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RESEARCH ARTICLE

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Intraindividual associations between active social media use, exhaustion, and bedtime vary according to age—A longitudinal study across adolescence

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Abstract

Introduction: The majority of adolescents engage with others online, and using social media is one of their top activities. However, there is little longitudinal evidence addressing whether active social media use is associated with study-related emotional exhaustion or delayed bedtime at the individual level of development during adolescence.

Method: A 6-year longitudinal survey study ($N = 426$, female, 65.7%) was conducted (2014–2019) in Finland when the participants were 13–19 years old. Utilizing a Random Intercept Cross-Lagged Panel Model, this study focused specifically on longitudinal within-person effects.

Results: No clear patterns between increased active social media use, increased emotional exhaustion, and delayed bedtime were found; however, the associations varied across the years of adolescence: active social media use and delayed bedtime were only associated in early adolescence; active social media use and emotional exhaustion were associated in both middle and late adolescence.

Conclusions: Intraindividual relations between adolescents' reported active social media use, emotional exhaustion, and sleeping habits are small, inconsistent, and vary according to age. Therefore, future research should focus on additional longitudinal studies to examine the specific practices of social media use during the different developmental stages of at-risk individuals.

KEYWORDS

adolescence, bedtime, exhaustion, sleeping habits, social media use, well-being

1 | INTRODUCTION

Connecting with others through social media applications has become a ubiquitous part of everyday life for adolescents (Global Kids Online, 2019; Smahel et al., 2020). However, additional longitudinal and diverse evidence is needed to forward the debate on whether constant online connectedness and significant screen time is inherently beneficial or detrimental to young people (Huang, 2017; Odgers & Jensen, 2020; Orben, 2020; Stiglic & Viner, 2019). It is challenging to construct simplified assumptions of the effects of social media on adolescents' well-being because their use of social media is not uniform; in addition, social media can affect the lives of individuals in many ways (Beyens et al., 2020; Valkenburg & Peter, 2013; Valkenburg & Piotrowski, 2017).

It has been suggested that social media use is related to lower psychological well-being (Appel et al., 2020; Keles et al., 2020; Orben, 2020) and disturbed sleep (Alonzo et al., 2020; Scott & Woods, 2019). For a slightly more nuanced picture, it has been hypothesized that the potential outcomes of social media use differ according to whether the online activity can be considered “active” or “passive.” Active social media use means that the user is targeting one-to-one interactions (e.g., sending messages or commenting on posts); in turn, passive social media use is more about scrolling through content without forging social connections with others (Verduyn et al., 2017). Active social media use may have the potential to enhance well-being through social connectedness (Appel et al., 2020; Orben, 2020), and in contrast, passive social media use has been associated with lower psychological well-being (Thorisdottir et al., 2019). A recent review, however, challenged these assumptions on active and passive social media use and their positive or negative effects on well-being (Valkenburg et al., 2021). In addition to the active or passive dichotomy, social media use can be viewed as *private* or *public*. For example, private active social media use means that the adolescent is sending messages privately, whereas public active social media use means that the adolescent is commenting on open posts. Overall, private social media use is more common, more synchronous, and more intimate (Valkenburg et al., 2021); thus, it may result in stronger associations with adolescents' psychological well-being.

The current study contributes to the body of longitudinal research that examines the intraindividual links between active social media use and adolescents' academic well-being and sleeping habits. Academic well-being is a significant contributor to overall psychological well-being during the years of adolescence (Kiuru et al., 2019), a period that is also characterized by risky media behavior (Valkenburg & Peter, 2013), sleeping difficulties (Inchley et al., 2020), and feelings of academic pressure (Löfstedt et al., 2020). One of the factors affecting academic well-being on a daily basis is late bedtimes, attributing to inadequate sleep duration (Curcio et al., 2006) as well as perceived school-related exhaustion, these often intertwined with each other. Perceived school-related emotional exhaustion is defined as a feeling of chronic fatigue regarding schoolwork and being drained of emotional energy over lengthy periods (Salmela-Aro et al., 2009).

For the purposes of this study, we utilized a simple operationalization that defined active social media use as an activity in which contributors actively send messages, share updates, and react to the actions of others. This type of operationalization includes both private and public active social media use; thus, it can also be defined as *mixed active social media use* (Valkenburg et al., 2021). We analysed the reciprocal within-person relationships between mixed active social media use, school-related emotional exhaustion, and bedtime on schooldays across the years of adolescence (from age 13 to 19). The study's theoretical approach is derived from the energy-depleting aspects of the *Demands-Resources Hypothesis* (Demerouti et al., 2001; Salmela-Aro & Upadyaya, 2014), which suggests that the imbalance between daily psychological demands and resources results in negative outcomes in an adolescent's life. Regarding active social media use, the *Demands-Resources Hypothesis* emphasizes that the well-being effects of social media use are dependent on whether the use of social media increases or decreases the demands and resources. Specifically, it is expected that active social media use that increases daily psychological demands will be reflected in both late bedtimes and academic exhaustion because of overtaxing. Difficulties falling asleep due to the stimulating effect of active social media use may delay bedtime and thus lead to feelings of exhaustion the following day. This cycle can disrupt academic well-being and cause longitudinal feelings of study-related emotional exhaustion.

Second, our approach employs the *Differential Susceptibility to Media Effects Model* (DSMM) (Valkenburg & Peter, 2013), which emphasizes that the effects of media are partially dependent on the individual's pre-existing developmental susceptibility (Valkenburg & Peter, 2013). Despite its theoretical importance, little is known about the developmental differences in the social media effects during the years of adolescence. The present study focuses on developmental susceptibility, particularly at the within-person level, by analysing the associations between active social media use, emotional exhaustion, and bedtimes during early, middle, and late adolescence.

1.1 | Social media use and study-related emotional exhaustion

School provides a context for adolescents' psychosocial health and development (Eccles & Roeser, 2011; Eccles, 2004), and symptoms of school burnout, including study-related emotional exhaustion, are connected to students' overall psychological well-being (Kiuru et al., 2019). Therefore, it is important to examine the effects of social media use on adolescents' academic well-being. Previous research that examined adolescents' digital media use confirmed an association between excessive internet use and school burnout, both in early (aged 12–14) and late adolescence (aged 16–18) (Salmela-Aro et al., 2017). In terms of specific digital practices, social media use has also been linked to school burnout (Evers et al., 2020), and specifically, mixed active social media use has been associated with an increase in school-related emotional exhaustion (Hietajärvi et al., 2019). As far as we know, however, the developmental differences have not yet been studied.

Given the ubiquitous presence of mobile technologies, adolescents can potentially receive social media notifications multiple times a day, thus increasing social demands and decreasing mental recovery time. According to the energy-depleting process of the *Demands-Resources Hypothesis*, prolonged demands may cause exhaustion if an individual lacks the personal resources to deal with them (Salmela-Aro & Upadyaya, 2014). In the school context, active use of social media could also be seen as a resource that increases social connectedness or provides an information source (Hietajärvi et al., 2019, 2020). On the other hand, active involvement in social media may generate feelings of constant availability, which could create challenges within friendships (Nesi et al., 2018). Following a multitude of social media feeds and spending too much time on these activities may further increase daily demands (Korunovska & Spiekermann-Hoff, 2020; Nesi et al., 2018) and lead to higher levels of exhaustion.

1.2 | Social media use and sleeping habits

Time spent on digital devices may displace other important activities, such as sleeping (Scott & Woods, 2019). Previous studies have outlined three mechanisms that potentially lead to digital activities interfering with sleep and sleeping habits: first, digital activities may replace sleep by delaying bedtime; second, physiological, cognitive, and emotional arousal may interfere with sleep (e.g., interactive digital gaming, computer-mediated studying, or chatting eagerly with friends); and third, exposure to bright light may disrupt the process of falling asleep (Cain & Gradisar, 2010; Hale et al., 2018). In adolescence, however, sleeping difficulties are common (Inchley et al., 2020), and biological and physiological changes increase the tendency to stay up late (Crowley et al., 2018; Galván, 2020). Behaviors that are common in young people (e.g., using a mobile phone while in bed) may further increase shuteye latency (time spent in bed before falling asleep) (Fossum et al., 2014) and thus further delay bedtime. The recommended sleep duration for optimal daytime functioning ranges between 8 and 10 h a night (Hirshkowitz et al., 2015); however, according to meta-analyses, 12–18-year-olds sleep, on average, less than 7 h per night before a school day (Galland et al., 2018). Delayed bedtime is likely to cause this short sleep duration because adolescents have limited ability to influence their school start times.

Overall, the time spent looking at digital screens has been associated with delayed bedtimes and shortened sleep durations (Hale & Guan, 2015). Specifically, social media use has been associated with difficulties in falling asleep (Arora et al., 2014; Scott et al., 2019) and sleep disturbances (Evers et al., 2020). In addition, poor sleep quality has been linked to overall school-related burnout or exhaustion (Liu et al., 2021; May et al., 2020), indicating that social media use may have a negative effect on academic well-being through reduced sleep (Orzech et al., 2016; see also Maksniemi et al., 2018). Social media use that leads to poor sleeping habits (Hale & Guan, 2015; Hökby et al., 2016) may result in the perception that schoolwork is more demanding, as well as contribute to depleted cognitive and social resources and increased emotional exhaustion.

1.3 | Purpose of the present study

Recent empirical evidence on social media use, psychological well-being, and sleeping habits has focused primarily on average or group-level effects and cross-sectional results, which do not reveal the behavioral and psychological patterns that occur at the individual level (Valkenburg & Peter, 2013). In addition, previous research has examined social media use in relation to psychological well-being and sleeping habits among adolescents, and little attention has been given to academic well-being. Our study extends the existing literature by focusing on the within-person level by differentiating the years of adolescence and thus the developmental stage that is emphasized by the *Differential Susceptibility to Media Effects Model* (Valkenburg & Peter, 2013).

The first hypothesis (*H1*) of the present study was that *active social media use is contemporaneously associated with increased emotional exhaustion and delayed bedtime, especially in late adolescence*. Based on previous literature, we expected to find that intraindividual fluctuations in active social media use would be correlated with academic exhaustion and later bedtimes (Evers et al., 2020). Furthermore, we expected to uncover stronger associations in late adolescence because academic pressure, social media use, and autonomy over one's own bedtime increases with age (Illingworth, 2020; Orzech et al., 2016; Scott et al., 2019).

The second hypothesis (*H2*) was *that emotional exhaustion is contemporaneously associated with delayed bedtime, especially in late adolescence*. We hypothesized that the associations would be stronger in late adolescence than early adolescence; this assumption was based on previous literature (Evers et al., 2020) and the indications that overall academic pressure and autonomy over one's own bedtime both increase over the years of adolescence (Illingworth, 2020; Orzech et al., 2016; Shochat et al., 2014).

The third hypothesis (*H3*) was that *active social media use predicts increased emotional exhaustion in the long term*. We hypothesized that higher active social media use would predict higher levels of exhaustion later in adolescence, as using digital media, particularly for social purposes, has been associated longitudinally with adolescents' overall school burnout (Hietajärvi et al., 2015, 2019; Salmela-Aro et al., 2017).

2 | METHODS

2.1 | Measures

2.1.1 | Active social media use

Table 1 The intensity of social media use and the level of engagement were measured on the social-media-networking dimension of the Socio-Digital Participation Inventory (Hietajärvi et al., 2016, 2019). Four items assessed the frequency of active social media use ("I chat;" "I visit and send messages via social media sites;" "I post updates or share interesting content;" "I post pictures or picture updates") on a seven-point frequency scale (1 = never, 2 = a couple of times a year, 3 = monthly, 4 = weekly, 5 = daily, 6 = multiple times a day, 7 = all the time). We selected these items specifically to represent the common conceptualization of the active use of social media, covering both private and public use (Hakkarainen et al., 2015; Hietajärvi et al., 2019; Orben, 2020). The validity of the scale has been established by several Finnish studies, which have focused on different age groups (Hietajärvi et al., 2015, 2019; Li, 2019). Cronbach's α showed moderate or good scale reliability and varied between .65 and .82 (see Table 2).

2.1.2 | Emotional exhaustion

School-related emotional exhaustion was assessed on one dimension of the School Burnout Inventory (SBI; Salmela-Aro et al., 2009), which consists of three subscales reflecting the emotional, cognitive, and behavioral components of burnout. Four items (e.g., "I feel overwhelmed with my schoolwork") assessed exhaustion, the emotional component of SBI, on a scale ranging from 1 (*completely disagree*) to 6 (*completely agree*). The validity of the scale has been established by different studies in Finland and with different age groups (e.g., Salmela-Aro & Upadyaya, 2014; Tuominen et al., 2020). Cronbach's α showed good scale reliability and varied between .77 and .86 (see Table 2).

TABLE 1 A summary of the descriptive statistics

	N	*M*	SD	SE	Min.	Max.	Range	Skew	Kurt
Time 1									
Active social media use	298	4.09	1.01	0.06	1	7	1–7	−0.59	0.06
Emotional exhaustion	295	2.81	1.07	0.06	1	6	1–6	0.56	−0.53
Bedtime	273	22.25 p.m.	00:46.20	00:03.00	21:00 p.m.	03:00 a.m.	-	1.33	4.76
Time 2									
Active social media use	367	4.08	1.00	0.05	1	7	1–7	−0.57	−0.05
Emotional exhaustion	358	2.98	1.25	0.07	1	6	1–6	0.44	−0.55
Bedtime	338	22:52 p.m.	00:53.40	00:03.00	20:30 p.m.	03:00 a.m.	-	0.98	2.64
Time 3									
Active social media use	252	4.32	0.93	0.06	1	7	1–7	−0.55	0.83
Emotional exhaustion	235	3.09	1.28	0.08	1	6	1–6	0.31	−0.70
Bedtime	204	23:14 p.m.	01:03.00	00:04.20	19:00 p.m.	05:00 a.m.	-	1.63	9.6
Time 4									
Active social media use	245	4.34	0.93	0.06	2	7	1–7	−0.04	0.63
Emotional exhaustion	275	3.23	1.12	0.07	1	5.75	1–6	0.12	−0.68
Bedtime	265	23:15 p.m.	00:57.00	00:03.60	19:00 p.m.	03:00 a.m.	-	0.54	2.36
Time 5									
Active social media use	284	4.26	0.92	0.05	1.75	7	1–7	0.16	0.80
Emotional exhaustion	256	3.34	1.24	0.08	1	6	1–6	0.18	−0.81
Bedtime	251	23:31 p.m.	01:00.60	00:03.60	22:00 p.m.	04:00 a.m.	-	1.03	1.8

Note: For the bedtime means, SDs and SEs are reported in hours and minutes; Time 1, aged 13–14; Time 2, aged 14–15; Time 3, aged 15–16; Time 4, aged 17–18; Time 5, aged 18–19.

TABLE 2 A summary of internal consistency estimates

Cronbach's α	α	SE	95% CI[a]
Active social media use, Time 1	.82	0.02	[0.79, 0.85]
Active social media use, Time 2	.77	0.02	[0.72, 0.81]
Active social media use, Time 3	.74	0.03	[0.67, 0.79]
Active social media use, Time 4	.64	0.04	[0.54, 0.71]
Active social media use, Time 5	.65	0.04	[0.57, 0.72]
Emotional exhaustion, Time 1	.77	0.02	[0.72, 0.81]
Emotional exhaustion, Time 2	.83	0.02	[0.80, 0.86]
Emotional exhaustion, Time 3	.86	0.02	[0.82, 0.88]
Emotional exhaustion, Time 4	.77	0.02	[0.72, 0.81]
Emotional exhaustion, Time 5	.83	0.02	[0.80, 0.86]

Abbreviation: CI, confidence interval.

[a]Bias-corrected and accelerated (BCA) bootstrap with 10,000 draws; Time 1, aged 13–14; Time 2, aged 14–15; Time 3, aged 15–16; Time 4, aged 17–18; Time 5, aged 18–19.

2.1.3 | Bedtime on schooldays

Self-reported bedtime was assessed with one question ("What time do you usually go to bed when you have school the next morning?"). The participants gave their answers in open-text boxes. The clock times were transformed into numeric expressions with continuous regular intervals (e.g., clock time 22:30 was transformed into value 22.50). If the participants provided several times or a timeframe (e.g., 21:00–22:00), we calculated the mean. A clock time that was past midnight (24:00) was coded higher in the regular interval continuum (e.g., 01:00 was coded as 25.00).

2.2 | Data collection and participants

Data were collected annually over 6 years (2014 = Time 1, 2015 = Time 2, 2016 = Time 3, 2018 = Time 4, and 2019 = Time 5). There was no data collection in 2017, and there was an educational transition from secondary school to upper-secondary school between Time 3 and Time 4. In the beginning of the study, the participants were in 7th grade (aged 13–14), which is the first year of secondary school. At the end of the study, they were in their final year of upper-secondary or vocational school (aged 18–19). Data were collected during two research projects in the Helsinki metropolitan area in Finland. Participants in both research projects were included in this study ($N = 426$, female, 65.7%). Of the 426 participants, 87.6% participated in at least four out of the five follow-up waves. Active social media use, school-related emotional exhaustion, and bedtime were assessed in each of the five waves.

Participation in the research was entirely voluntary, and informed consent forms were collected from the adolescents and their parents at the beginning of the longitudinal study. The data collection for the first 3 years (2014–2016) was organized as a convenience sample across comprehensive schools: schools that were in a position to manage the data collection organized it during school hours. All students who were willing to take part in the study and were present at school during the data collection were included as participants. In 2018 (Time 4), individuals who had not been reached during the school collections were contacted personally via text message and asked to fill in the questionnaire. In 2019 (Time 5), students were only contacted via text message, and the schools were not involved in the data collection. A gift card (value 10 euros) was sent in 2018 and 2019 to all participants who filled in the questionnaire. The attrition in the number of participants could have been related to several factors: schools or teachers being unable to organize the data collection, students being absent on the collection day, or participants' unwillingness to respond. The Ethical Review Board in the authors' institution approved the study protocol.

2.3 | Analytical strategy

As a preliminary analysis, we screened the questionnaire data for the amount and patterns of missing values using the IBM Statistical Package for Social Sciences (SPSS), version 25. We assessed the internal consistency of the active social media use and emotional exhaustion scales by computing the bootstrapped confidence intervals and point estimates of Cronbach's α

coefficients using the R-package MBESS (Kelley, 2016). Table 2 shows the internal consistencies. The data, code, and supplementary material can be downloaded from: https://osf.io/5vtsn/.

To test our hypotheses, we built a random intercept cross-lagged panel model (RI-CLPM; see Hamaker et al., 2015) to separate the within-person from the between-person relations. To investigate the robustness of the results regarding gender differences, participants' gender was controlled for in the model by adjusting the random intercepts for gender mean differences (see Supporting Information Material). Model fit (Hu & Bentler, 1998) was evaluated based on the χ^2 and the root mean square error of approximation (RMSEA) with an approximate acceptable cut-off value of less than 0.08, the standardized root mean residual (SRMR) with an approximate cut-off of less than 0.08, and the comparative fit index (CFI) and the Tucker-Lewis index (TLI) with acceptable cut-off values of more than 0.90.

For the analyses, we used Mplus 8.3 (Muthén & Muthén, 2018) in conjunction with R and RStudio (RStudio Team, 2019; Team R, 2018) with the MplusAutomation package (Hallquist & Wiley, 2018). Estimations were based on maximum likelihood with standard errors robust for non-normality (MLR) and full information maximum likelihood (FIML) was used to handle the missing data.

Figure 1 depicts the theoretical RI-CLPM, which was chosen to decompose the variance and the variables in two parts: (1) time-invariant "between-person" factors (random intercepts for active social media use, emotional exhaustion, and bedtime) represent the stable, trait-like typical level of each individual across the study; (2) time-varying "within-person" factors represent the temporary increases and decreases of the individual's values in comparison to the individual's own typical level. These within-person factors were used to estimate the longitudinal autoregressive and cross-lagged effects (Hamaker et al., 2015). The autoregressive paths represent the amount of within-person carryover effects, which indicate that expected scores on active social media use are likely to be followed by occasions on which the participant still scores above the expected level for emotional exhaustion or bedtime—and vice versa (Hamaker et al., 2015). Active social media use, exhaustion, and bedtime at the within-level at Time 1 were correlated with the within-person residuals at all subsequent measurement times. The residual correlations in Times 2–5 are referred to as correlated change in the text and in the tables.

3 | RESULTS

3.1 | Missing value analysis

With regard to the missing data, we carried out separate analyses of the questionnaire items at each time point; we also conducted longitudinal analysis to identify any systematic dropout (see Supporting Information Material). Of the

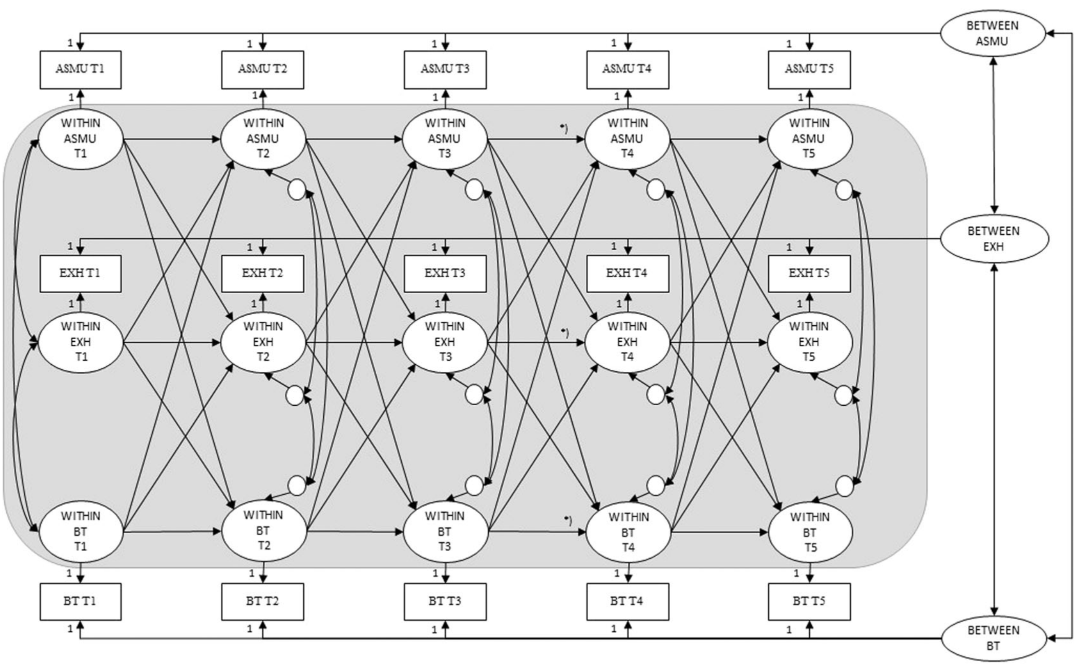

FIGURE 1 Theoretical random intercept cross-lagged panel model. *Note*: ASMU, active social media use; BT, bedtime on schooldays; EXH, school-related emotional exhaustion; T1–T5 indicates the measurement of time (T1, aged 13–14; T2, aged 14–15; T3, aged 15–16; T4, aged 17–18; T5, aged 18–19); *2-year gap in data collection and educational transition from comprehensive school to upper-secondary school

426 participants, 72 (16.9%) participated twice, 130 (30.5%) participated three times, and 224 (52.5%) participated in four or more of the five data collection events. All participants participated in the data collection at least once during Times 1–3 and Times 4–5. Little's MCAR test result was χ^2 (4135) = 4308.064, $p = .030$ for the longitudinal data, but the normed χ^2 was acceptable (4308.064/4135 = 1.04), indicating only minor violation of the MCAR regarding missing patterns in the longitudinal data.

3.2 | Longitudinal within-person associations between active social media use, exhaustion, and bedtime

Our primary model fitted the data well (see Table 3). In the RI-CLPM model, all structural parameters were freely estimated (see the theoretical model in Figure 1). To confirm our model selection, the RI-CLPM was compared to the traditional cross-lagged panel model (CLPM) using the Satorra-Bentler scaled χ^2 difference test. In the traditional CLPM, variance from the between- and within-levels are not separated, and the structural paths are estimated based on the observed variables. The χ^2 test showed (see Table 3) that the RI-CLPM was a more suitable model than the traditional CLPM (Satorra-Bentler scaled $\Delta\chi^2(6) = 61.72$, $p < .001$).

Table 4 presents the model-based within- and between-level correlations between active social media use, emotional exhaustion, and bedtime. Table 5 presents the model-based standardized cross-lagged within-level model estimates, and Figure 2 presents the within-level associations between the three variables across the five measurement times. With regard to our first hypothesis (H1: *Active social media use is contemporaneously associated with increased emotional exhaustion and delayed bedtime, especially in late adolescence*), the model showed that there was no clear pattern between active social media use, emotional exhaustion, and bedtime across adolescence, meaning that statistically significant associations varied depending on the measurement time. There was a statistically significant correlated change between active social media use and emotional exhaustion in Time 2 and Time 4, meaning that when participants reported more than usual active social media use they simultaneously reported more emotional exhaustion. The model showed that when the participants reported more frequent active social media use (above their own typical level) in Time 2 (participants aged 14–15) and in Time 4 (participants aged 17–18), they simultaneously reported higher levels of school-related exhaustion (Time 2: $r = .19$, $p = .009$, 95% confidence interval [CI] [0.05, 0.33]; Time 4: $r = .32$, $p = .002$, 95% CI: [0.12, 0.51]). Active social media use was associated with delayed bedtime only in Time 1 ($r = .14$, $p = .045$, 95% CI: [0.00, 0.28]), meaning that when participants in early adolescence (aged 13–14) reported more than usual active social media use, they simultaneously reported delayed bedtime.

Regarding our second hypothesis (*H2: Emotional exhaustion is contemporaneously associated with delayed bedtime, especially in late adolescence*), there was a statistically significant correlated change between emotional exhaustion and bedtime only in Time 4, meaning that when adolescents in Time 4 (aged 17–18) reported higher emotional exhaustion (above their own mean), they also reported later than usual bedtimes ($r = .24$, $p = .002$, 95% CI: [0.09, 0.38]).

Regarding our third hypothesis (*H3: Active social media use predicts increased emotional exhaustion in the long term*), our model further indicated only one statistically significant cross-lagged path. Active social media use in Time 2 predicted higher levels of emotional exhaustion 1 year later ($B = .24$, $p = .020$, 95% CI: [0.04, 0.44]).

4 | DISCUSSION

This longitudinal study investigated within-person associations between active social media use, school-related emotional exhaustion, and bedtime on schooldays during six years of adolescence. Utilizing a RI-CLPM, we focused primarily on the intraindividual levels in early, middle, and late adolescence.

TABLE 3 Summary of model fits

	Fit indices							
	χ^2	scf	*df*	*p*	RMSEA	CFI	TLI	SRMR
CLPM	123.732	1.0469	54	*<.001*	0.055	0.903	0.812	0.077
RI-CLPM	58.562	1.0386	48	*.141*	0.023	0.985	0.968	0.071
RI-CLPM with gender as a covariate	59.735	1.0386	48	*.119*	0.024	0.986	0.964	0.067

Abbreviations: CFI, comparative fit index; RI-CLPM, random intercept cross-lagged panel model; RMSEA, root mean square error of approximation; scf, scaling correction factor for MLR estimator; SRMR, standardized root mean residual; TLI, Tucker-Lewis index.

TABLE 4 Model-based standardized within- and between-level correlations linking active social media use, emotional exhaustion, and bedtime

	Active social media use and emotional exhaustion				Active social media use and bedtime				Bedtime and emotional exhaustion			
	r	SE	*p*	95% CI	*r*	SE	*p*	95% CI	*r*	SE	*p*	95% CI
Within-level correlations												
Time 1	.066	0.077	.394	−0.086 to 0.218	.143	0.071	.045	0.003– 0.283	−.030	0.105	.779	−0.236 to 0.177
Time 2 (correlated change)	.188	0.072	.009	0.047–0.329	.036	0.087	.679	−0.135 to 0.207	.153	0.083	.067	−0.011 to 0.316
Time 3 (correlated change)	.143	0.085	.091	−0.023 to 0.309	−.156	0.111	.158	−0.373 to 0.061	−.045	0.098	.647	−0.236 to 0.147
Time 4 (correlated change)	.316	0.101	.002	0.117–0.514	.041	0.099	.677	−0.153 to 0.236	.235	0.076	.002	0.086– 0.384
Time 5 (correlated change)	.125	0.106	.239	−0.083 to 0.334	.060	0.081	.456	−0.098 to 0.219	.071	0.104	.494	−0.133 to 0.275
Between-level correlations	.107	0.118	.363	−0.124 to 0.339	.036	0.172	.836	−0.302 to 0.373	.076	0.201	.707	−0.318 to 0.469

Note: Time 1, aged 13–14; Time 2, aged 14–15; Time 3, aged 15–16; Time 4, aged 17–18; Time 5, aged 18–19.

Abbreviation: CI, confidence interval.

TABLE 5 Model-based standardized cross-lagged within-level estimates linking active social media use, emotional exhaustion, and bedtime

Within-level			**From Time 1 to Time 2**				**Within-level**			**From Time 2 to Time 3**			
Outcome		**Predictor**	**Est.**	**SE**	***p***	**95% CI**	**Outcome**		**Predictor**	**Est.**	**SE**	***p***	**95% CI**
Active social media use (ASMU)	←	ASMU	0.420	0.080	.000	0.264–0.576	Active social media use (ASMU)	←	ASMU	0.380	0.103	.000	0.177–0.583
		EXH	0.133	0.070	.056	−0.003 to 0.270			EXH	0.067	0.093	.473	−0.116 to 0.249
		BT	−0.006	0.092	.952	−0.185 to 0.174			BT	0.017	0.104	.873	−0.187 to 0.220
Emotional exhaustion (EXH)	←	EXH	0.215	0.094	.022	0.032– 0.399	Emotional exhaustion (EXH)	←	EXH	0.272	0.104	.009	0.068–0.476
		ASMU	−0.018	0.079	.821	−0.173 to 0.137			ASMU	0.236	0.102	.020	0.037–0.436
		BT	0.000	0.097	.998	−0.189 to 0.190			BT	−0.083	0.102	.413	−0.283 to 0.116
Bedtime (BT)	←	BT	0.447	0.118	.000	0.216– 0.678	Bedtime (BT)	←	BT	0.229	0.126	.071	−0.019 to 0.476
		ASMU	−0.002	0.067	.981	−0.133 to 0.130			ASMU	0.090	0.080	.260	−0.066 to 0.246
		EXH	−0.079	0.079	.320	−0.235 to 0.077			EXH	0.131	0.082	.109	−0.029 to 0.291
Within-level			**From Time 3 to Time 4**				**Within-level**			**From Time 4 to Time 5**			
Outcome		Predictor	Est.	SE	*p*	95% CI	Outcome		Predictor	Est.	SE	*p*	95% CI
Active social media use (ASMU)	←	ASMU	−0.120	0.170	.479	−0.454 to 0.213	Active social media use (ASMU)	←	ASMU	.254	.160	.113	−0.060 to 0.568
		EXH	0.196	0.173	.256	−0.143 to 0.536			EXH	.018	.120	.879	−0.216 to 0.253
		BT	0.056	0.098	.569	−0.137 to 0.249			BT	−.103	.118	.380	−0.333 to 0.127
Emotional exhaustion (EXH)	←	EXH	0.255	0.111	.022	0.037 to 0.472	Emotional exhaustion (EXH)	←	EXH	.434	.102	.000	0.235–0.634
		ASMU	0.171	0.112	.125	−0.048 to 0.390			ASMU	.170	.120	.155	−0.064 to .0404
		BT	−0.031	0.100	.755	−0.228 to 0.165			BT	.195	.119	.101	−0.038 to 0.427
Bedtime (BT)	←	BT	0.309	0.124	.013	0.066– 0.552	Bedtime (BT)	←	BT	.497	.095	.000	0.312–0.683
		ASMU	−0.076	0.127	.551	−0.324 to 0.173			ASMU	.055	.120	.648	−0.180 to 0.290
		EXH	−0.055	0.113	.630	−0.277 to 0.168			EXH	−.030	.099	.758	−0.224 to 0.163

Note: Time 1, aged 13–14; Time 2, aged 14–15; Time 3, aged 15–16; Time 4, aged 17–18; Time 5, aged 18–19.

Abbreviation: CI, confidence interval.

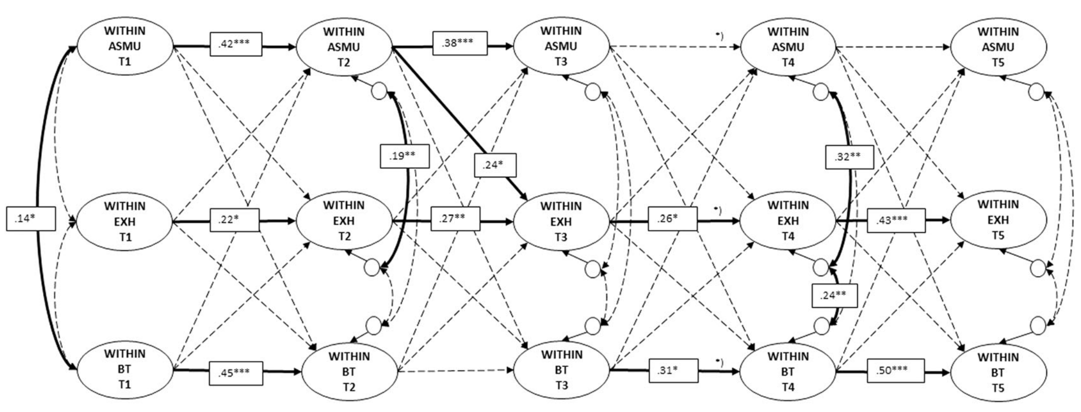

FIGURE 2 Within-person paths from the random intercept cross-lagged panel model. ASMU, active social media use; BT, bedtime on schooldays; EXH, school-related emotional exhaustion. Black solid lines indicate that effects are statistically significant (*** $p < .001$, ** $p < .01$, * $p < .05$), and dashed lines indicate statistically nonsignificant effects; two-way arrows (T2–T5) represent correlated changes between active social media use, emotional exhaustion, and bedtime; *Note*: T1–T5 indicate the measurement of time (T1, aged 13–14; T2, aged 14–15; T3, aged 15–16; T4, aged 17–18; T5, aged 18–19); *2-year gap in data collection and educational transition from comprehensive school to upper-secondary school

Our results showed inconsistent associations between active social media use, emotional exhaustion, and bedtime across the years of adolescence. This is in line with the DSMM framework; according to this framework, the developmental stages mediate the effects of media use (Valkenburg & Peter, 2013). Active social media use was associated with delayed bedtimes only in early adolescence when participants were aged 13–14. In middle adolescence (aged 14–15) and in late adolescence (aged 17–18) when the participants reported an increase in active social media use, they simultaneously reported higher school-related emotional exhaustion. In addition, in late adolescence when the participants reported delayed bedtime, they simultaneously reported an increase in emotional exhaustion. Our longitudinal results suggested that an increase in active social media use in mid-adolescence (aged 14–15) predicted an increase in exhaustion 1 year later (aged 15–16).

4.1 | Active social media use was associated with emotional exhaustion

Active social media use has been associated with school burnout among adolescents in previous studies (Hietajärvi et al., 2019), and our findings contribute to the scientific evidence indicating that active social media use may have a small impact on adolescents' emotional exhaustion; however, the evidence supporting this effect is inconsistent. Our results showed that when adolescents reported an increase in active social media use, they simultaneously reported an increase in emotional exhaustion at ages 14–15 and 17–18. Previous studies have indicated a reciprocal association between active social media use and school burnout (Hietajärvi et al., 2019); however, this reciprocal association was not found in the present study. Our results indicated that an increase in active social media use predicts an increase in exhaustion one year later, but this association was only observed in late adolescence. These inconsistent results reveal the multidimensionality of social media use. It is difficult to establish whether spending time on social media leads to lower academic well-being or whether the use of social media is a maladaptive coping mechanism for pre-existing challenges at school (Alonzo et al., 2020). The evidence from the present study did not suggest that active social media use delays bedtimes and thus interferes with academic well-being, although systematic reviews suggest that sleep quality may have a mediating role between (excessive) social media use and mental health outcomes (Alonzo et al., 2020).

In the present study, emotional exhaustion was associated with active social media use and later bedtimes in late adolescence, but active social media use was not associated with later bedtimes. These findings are important, as adolescents who develop unhealthy sleeping habits could be at risk of school burnout (May et al., 2020). To some extent and for some adolescents, social media use is associated with academic well-being; however, the mechanism appears to be more complex than the common explanation that time spent on social media reduces time spent sleeping and thus increases psychological ill-being (Hietajärvi et al., 2022).

4.2 | Active social media use and bedtime were only related in early adolescence

In previous studies, engagement in social media has been associated with delayed bedtimes (Arora et al., 2014; Fobian et al., 2016; Hale & Guan, 2015; Orzech et al., 2016). On the other hand, some studies have suggested that the use of digital technology before bedtime is not strongly related to the timing of bedtime (Orben & Przybylski, 2020). Our results showed an association between active social media use and later bedtimes in early adolescence (at age 13–14). This was against our hypothesis, as we assumed that the associations would be more likely to occur in late adolescence. Our finding indicates that using social media for social purposes may not have a strong influence on bedtimes, especially in the later phases of adolescence. Younger adolescents could be more vulnerable to this type of social media effect if they lack the self-regulation skills required to manage digital practices. Online platforms are often restricted to people over 12–13 years of age; therefore, it is possible that the novelty effect for younger adolescents leads to an over-use of social media. Over time, the novelty value of the applications decreases, and older adolescents also develop routines and practices to handle and regulate their use of social media. In addition, Kaye et al. (2020) have shown that the technical development of digital devices affects the measurement of social media use, especially as the functions of devices develop at a rapid pace; this technological advancement may explain the different results in early and late adolescence in the present study.

This study focused on active social media use that involved some degree of social connection. Some digital practices are potentially more problematic than other regarding sleeping habits. It is therefore important to separate the different digital practices in terms of how physiologically, cognitively, or emotionally arousing they are for an individual. The time spent on these activities may be secondary, as it could result in quantifying non-problematic use instead of focusing on the functions and motivations for usage. Spending time on social media has become an integral part of life and does not necessarily constitute an additional daily activity that reduced the time spent on other tasks. On average, however, long and frequent checking of social media before bedtime can increase general cognitive arousal, which may interfere with the process of falling asleep (Alonzo et al., 2020); however, an individual's tendency to worrying, their ability to cope with social interactions, and their developmental stage should also be considered as relevant factors (Hietajärvi et al., 2022).

5 | LIMITATIONS

This study has its limitations when drawing further conclusions. The purpose was to investigate person-level development in active social media use and how it relates to emotional exhaustion and bedtime. Although school plays a significant role in adolescence and school-related exhaustion is an important topic for research, we did not control for overall exhaustion or the other two dimensions of school burnout (cynicism towards the meaning of school and a sense of inadequacy at school) (Salmela-Aro et al., 2009).

We acknowledge that the true frequency of active social media use among the participants may be different than what was indicated by the study's self-reported measurements (Andrews et al., 2015), as self-reports may differ from actual use (Hodes & Thomas, 2021; Johannes et al., 2021). It is possible that our model results could have shown more significant associations if objective or more accurate measurements were available. In addition, our research addressed a narrow avenue of digital engagement, and other digital activities, such as passive social media use or study-related digital practices, were not included. We measured the frequency of social media use rather than the time spent on various social media platforms; this ensured that the yearly measures were more comparable and stable over time despite the unavoidable rapid development of technology and methods for digital engagement (Kaye et al., 2020).

Moreover, we did not study social media use in the evening or during the night, although one could assume that adolescents who are frequent users of social media also access online content in the evening. Knowing the precise timing of social media use would have been beneficial when investigating the associations with delayed bedtime. The bedtime measures in this study were also self-reported: the participants were asked to provide the average time they went to bed on schooldays; however, this did not specify the time they fell asleep or identify the common habit of using a mobile phone while in bed. As we did not measure the shuteye latency (interval from bedtime to shuteye time), it is possible that adolescents overestimated or underestimated the reported bedtime (Saxvig et al., 2021). We acknowledge that only self-reported bedtimes were investigated, and our study lacked data on specific sleep duration.

Although the longitudinal nature of our data is a clear strength, the resulting uneven attendance of the participants across the data collection period is a small weakness, which increased sampling variation and the need to rely on model assumptions. However, full information maximum likelihood (FILM) performs better and with less bias than data-deletion-based methods, even with a large amount of non-monotone missing data (Graham, 2009; Lee et al., 2019; Zaninotto & Sacker, 2017). Nevertheless, the estimates reported in the study are heavily model-based and should be treated as such.

The lag between measurement times was a minimum of 1 year, and little is known about the developments within the years. However, the participants were asked to reflect on the average frequency of social media use, average feelings related to emotional exhaustion, and average bedtime on schooldays. Although our sample cannot be considered representative, it is from an urban population with an average financial status and a standard level of school performance (see Supporting Information Materials).

6 | FUTURE RESEARCH AND CONCLUSIONS

The results clearly indicated that active social media use did not appear to have a strong overall effect on exhaustion or bedtimes. However, the effects of social media use on psychological well-being may be stronger for some adolescents; thus, further studies should focus on identifying the relevant moderators (Hietajärvi et al., 2022; Ito et al., 2020). The present study focused more on the lack of academic well-being among adolescents; hence, future research should include the positive aspects. It would be useful, for example, to consider social dimensions such as connectedness to peers and the school community. It would also be beneficial to investigate the many mechanisms and psychological aspects that potentially shed light on the extent to which screen-based activities constitute an antecedent or a consequence of academic well-being and sleeping habits; additional research should also investigate how the various contextual factors moderate any associations (Dickson et al., 2019; Hietajärvi et al., 2022). Future studies should also focus on precise research designs and measures and the advancement of data collection procedures. Daily-level processes could be identified by combining the experience sampling method with the measurement of physical activity (e.g., devices tracking sleep patterns).

To conclude, based on the evidence to date, the intraindividual relations between active social media use, emotional exhaustion, and bedtimes are small, inconsistent, and vary according to adolescents' age. However, the small effects may still be interesting, significant, and worth deeper investigation (Valkenburg, 2015); in addition, adolescents with offline vulnerabilities (e.g., school-related exhaustion) may be more at risk of being harmed by their online activity. To advance the research, additional longitudinal studies should examine objective or highly accurate social media use among at-risk individuals during the different developmental stages across the years of adolescence.

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CONFLICTS OF INTERESTS

The authors declare no conflict of interest.

ETHICS STATEMENT

This study was approved by The Ethical Review Board in the University of Helsinki.

AUTHOR CONTRIBUTIONS

Erika Maksniemi conceived of the study, participated in the design and coordination, and in organizing the data collection and curation, conducted the statistical analyses and drafted the manuscript; Lauri Hietajärvi took part in the data collection, its design and interpretation, supervised the statistical analyses and in writing the manuscript; Elina E. Ketonen participated in the design and data collection, and in writing the manuscript; Kirsti Lonka participated in the design of the study, administered the research project, and contributed to writing the manuscript; Kati Puukko participated in the design and data collection, and in writing the manuscript; Katariina Salmela-Aro participated in the design of the study, administrated the research project, and contributed to writing the manuscript. All the authors read and approved the final manuscript.

DATA AVAILABILITY STATEMENT

The authors confirm that the data supporting the findings of this study are available within the article [and/or] its supplementary materials. The OSF project contains all necessary files to reproduce the analysis in MPlus and R. The code to reproduce these analyses is available at https://osf.io/5vtsn/.

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