition, these methods are easy to administer and relatively inexpensive, and, thus, more feasible in large-scale studies. Moreover, we adapted the questions on digital media use from the WHO HBSC study, which have shown an acceptable reliability (Bobakova et al., 2014; Y. Liu et al., 2010; Vereecken C, 2001). We only asked adolescents about the time when they stopped using electronic devices in the evening at follow-up, and not about the time when they actually went to bed or woke up. However, we believe that using bedtime delay because of digital media use as one variable provides an interesting aspect to the identified behavior patterns. The response rate for the Fin-HIT pilot study was 14%, which may limit the generalizability of the results to the whole adolescent population in Finland. Altogether, 64% of preadolescents included in this analysis also participated in the follow-up study four years later. The parental education level of adolescents who participated in the follow-up study was higher compared to those who did not participate, which may limit the generalization of our findings to adolescents with a low socioeconomic status.

5. Conclusions

We identified four different profiles of digital media use (including a related bedtime delay) and physical activity among 15 years old adolescents. About 30% belonged to the healthiest behavior profile characterized by *moderate digital media use and high leisure-time physical activity*, whereas 23% belonged to the unhealthiest behavior profile characterized by *high passive digital media use and gaming with low leisure-time physical activity*. Higher amount of physical activity and better perception of athletic competence at 11 years of age predicted belonging to healthier digital media use and physical activity behavior profiles at 15 years of age. Our findings highlight the importance of physical activity and related self-esteem during preadolescence as predictors of future digital media use and physical activity behaviors.

Ethics approval and consent to participate

The Coordinating Ethics Committee of the Hospital District of Helsinki and Uusimaa approved the study protocol (169/13/03/00/10). All children who participated in the study and one of their guardians provided their written informed consent.

Availability of data and materials

The datasets used and/or analyzed for the current study as well as code and analysis materials can be downloaded from https://osf.io/d4jhe/.

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Authors' contributions

Elina Engberg: Conceptualization; Funding acquisition; Investigation; Writing - original draft; Writing - review & editing. Lauri Hietajärvi: Conceptualization; Formal analysis; Methodology; Data curation; Visualization; Writing - review & editing. Erika Maksniemi: Conceptualization; Writing - review & editing. Jari Lahti: Writing - review & editing. Kirsti Lonka: Writing - review & editing. Katariina Salmela-Aro: Writing - review & editing. Heli Viljakainen: Funding acquisition; Project administration; Resources; Writing - review & editing. All authors read and approved the final manuscript.

Declaration of competing interest

None.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.mhpa.2022.100448.

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