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How do depression, duration of internet use and social connection in adolescence influence each other over time? An extension of the RI-CLPM including contextual factors

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ABSTRACT

There are opposing views on the relationship between adolescents' use of the Internet and their well-being, e.g. the Internet-enhanced self-disclosure hypothesis and the Evolutionary mismatch model, which give an opposite picture of the dynamics that may lead to positive versus adverse effects, respectively. Hence, the present paper aims to shed light on the bidirectional longitudinal relationships between the duration of Internet use, social connections, and depression. Data were collected at four time points, each one year apart, in 37 Swiss middle schools. The analytical sample includes a large sample of 981 early adolescents (M = 11.37, SD = 0.55; 53.9% females). All measures are self-report and comprise depression, duration of internet use, and social connection. Data were analyzed by applying an extension of the Random Intercept-Cross Lagged Panel Model, which includes the role of covariates, i.e. as gender, quality of family relations, ownership of personal Internet-enabled devices, and social desirability, in predicting the random intercepts. Results showed that, at the within-person level, a higher duration of Internet use increased depression, and, to a lower extent, higher depression levels increased the duration of Internet use. These effects were not mediated by more offline time spent with peers. At the between-person level, heavier Internet users reported higher levels of social connections with friends. Being female and possessing Internet-enabled mobile devices contributed to higher levels of initial depressive symptoms, whereas having a good family relationship was a protective factor. Results partly sustain both theoretical models and underline the importance of including contextual factors in explaining such relationships.

1. Introduction

Adolescence is a time of increased vulnerability to depression (Hankin et al., 1998), and it is not surprising that 13% of teenagers aged 12 to 17 in the U.S. have experienced at least one episode of depression (Pew Research Center, 2019). In Switzerland, 36% of younger people (15–35 years) reported having experienced depressive symptoms, with girls being more affected than boys (Birmaher et al., 1996; Schuler, Tuch, Buscher, & Camenzind, 2016, p. 80; Thapar et al., 2012a, 2012b). Adolescent depression leads to poorer educational and health outcomes (Birmaher et al., 1996; Fergusson & Woodward, 2002), including long-term psychiatric problems and substance use (Knapp et al., 2002). Hence, identifying different protective and risk factors is urgently needed to design effective interventions and therapies to reduce the disease burden.

There is an ongoing debate about whether the use of the Internet has detrimental effects on young people's mental health. The link between Internet use and depression has received considerable attention, and the results have been summarized as small or even null (Allen & Haidt, 2020; Orben, 2020; Orben et al., 2019a; Orben & Przybylski, 2019). Two competing theories, i.e. the Internet-enhanced self-disclosure hypothesis (Valkenburg & Peter, 2009) and the Evolutionary mismatch model (Sbarra et al., 2019), give a contradictory picture of the dynamics that may lead to positive versus adverse effects, respectively. Both theories link online activities to the social sphere and, subsequently, to well-being. To date, longitudinal studies able to provide a comprehensive picture of the dynamics of the effects of Internet use on adolescents' mental health, also considering the role of covariates, are rare.

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In the present paper, we drew from these two contradictory theoretical approaches to investigate how depressive symptoms, social connection, and duration of Internet use are associated by separating between- and within-person effects over four years in a large representative sample of early adolescents. In addition, we considered covariates such as gender, the quality of family relations, and ownership of Internet-enabled devices in an Extended version of the Random-Intercept Cross-Lagged Panel Model (RI-CLPM; Mulder & Hamaker, 2020).

2. *Internet-enhanced self-disclosure hypothesis* versus the *Evolutionary mismatch model*

Two comprehensive models linked Internet use to social connection and well-being. According to the Internet-enhanced self-disclosure hypothesis, developed over a decade ago by Valkenburg and Peter (2009), online activities foster self-disclosure and the quality of relationships, with a positive effect on well-being. In general, virtual communities gain positive reinforcement of social connection and enhance social capital (Ahn, 2012). The richness of online communication may augment the number and frequency of possibilities for young people to interact and disclose personal facts and information, which, in turn, augments well-being. Internet-mediated interaction allows individuals to be less concerned about how the other part perceives them. This also applies to adolescents with difficulties (e.g., higher levels of depression and anxiety) who find the opportunity to freely interact and disclose their whereabouts online. According to this view, socially "rich" and "not-rich" adolescents would get richer. Indeed, time online would act as an *extended space for socialization*, as long as offline connections are maintained and further developed (Desjarlais & Willoughby, 2010; Valkenburg & Peter, 2007). At the same time, socially poor adolescents may compensate for few and low-quality friendships by spending more time communicating online, and safely exploring peer relationships, thus increasing their perception of social support and reinforcing their social skills (Desjarlais & Willoughby, 2010; Kraut et al., 2002). In both cases, online communication with peers may promote a sense of belonging and self-disclosure, also outside the online world. In general, self-disclosure has a positive influence on well-being not only by strengthening interpersonal relationships and social bonds but also by producing a variety of health benefits (e.g., improving psychological and physical health, Sloan, 2010), and it is a crucial process for identity development (Davis, 2012). Hence, (online) self-disclosure is related to friendship formation and maintenance, especially in the adolescent years (Valkenburg and Peter, 2009), and it is a crucial component of high-quality friendships, which, in turn, predict adolescent well-being (Rueger et al., 2016). From a biological point of view, individuals with many and high-quality social connections show lower reactivity to stressors, leading experts to speak of "social buffering" against stress (Gunnar & Hostinar, 2015), as *being together allows to recover better* (Holt-Lunstad, 2017; Kikusui et al., 2006). Importantly, according to this hypothesis, the effect on well-being depends also on several personal and contextual factors, such as gender and the type of technology used (Valkenburg and Peter, 2009).

The Internet-enhanced self-disclosure hypothesis provides a valuable and comprehensive theoretical background to explain the positive effects of Internet use on social connection and well-being. On the other hand, one can sustain the opposite: Internet use may impoverish social connections, thus diminishing well-being. For example, a systematic review revealed that online technology could provide occasions for youth to develop and maintain a feeling of connectedness to others, but its use can also lead to poor peer relationships, thus contributing to mental health problems among adolescents (Wu et al., 2016). The latter finding is also sustained by the Evolutionary mismatch model (Sbarra et al., 2019). According to the author's view, Internet-related activities (especially smartphone and social media use) may reverse what ancestrally was an adaptive behavior into a new maladaptive one. For example, creating close relationships, self-disclosing information, and being responsive to others' needs are all crucial processes that promote intimacy, security, trust, and cooperation; however, they have been altered by Internet-based communication. This *mismatch* would be the result of environmental changes (i.e., the advent of digital transformation). Accordingly, the use of Internet-enabled devices may interfere – not promote – with the quality of everyday social interactions. For example, self-disclosure may enhance social bonds only if it is followed by a responsive behavior from the interlocutor, who understands and validates the speaker. However, using the Internet to communicate may provide a *superficial* disclosure followed by a *superficial* response, which cannot be compared to the ones obtained through face-to-face interactions. Instead, the latter would diminish and lose the initial ancestral meaning. A study comparing social interactions through face-to-face communication, telephone calls, and the Internet revealed that interactions via the Internet were perceived of significantly lower quality. Also, intimate relationships were maintained more often through face-to-face communication and telephone calls than through the Internet (Baym et al., 2004). At the same time, a study using neuroscientific data showed that emotional support conveyed through an in-person interaction diminished the experience of negative emotions (and deactivated the related neural correlates) in a way that online help did not (Morese, Lamm, Bosco, Valentini, & Silani, 2019). The difficulty of establishing deep and meaningful friendships online would be detrimental to overall well-being. At the same time, Internet use (especially through the smartphone) may interfere with ongoing activities, not only by displacing time for activities like homework, physical exercise, sleep, and social time with family and friends, which are known to protect from negative outcomes (Camerini, Gerosa, & Marciano, 2020), but also by interfering with the basic cognitive processes of personal communication (e.g., phubbing, lower attention to social cues, lack of appropriate responsiveness, and low empathy). In particular, according to this view, the more time spent online interacting with many different people, the less intimacy created with any of them. The result of this process is quite obvious: By diminishing relationship satisfaction, Internet use reduces well-being and augments symptoms of depression, loneliness, and anxiety. Online interactions do not provide enough interpersonal cues, thus decreasing the strength of interpersonal connection, which eventually makes social support effective (Shensa, 2020). Besides, adolescents who interact online with friends might be incapable of handling real-life relations and would experience loneliness and social disconnection more often (Konrath, 2012; Wu et al., 2016). Also, they might be unwilling to tolerate the boredom of staying alone (Davis, 2012).

2.1. *Depression and duration of internet use*

Depressive symptoms have been related to Internet use ever since the Internet took shape. When it comes to longitudinal studies disentangling between- and within-person effects, a study using the RI-CLPM found small but statistically significant cross-lagged effects at the within-person level for total screen time and symptoms of depression (Houghton et al., 2018). Screen time (in terms of social media, television, video gaming, and computer use) was also investigated as a predictor of depression in adolescents by Boers, Afzali, Newton, and Conrod (2019). They found that depressive symptoms increased steadily in the sample and, at the within-person level, any further increase in social media use was associated with increased depression later, indicating that the recurring exposure to idealized images decreased self-esteem and augmented depression. At the between-person level, mean levels of computer use over four years were associated with higher levels of depression.

Some researchers made use of new methodological approaches to investigate depression and causal correlates in real-time. For example, Raudsepp (2016) used Ecological Momentary Assessments for six consecutive days in adolescent girls and repeated that annually for six years. He found that initial levels of depressive symptoms predicted the

involvement in sedentary behaviors, including Internet use, whereas no associations emerged in the opposite direction. In a similar way, using Ecological Momentary Assessment, Moreno, Jelenchick, Koff, and Eickhoff (2012) found a U-shaped association between depression and Internet use from data collected in older adolescents. In their study, depression levels were higher at both low and high levels of Internet use and lower at moderate levels.

Internet use has been linked to depressive symptoms, especially when the Internet is used for social networking (e.g., Chen & Lee, 2013; Elhai et al., 2018), as in the case of the current study. This assumption also aligns with a Swiss report indicating that, in general, measures of Internet use correlate with social networking activities and smartphone use in Swiss adolescents (p.25 and p.30; Süss et al., 2020). Today, 90% of activities carried out on the Internet by adolescents are related to social media platforms (Süss et al., 2020). Applying the RI-CLPM with data collected from adolescents over six years, Puukko et al. (2020) reported that, although social media use and depressive symptoms grew increasingly across adolescent years, depressive symptoms were associated with a small and inconsistent increase in active social media use, whereas no significant result was found for the reverse relationship. Hence, the authors concluded that the association between social media use and depression had been exaggerated. Coyne, Rogers, Zurcher, Stockdale, and Booth (2020) followed adolescents aged 12 at T1 over eight years and found that, at the between-person level, time spent on social media was moderately related to anxiety and depression. However, within-person results did not reveal any causal associations between social media use and mental well-being over time, suggesting that the relation may involve other processes and cofounding variables, including personal and contextual factors.

Systematic reviews focusing on the (bidirectional) relationship between social media use and depression (e.g., Anderson, Steen, & Stavropoulos, 2017; Baker & Algorta, 2016; Keles et al., 2020; Vidal, Lhaksampa, Miller, & Platt, 2020) pointed toward a positive relationship, but they also acknowledged that the relationship between the two concepts is rather complex. Future research should consider potential mediators and moderators pertaining to psychological, behavioral, individual, and social factors. Furthermore, three meta-analyses focusing on social media use and depression (Ivie, Pettitt, Moses, & Allen, 2020; McCrae et al., 2017; Yoon et al., 2019) found a positive and small effect between the two concepts, although heterogeneity levels were high, thus calling for further research that includes contextual factors. Since past empirical evidence and theoretical frameworks point towards a bidirectional relationship between depression and Internet use, we hypothesized the following relations at the within-person level:

HP1. . The duration of Internet use has a positive and longitudinal impact on depression.

HP2. . Depression has a positive and longitudinal impact on the duration of Internet use.

In addition, at the between-person level, we hypothesized that:

HP3. . Adolescents who report a higher duration of Internet use also report higher levels of depression.

2.2. Depression and social connection

The need for social connection is rooted in human biology and lasts throughout the entire lifespan. Humans experience distress when social connections are lacking or damaged and, since social pain shares the same neural emotional response as physical pain (Cacioppo & Patrick, 2008; Holt-Lunstad, 2017), being socially isolated has a disruptive effect on both psychological and physical well-being. Psychosocial stress, caused by social rejection and negative quality of relationships, increases the risk for depression, especially during adolescence (Slavich & Irwin, 2014; Thapar et al., 2012a, 2012b). The temporal precedence, i.e. missing social connection leads to poor health, has been investigated by diverse prospective studies, whose results have been summarized in several meta-analyses (e.g., Holt-Lunstad et al., 2010; Roelfs et al., 2011; Shor & Roelfs, 2015). One meta-analysis underlined that social support is an important protective factor against depression in adolescence (Rueger et al., 2016), although the source for effective social support varies. In particular, support from family members and peers has been reported as most protective against depressive symptoms, compared to social support from teachers and close friends. A strong association between social support (in particular from family and friends) and the absence of depressive symptoms in adolescent years was also found in the review of Gariépy, Honkaniemi, and Quesnel-Vallée (2016). The review furthermore found that girls benefited more from good family relations and parental support. Longitudinal studies showed that lack of social support and peer rejection temporally predicts the onset of adolescent depressive symptomatology (Nolan, Flynn, & Garber, 2003; Prinstein & Aikins, 2004; Sentse, Lindenberg, Omvlee, Ormel, & Veenstra, 2010; Shochet, Smith, Furlong, & Homel, 2011; Witvliet, Brendgen, van Lier, Koot, & Vitaro, 2010; Young, Berenson, Cohen, & Garcia, 2005).

Similarly, results from experimental studies showed that, after completing tasks eliciting the experience of peer rejection, adolescent participants experienced negative emotional responses, including distress, negative affective response, deflected mood, and anxiety (La Greca & Harrison, 2005). In addition, depression levels predicted peer rejection and poor quality of relations, as well as problems in social adjustment (e.g., Little & Garber, 1995; Margolese et al., 2005; McDonald et al., 2010; Teo et al., 2013). Considering past evidence on the impact of social connectedness on depression, we formulated the following longitudinal relationships at the within-person level:

HP4. . Social connection with peers has a negative and longitudinal impact on depression.

HP5. . Depression has a negative and longitudinal impact on social connection with peers.

In addition, at the between-person level, we hypothesized that:

HP6. . Adolescents who report higher levels of social connection with peers also reported lower levels of depression.

2.3. Internet use and social connection

Nowadays, friendships in adolescence are established and maintained both offline, e.g., at school, and online, e.g., through social networking. Although the current study investigates offline social relationships, social media use is a form of networking listed as the most popular online leisure activity among Swiss adolescents (Süss et al., 2020), meaning that the great majority of time on the Internet is devoted to it. A systematic review by Wu et al. (2016) revealed that adolescents use the Internet to interact and connect with school peers and friends, facilitated by the accessible features of social media platforms. Internet-based communication allows adolescents to maintain a constant connection with their friends also offline. Oftentimes, the use of *lightweight* messages enables a sense of *co-presence* among peers (Okabe, 2005). Online exchanges enhance adolescents' friendship circles by allowing communication with whom they interact less frequently in offline situations (Davis, 2012). However, the Internet can also be used for non-social activities such as visiting news pages or streaming platforms. In a longitudinal study (Selfhout et al., 2009), adolescents with low-quality friendships who frequently surfed online, independently of the type of online activity, showed more depressive and anxiety symptoms over time. According to the authors, Internet surfing may lead to a vicious cycle in which ongoing gratifying activities go at the expense of long-term gratifications derived from high-quality offline social connections. However, the effects of Internet use and online communication on well-being may be confounded since adolescents who spend more time (communicating) online also use the Internet more in general

(Camerini, Gerosa, et al., 2020; Subrahmanyam et al., 2001). Considering the increasing time adolescents spend online (Süss et al., 2020), it is now critical to investigate how time online influences the time spent with friends in the long run and how the two are causally linked to depressive symptomatology at the within-person level. Given the competing theoretical assumptions of the Internet-enhanced self--disclosure hypothesis and the Evolutionary mismatch model, as well as mixed evidence on the link between Internet use and social connection, we formulated research questions rather than hypotheses at the within-person level:

RQ1. How do social connection with peers and duration of Internet use impact each other over time?

In addition, at the between-person level, we formulated that:

RQ2. . Do adolescents who report higher levels of social connection with peers also report a higher duration of Internet use?

2.4. Socio-demographic and contextual factors

Different socio-demographic and contextual factors play a key role in the longitudinal relationships among depression, Internet use, and social connection with peers. For example, prior research highlighted that girls are more active on social networking sites (Waller, Willemse, Genner, Suter, & Süss, 2016) and at higher risk for depression (Boris Birmaher et al., 1996; Thapar et al., 2012a,2012b). From the socio-cultural viewpoint, girls experience higher interpersonal dependence, more self-image and self-esteem concerns, and they show an increased need for external approval and success than boys (Weller et al., 2006). Thus, girls may use digital media extensively to seek online social relationships and role models they can compare to. At the same time, the enlargement of the social sphere and the onset of puberty make adolescents, and girls in particular, more preoccupied and worried about their social standing (McElhaney et al., 2008). Overall, these factors would diminish well-being. Additionally, in adolescents, higher levels of depression were found to be linked to the short allelic variant of the promoter polymorphism in the serotonin transporter gene (5-HTTLPR) (Lee et al., 2008), which is associated with various mood and anxiety-related problems as well as addictive behaviors (Oo et al., 2016). Girls carrying the short 5-HTTLPR allele react in a different way to environmental (social) stress factors and thus are at higher risk of depressive symptoms, whereas males seem to be more protected from depression (Sjöberg et al., 2006). Also, during puberty, girls tend to produce an increased cortisol response to stressful events, leading to a higher risk for depression during this period (Stroud et al., 2011).

A good family climate plays a key role in regulating Internet use, thus diminishing the risk of developing problematic online behaviors in children (Faltýnková, Blinka, Ševčíková, & Husarova, 2020; Marciano, Petrocchi, et al., 2020). A good family climate also promotes better parental knowledge of children's online activities, which is a crucial prerequisite for parental mediation of Internet activities (Marciano, Schulz, & Camerini, 2020). During the early adolescents years, there may be an overlap of the social sources (i.e., family and friends) of social provisions like support, closeness, and affection that promote well-being (Furman & Buhrmester, 1985). Although peers gain more importance during puberty (Brown & Larson, 2009), the family is still an anchor for pupils who lack satisfying friendships and *vice versa*. Hence, when one source is not functioning adequately, relations in the other domain increase in importance (Gauze et al., 1996). When the family climate is suboptimal, the individual development and needs satisfaction are limited. Thus, adolescents are willing to enhance social life outside the family. Hence, the quality of family relations may influence well-being in both directions.

Finally, personal access to the Internet is an important contextual factor as it facilitates an unsupervised and greater use of the Internet by adolescents. Personal Internet access has increased dramatically after the launch of the iPhone in 2007 and the iPad in early 2010. The age at which parents give their children their first Internet-enabled device is getting lower and lower (Moreno et al., 2019), and tweens are becoming early adopters and avid Internet and mobile device users (Lauricella et al., 2014). Access to the Internet has been related to less time for other activities such as sleep, doing homework, and sport (Marciano & Camerini, 2021) as well as less time spent in green space (Camerini et al., 2022) which are protective factors for mental health; at the same time, digital media ownership was also associated with more time spent with friends (Camerini, Gerosa, et al., 2020). However, research on adolescent smartphone ownership, and its consequences, is still in its infancy. While some researchers stated that there is no preferred age for adolescents to own a smartphone and that early smartphone ownership does not predict general well-being in later years (Bass, 2014; Vaterlaus et al., 2021), other experts argued that access to technology is related to lower levels of well-being in youth, with females and early adolescents being more vulnerable to experience negative outcomes (Orben et al., 2022; Twenge, 2020). Such finding led some researchers to sustain that smartphones should be banned for children and tweens (Stein, 2018; Wiederhold, 2019).

This study considered gender, family climate, and technology ownership as factors that are deemed to influence the bidirectional relationships between Internet use, social connection, and depression. Such a wider perspective is rarely considered in longitudinal research applying the random intercept cross-lagged panel model (RI-CLPM), as is the case in the present study. Additionally, the strength of the study lies in the long-term approach covering four years and this is important to better test the bidirectional hypotheses, especially in terms of within-person effects.

3. Methods

3.1. Data collection

We used data from waves 3 to 6 (following T1 to T4) of the ongoing MEDIATICINO longitudinal study. Data were collected in spring every year, with T1 in 2016 and T4 in 2019. Participants were approximately 1/3 of the underlying population and representative of adolescents born in 2004/5 in Ticino, Italian-speaking Switzerland. Participants were randomly selected at the class level at the beginning of the larger longitudinal study in 2014, when they attended primary school. In 2016, the cohort entered obligatory middle school and was distributed across public and private middle schools in different districts with small to medium size cities of Ticino. Of these schools, all 35 public schools and two private schools participated in the study, which assured the continuation of the majority of the participants in the study and a good representation of the underlying population. Additional students were randomly selected in 2016 to compensate for dropouts once students entered middle school. In MEDIATICINO, students got automatically enrolled in the public school closest to their residence. Alternatively, they can choose to attend a private school of their choice against payment. Although no data on the socio-economic situation of families at the level of the school district is available, the enrollment of the majority of the students according to their residence minimizes the systematic aggregation of students from the same socio-economic background.

Study participants filled out a paper-and-pencil questionnaire at school. A teacher was present to provide further instructions upon request. Of the distributed questionnaires ($n = 1492$ at T1, $n = 1460$ at T2, $n = 1419$ at T3, and $n = 1391$ at T4), schools returned 1375 successfully completed questionnaires at T1 (92%), 1307 at T2 (98%), 1374 at T3 (97%), and 1224 at T4 (88%). The main reasons for sample attrition were students being absent during the day of data collection as well as students' drop out of school or change of school. A unique identifier was assigned to each student by the regional education administration and used to match all collected data across the four waves. This procedure assured an anonymous data collection and analysis. Furthermore, students were free to opt-out of questionnaire

completion each year. Ethical approval of the study was received by the regional education administration.

4. Analytical sample

The initial sample for the present study included 1009 students whose answers were available for all four waves, with less than 10% of missing data on the measures of interest. After outliers, defined as ± 3.5 standard deviations from the mean, were removed (n = 28), the analytical sample included 981 participants. Based on T1 data, 53.9% were female (n = 529), and the averaged age was 11 years (M = 11.37, SD = 0.55). The Little's MCAR test, which compares the differences between the estimated and the observed means in each missing data pattern, showed data of manifest variables included in the model (duration of Internet use, depression, and social connection) were missing completely at random (MCAR) ($\chi 2 = 404.66$, $p = .056$). In other words, the probability that a value was missing was not related to the value of another observed variable or to other values of the variable itself. Hence we used a Bayesian regression imputation method and a predictive mean matching model to impute the remaining missing values.

4.1. Measures

All measures of this study were based on self-report. Measures were translated from English into Italian when necessary, and independent back-translation was performed to assure linguistic validity. Means, standard deviations, and reliability measures for each concept, at each wave, are summarized in Table 1. A complete list of items and response options can be found in Table 1 in the Appendix.

Depression was measured with seven items from the Center for Epidemiological Studies Depression Scale for Children (CES-DC; Roberts et al., 1990). This scale aims to measure general depressive symptoms and thus does not provide a clinical diagnosis for depression. Response options ranged from 0 "not at all" to 3 "a lot" ($\alpha_{T1} = 0.87$; $\alpha_{T2} = 0.90$; $\alpha_{T3} = 0.90$; $\alpha_{T4} = 0.91$).

Duration of Internet use was measured asking participants two separate questions on the duration of Internet use on a typical school day and on a typical weekend day. Response options ranged from 0 "never" to 8 "5 or more hours". We calculated a weighted average of duration of Internet use using the formula [(Internet use on a weekday*5 + Internet use on a weekend day*2)/7)] ($r_{T1} = 0.79$, $p < .001$; $r_{T2} = 0.83$, $p < .001$; $r_{T3} = 0.82$, $p < .001$; $r_{T4} = 0.84$, $p < .001$). To note, according to more detailed data on digital media use collected in our sample in 2019, duration of Internet use was highly correlated with social-based activities like smartphone use ($r = 0.766$, $p < .001$), social media use ($r = 0.650$, $p < .001$), and instant messaging ($r = 0.604$, $p < .001$). Whereas, the duration of Internet use correlated less with video-gaming ($r = 0.282$, $p < .001$) and watching TV/videos ($r = 0.343$, $p < .001$).

Social connection was measured by asking participants how much time they spent together with friends outside the school during a typical school day. Response options ranged from 0 "never" to 8 "5 or more hours".

Furthermore, we measured socio-demographic and contextual factors modeled as covariates as follows:

Gender was measured at T1 and coded as 1 "female" and 0 "male".

Quality of family relations was measured at T1 with eight items from Venkatraman et al. (2010) on a 5-point scale ranging from 1 "never or almost never" to 5 "always or almost always" (M = 4.36, SD = 0.61, $\alpha_{T1} = 0.833$).

Ownership of personal Internet-enabled devices was measured at T1 by asking participants which mobile devices (i.e., smartphone, tablet/laptop) with Internet access they own for personal use. 47.2% (n = 463) and 67.8% (n = 665) of the final sample answered to own a tablet/laptop and a smartphone, respectively, and 42.8% (n = 420) owned two or more devices.

Social desirability was measured at T1 with the 13-item Children's Social Desirability Short scale (CSD-S; Camerini & Schulz, 2018). The scale used a binary answer format with 0 "no" and 1 "yes". After partial item recoding, all answers were averaged, with higher scores indicating a higher propensity to answer in a socially desirable manner (M = 0.68, SD = 0.30). We controlled for social desirability bias since it is a frequent, systematic bias in studies based on self-report data, especially when collected from children and adolescents and on sensitive topics, increasing the likelihood to report in a socially desirable manner (Camerini & Schulz, 2018).

4.2. Analytical plan

First, to identify potential systematic bias, we conducted independent samples *t*-tests and Pearson's χ^2 statistic to check whether the analytical sample differed significantly from students who were excluded due to missing or outlier data.

Second, we tested the measurement invariance for the latent construct of depression with respect to gender and over time. Confirmatory factor analyses were run with a diagonally weighted least squares estimator (DWLS) for ordinal variables (Bollen & Long, 1993). Once the configural invariance between males and females was established, weak (constraining factor loadings), and strong (constraining both factor loadings and item intercepts) invariance were tested (Hirschfeld & Von Brachel, 2014). A χ^2 difference test was calculated to compare each nested model, but, considering its sensitivity to large sample sizes (Brannick, 1995; Curran et al., 2002), other fit indices were evaluated (Chen, 2007; Cheung & Rensvold, 2002). In particular, invariance of nested models was established if ΔCFI and ΔRMSEA were below 0.01 and 0.015, respectively (Chen, 2007; Cheung & Rensvold, 2002). We also tested the longitudinal invariance of the depression scale across the four data points (Hirschfeld & Brachel, 2014).

Third, to estimate the within- and between-person source of variance across the four waves, we calculated intra-class correlation coefficients

Table 1
Means, standard deviations, and bivariate correlation coefficients among all concepts.

	M (SD)	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1.Depression$_{T1}$	.49 (.56)	1										
2.Depression $_{T2}$	.59 (.66)	.310**	1									
3.Depression $_{T3}$	.67 (.71)	.222**	.341**	1								
4.Depression $_{T4}$	.71 (.72)	.182**	.335**	.427**	1							
5.Social connection $_{T1}$	3.19 (2.2)	.122**	.069*	.107**	.061	1						
6.Social connection $_{T2}$	3.76 (2.26)	.111**	.112**	.039	.030	.421**	1					
7.Social connection $_{T3}$	4.13 (2.32)	.060	.062	.078*	.072*	.356**	.433**	1				
8.Social connection $_{T4}$	4.38 (2.24)	.015	.042	.072*	.094**	.266**	.325**	.455**	1			
9.Internet use $_{T1}$	2.13 (1.68)	.186**	.153**	.134**	.120**	.285**	.191**	.228**	.169**	1		
10.Internet use $_{T2}$	2.90 (1.89)	.116**	.214**	.144**	.176**	.192**	.279**	.206**	.160**	.464**	1	
11.Internet use $_{T3}$	3.86 (2.00)	.100**	.177**	.150**	.168**	.205**	.205**	.326**	.232**	.428**	.459**	1
12.Internet use $_{T4}$	4.23 (1.91)	.105**	.146**	.171**	.182**	.153**	.186**	.233**	.259**	.359**	.345**	.559**

Note: N=981; T1 = Time 1, T2 = Time 2, T3 = Time 3, T4= Time 4; **p < .001; *p < .05.

(ICCs) of depression, duration of Internet use, and social connection. Fourth, we ran a series of Repeated Measures Analysis of Variance (ANOVA) to explore how the three constructs developed over the four years, and we calculated bivariate correlations among the variables in the model.

Eventually, we estimated an extended version of the RI-CLPM, including covariates and following the procedure by Mulder and Hamaker (2020). We used the "lavaan" package (Rosseel, 2012) in R statistical software (R Core Team, 2013). All the observed variables were mean-centered before they were entered in the main analysis, i.e. grand means represented the means of all units per occasion. First, a fully unconstrained model was tested. Then, at each following step of the model building procedure, autoregressive effects, and cross-lagged effects were constrained to be equal across all waves, variances and covariances of the latent variables were also constrained to be equal at T2, T3, and T4. Once the appropriate model was established, covariates were added as time-invariant predictors of the intercepts of depression, duration of Internet use, and social connection.

To deal with non-normally distributed data, we used the maximum likelihood estimator with robust (Huber-White) standard errors and a scaled test statistic (MLR). To evaluate the model goodness of fit, we inspected different fit indices, including the Comparative Fit Index (CFI), the Root Mean Square Error of Approximation (RMSEA), and the Standardized Root Mean Square Residual (SRMR). Given the large sample size for this study, the χ^2 value was not considered to be a good indicator of model fit. Byrne (2016) suggests accepting a model when the CFI is higher than 0.90 and close to 0.95, the RMSEA is 0.08 or less, and the SRMR is 0.05 or less. At each step, to choose the more parsimonious model, model results were compared to the previous ones considering the χ^2 statistic, ΔCFI and ΔRMSEA, together with a decrease in AIC and BIC, to detect any significant change in the model fit (Chen et al., 2008; Cheung & Rensvold, 2002). The data and R code for the main analyses are available at the following link: https://osf.io/bt57j.

5. Results

5.1. Preliminary results

The comparison of sample characteristics between the analytical sample (n = 981) and students excluded from T1 due to missing or outlier data (n = 394) revealed that the analytical sample was composed of more females ($\chi^2 = 20.078$, $p < .001$), and dropped participants were more likely to own a tablet/laptop ($\chi^2 = 7.806$, $p = .005$) or a smartphone ($\chi^2 = 8.862$, $p = .003$). In addition, dropped participants tended to report higher levels of depression at T1 ($t = 3.33$, $p = .001$), more duration of Internet use ($t = 3.647$, $p < .001$), lower levels of social desirability ($t = -4.12$, $p < .001$), and lower quality of family relationships ($t = -4.41$, $p < .001$).

Measurement invariance testing showed that the depression scale reached strong invariance for gender at all four data points and also strong longitudinal invariance (see Table 2 in the Appendix). Repeated measures ANOVA indicated that the three concepts of depression, Internet use, and social connection had a significant linear increase over time (see andFigure1 in the Appendix). ICC estimations showed that the variance of around 30% (ICC = 0.303) in depression, 30% in duration of Internet use (ICC = 0.302), and 35% in social connection (ICC = 0.349) was due to trait-like, between-person differences. Bivariate correlation analysis (Table 1) revealed positive and significant relationships among the three concepts over the four measurement points. However, correlation coefficients were mainly small (especially between social connection and depression), although the large sample size.

5.2. RI-CLPM model results

Considering different goodness-of-fit indices, the model building procedure indicated Model 4 (with autoregressive and cross-lagged

Table 2
Final RICLPM model estimates.

Model 3	Unstandardized Beta	S.E.	p-value	Standardized Beta (β)
Between-person effects				
Correlations				
$depression_i$ with social $connection_i$	.061		.601	
social $connection_i$ with Internet use_i	.450		**.000**	
$depression_i$ with Internet use_i	.225		**.075**	
Covariates				
Gender (Female) → $depression_i$	.235	.027	**.000**	.407
Social desirability → $depression_i$	−.188	.046	**.000**	−.198
Smartphone ownership → $depression_i$	.061	.027	**.025**	.099
Tablet/Laptop ownership → $depression_i$	.076	.026	**.004**	.133
Family relations → $depression_i$	−.168	.025	**.000**	.-355
Gender (Female) → social $connection_i$	.075	.104	.471	.031
Social desirability → social $connection_i$	−.406	.177	**.022**	−.101
Smartphone ownership → social $connection_i$	.620	.109	**.000**	.238
Tablet/Laptop ownership → social $connection_i$	.323	.102	**.002**	.133
Family relations → social $connection_i$	−.257	.096	**.008**	−.128
Gender (Female) → Internet use_i	.063	.083	.449	.029
Social desirability → Internet use_i	−.585	.143	**.000**	−.165
Smartphone ownership → Internet use_i	.744	.081	**.000**	.324
Tablet/Laptop ownership → Internet use_i	.627	.080	**.000**	.292
Family relations → Internet use_i	−.468	.073	**.000**	−.266
Within-person effects				
Auto-regressive paths				
$depression_{T1}$ → $depression_{T2}$	.229	.042	**.000**	.180
$depression_{T2}$ → $depression_{T3}$	.229	.042	**.000**	.226
$depression_{T3}$ → $depression_{T4}$	.229	.042	**.000**	.229
social $connection_{T1}$ → social $connection_{T2}$	.197	.036	**.000**	.190
social $connection_{T2}$ → social $connection_{T3}$	.197	.036	**.000**	.196
social $connection_{T3}$→ social $connection_{T4}$	.197	.036	**.000**	.197
Internet use_{T1} → Internet use_{T2}	.278	.038	**.000**	.218
Internet use_{T2} → Internet use_{T3}	.278	.038	**.000**	.274
Internet use_{T3}→ Internet use_{T4}	.278	.038	**.000**	.278
Cross-lagged paths				
$depression_{T1}$ → social $connection_{T2}$	.105	.095	.266	.027
$depression_{T2}$ → social $connection_{T3}$	.105	.095	.266	.035
$depression_{T3}$ → social $connection_{T4}$	.105	.095	.266	.035
$depression_{T1}$→ Internet use_{T2}	.142	.075	**.059**	.043

(continued on next page)

Table 2 (*continued*)

Model 3	Unstardardized Beta	S.E.	p-value	Standardized Beta (β)
$depression_{T2}$ → Internet use_{T3}	.142	.075	**.059**	.054
$depression_{T3}$ → Internet use_{T4}	.142	.075	**.059**	.055
social $connection_{T1}$ → $depression_{T2}$	−.002	.009	.832	−.006
social $connection_{T2}$ → $depression_{T3}$	−.002	.009	.832	−.006
social $connection_{T3}$ → $depression_{T4}$	−.002	.009	.832	−.006
social $connection_{T1}$ → Internet use_{T2}	.011	.023	.639	.012
social $connection_{T2}$ → Internet use_{T3}	.011	.023	.639	.013
social $connection_{T3}$ → Internet use_{T4}	.011	.023	.639	.012
Internet use_{T1} → $depression_{T2}$	.027	.012	**.021**	.055
Internet use_{T2} → $depression_{T3}$	.027	.012	**.021**	.070
Internet use_{T3} → $depression_{T4}$	.027	.012	**.021**	.071
Internet use_{T1} → social $connection_{T2}$	.024	.037	.521	.016
Internet use_{T2} → social $connection_{T3}$	.024	.037	.521	.020
Internet use_{T3} → social $connection_{T4}$	.024	.037	.521	.020
Residuals correlations				
$depression_{T1}$ with social $connection_{T1}$	.067	.041	.100	.073
$depression_{T2}$ with social $connection_{T2}$	.073	.031	**.017**	.063
$depression_{T3}$ with social $connection_{T3}$	.073	.031	**.017**	.063
$depression_{T4}$ with social $connection_{T4}$	.073	.031	**.017**	.063
$depression_{T1}$ with Internet use_{T1}	.039	.032	.216	.063
$depression_{T2}$ with Internet use_{T2}	.095	.025	**.000**	.098
$depression_{T3}$ with Internet use_{T3}	.095	.025	**.000**	.098
$depression_{T4}$ with Internet use_{T4}	.095	.025	**.000**	.098
Internet use_{T1} with social $connection_{T1}$	.320	.111	**.004**	.138
Internet use_{T2} with social $connection_{T2}$	.503	.075	**.000**	.171
Internet use_{T3} with social $connection_{T3}$	.503	.075	**.000**	.171
Internet use_{T4} with social $connection_{T4}$	.503	.075	**.000**	.171

Legend: T1 = Time 1; T2 = Time 2; T3 = Time 3; T4 = Time 4; i = latent intercept.

paths as well as residuals constrained to be equal across time) as the more parsimonious model (see Table S6 in the Appendix for model fit comparisons). At this point, we added the covariates to the final model that showed good model fit ($\chi^2 = 243.355$, $df = 96$, $p < .001$, CFI = 0.946, RMSEA = 0.041 [90% CI = 0.034 - 0.047], SRMR = 0.038) (See Fig. 1). We ran the analyses with and without outliers (n = 28). The autoregressive and cross-lagged results remained basically the same. The only exceptions were that smartphone ownership did not predict the random intercept of depression.

At the within-person level, we found significant autoregressive effects for depression (T1 to T2: $\beta = 0.180$, $p < .001$; T2 to T3: $\beta = 0.226$, $p < .001$; and T3 to T4: $\beta = 0.229$, $p < .001$), indicating that depression levels above the participant's mean at one time point predicted an increase in the level of the same variable one year later. We also found autoregressive effects for social connection (T1 to T2: $\beta = 0.190$, $p < .001$; T2 to T3: $\beta = 0.196$, $p < .001$; and T3 to T4: $\beta = 0.197$, $p < .001$) and for Internet use (T1 to T2: $\beta = 0.218$, $p < .001$; T2 to T3: $\beta = 0.274$, $p < .001$; and T3 to T4: $\beta = 0.278$, $p < .001$).

Moving on to the cross-lagged effects, Internet use at T1 significantly positively predicted depression levels at T2 ($\beta = 0.055$, $p = .021$). The same effect occurred in the following years ($T2_{Internet\ use}$ to $T3_{depression}$: $\beta = 0.070$, $p = .021$; $T3_{Internet\ use}$ to $T4_{depression}$:$\beta = 0.071$, $p = .021$), indicating that the time spent on the Internet above the participant's mean at one-time point positively impacted depression levels in the following year, controlling for depression levels at the previous time point. Interestingly, also the opposite occurred, although the results were smaller and marginally significant. More precisely, depression levels at T1 positively predicted duration of Internet use at T2 ($\beta = 0.043$, $p = .059$). The same effect occurred in the following years ($T2_{depression}$ to $T3_{Internet\ use}$: $\beta = 0.054$, $p = .059$; $T3_{depression}$ to $T4_{Internet\ use}$: $\beta = 0.055$, $p = .059$). We neither found cross-lagged effects between duration of Internet use and social connection nor between depression and social connection.

Within-person correlations among the residuals between depression and social connection, as well as between social connection and duration of Internet use, were positive and significant at T2, T3, and T4, but not at T1. Residuals correlations between depression and duration of Internet use were significant and positive at all four measurement points.

At the between-person level, we found a significant correlation between the random intercepts of social connection and duration of Internet use ($r = 0.450$, $p < .001$), indicating that adolescents who spent more time with friends as an indicator of social connection also reported more time on the Internet. In addition, the random intercepts of depression and duration of Internet use were also partially correlated (r = 0.225, p = .075). Table 2 summarized the model results, while Table 3 summarizes all hypotheses and research questions and the final decisions based on our study findings.

Looking at the role of covariates, gender was a significant predictor of the intercept of depression (B = 0.235, p < .001), indicating that females showed higher levels of depression over time. In addition, students with a higher propensity to answer in a socially desirable manner reported lower levels of depression (B = −0.188, p < .001), social connection (B = −0.406, p = .022), and duration of Internet use (B = −0.585, p < .001).

Owning a smartphone (B = 0.061, p = .025) and a laptop/tablet with Internet access (B = 0.076, p = .004) positively influenced the intercept of depression. This finding indicates that students with a personal device also showed higher levels of depression. Furthermore, owning a smartphone largely and positively predicted the intercept of social connection (B = 0.620, p < .001) and duration of Internet use (B = 0.744, p < .001). Tablet/laptop ownership showed similar yet smaller effects for social connection (B = .323, p = .002) and duration of Internet use (B = 0.627, p < .001). Finally, good family relations negatively predicted the intercept of depression (B = −0.168, p < .001), social connection (B = −0.257, p = .008) and duration of Internet use (B = −0.468, p < .001). The path coefficients for all covariates are summarized in Table 2.

6. Discussion

The present study used an extended version of the RI-CLPM (Mulder & Hamaker, 2020) to disentangle the within- and between-person effects of depression, duration of Internet use, and social connection with peers over four years in a large sample of early to mid adolescents in Switzerland. In doing so, we filled a gap and analyzed longitudinal data from the critical period of adolescence (Larsen & Luna, 2018), while considering contextual factors that played a role in the development of these concepts and their relationships. We aimed to test two competing theoretical models, i.e. the Internet-enhanced self-disclosure hypothesis (Valkenburg and Peter, 2009) and the Evolutionary mismatch model (Sbarra et al., 2019), linking Internet use, social connection, and well-being, here measured in terms of depression. Model results pointed

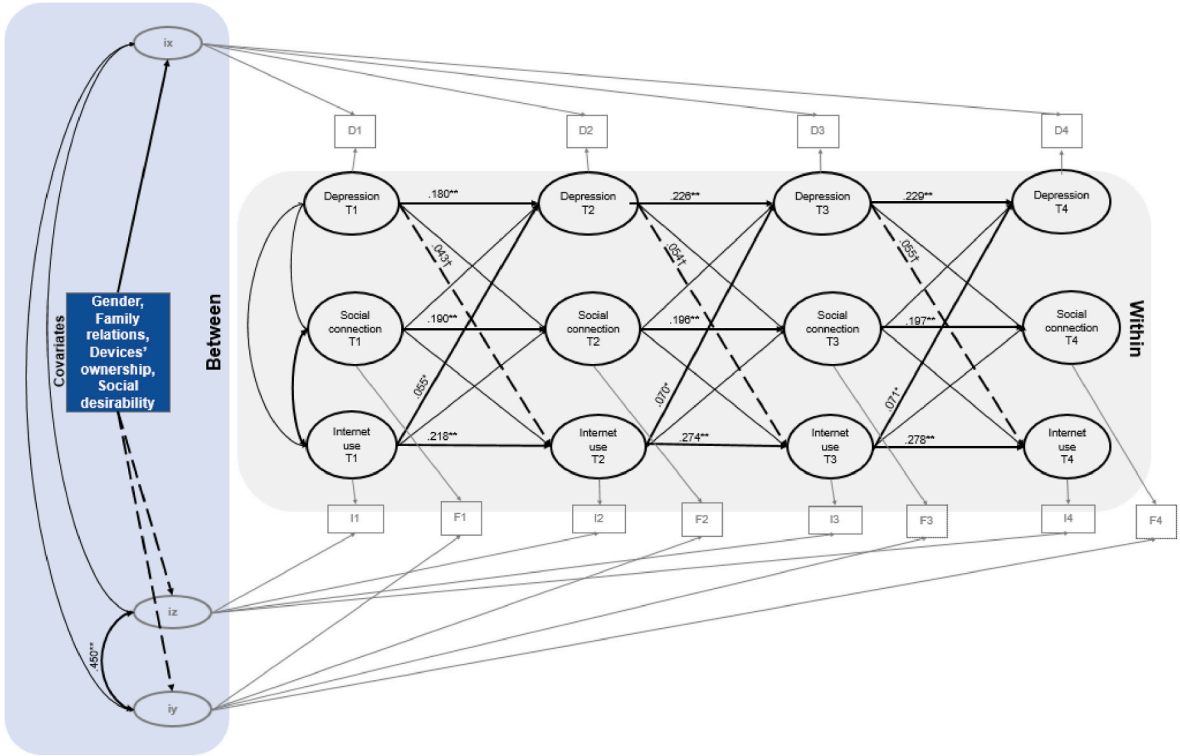

Fig. 1. An extension of the RI-CLPM with covariates affecting the random intercepts.

Table 3
Overview of study hypotheses/research questions and final decisions/answers.

Hypothesis/research question	Level of analysis	Final decision/ answer
HP1. Duration of Internet use has a positive and longitudinal impact on depression over time.	Within-person	Supported
HP2. Depression has a positive and longitudinal impact on the duration of Internet use over time.	Within-person	Partially supported
HP3. Adolescents who report a higher duration of Internet use also report higher levels of depression.	Between-person	Rejected
HP4. Social connection with peers has a negative and longitudinal impact on depression over time.	Within-person	Rejected
HP5. Depression has a negative and longitudinal impact on social connection with peers over time.	Within-person	Rejected
HP6. Adolescents who report higher levels of social connection with peers also reported lower levels of depression.	Between-person	Rejected
RQ1. How do social connection with peers and duration of Internet use impact each other over time?	Within-person	No effects
RQ2. Do adolescents who report higher levels of social connection with peers also report higher duration of Internet use?	Between-person	Yes

Legend: D = Depression, I = Internet use, F =Social connection with friends, T1 = Time 1, T2 = Time 2, T3 = Time 3, T4 = Time 4, i = intercept, x = latent variable for depression, y = latent variable for social connection with friends, z = latent variable for Internet use. Correlation among residuals are not displayed. **p < .01, *p < .05, †p < .1.

towards four major findings, which partly sustain both theoretical models. The first, and most important, is that, at the within-person level, higher levels of Internet use cause an increase in depressive symptoms over time. To note, in both cases, the size of the effect was small, which reflects the results of previous literature (Orben, 2020; Orben et al., 2019). The second major finding, at the between-person level, is the positive association between social connection with peers and the amount of Internet use: In other words, adolescents who spend more time with peers are also online for a longer time. Thirdly, we found no other longitudinal within-person effects, i.e., no influence of duration of Internet use on social connectedness, and *vice versa*, as well as no influence of connectedness on depressive symptoms, and *vice versa*. The fourth noteworthy result is that all the considered covariates, i.e., gender, quality of family relations, and Internet-enabled device ownership, had a significant explanatory effect on the intercept of all the three included variables, thus giving a more comprehensive picture of the results. Hence, future studies should consider including contextual variables in modeling longitudinal relationships. Also, due to the heterogeneity of results, it possible that individual effects in positive and negative directions summed up in null effects. Hence, a closer look to the individual dynamics, allowing to consider both the person-specific component (e.g., Valkenburg, 2022; Beyens et al., 2020) and the temporal fluctuations (Marciano et al., 2022) would further provide insight into the direction of the effects, and how they differ at the individual level.

But how can the results be interpreted? The first major finding means that the worries about deleterious effects of high Internet use on depression have a basis, while effects on social connectedness appear to be unfounded. In line with other longitudinal findings (e.g., Houghton et al., 2018), it cannot be easily dismissed that the use of the Internet has detrimental effects on young people's mental health. In particular, this result provides partial support for the Evolutionary mismatch model, stating that the time spent with online activities would go to the detriment of well-being through diverse mechanisms. Although Internet use does not augment or diminish (offline) social connections with friends at the within-person level, it may interfere with other offline social or non-social activities (e.g., physical activity, sleep, quality time with family members), with consequences for their mental well-being (Biddle et al., 2019; Cairns et al., 2014). Furthermore, this finding underlines the need to explore further what type of Internet activities adolescents

primarily engage in and how these contribute to depression. For example, previous studies have found that the consumption of social media contents fosters social comparison mechanisms in which predominantly female users relate themselves to idealized representations of others, which creates dysfunctional beliefs about the self. By doing so, online social comparison might diminish self-esteem and increment depression and anxiety levels (McCarthy & Morina, 2020; Sherlock & Wagstaff, 2019) as well as ruminative thoughts (Feinstein et al., 2013). At the same time, adolescents can bump into aggressive and risky contents, including cyberbullying, which lead to higher anxiety and depression levels over time (Camerini, Marciano, et al., 2020; Marciano, Schulz, et al., 2020). Our results partially sustained also the inverse effect, i.e. higher levels of depressive symptoms lead to higher Internet use. It is possible that young people may go online to escape from everyday problems (Subudhi et al., 2020), and adolescents who already experience depression and loneliness tend to have negative perceptions of their own social skills (Segrin, 2000), thus finding the online environment a safer and more comfortable place in which they can interact more freely. When both dynamics are in operation, a vicious circle can occur, where Internet use causes depressive symptoms, which in turn furthers attention to the Internet, which, in turn, increases depression through the mechanisms just outlined. The consequences of such a mutual reinforcement would be at the basis of mental health problems (Caplan, 2003). However, future studies should replicate this result.

The second major finding is partly in line with the Internet-enhanced self-disclosure hypothesis: Adolescents who are well connected with their peers also spend more time online. Adolescents today spend a great deal of their online time on social media and instant messaging applications, which encourage adolescents to communicate with existing friends (Valkenburg & Peter, 2007). This is not surprising, considering that adolescents in middle school focus their attention on building and maintaining peer relationships (Nickerson & Nagle, 2005). Staying online to interact with friends is the new normality, so one activity does not anymore go at the expense of the other. Hence, according to this view, *the socially rich teen stays rich*, both offline and online. More precisely, time spent online, especially for communicating with friends, may enhance self-disclosure through hyperpersonal communication, which, in turn, may improve friendship quality and well-being (Valkenburg & Peter, 2009). However, our results only partially sustained these assumptions although previous research underlined that social ties can be promoted online (Lee, 2009), we did not find any within-person effect between Internet use and social connection with friends. Hence, we cannot state that *offline* social connection is fostered by *online* interaction. Future studies disentangling between- and within-person effects of Internet use and social connection are thus needed to determine whether a causal mechanism between the two exists or whether the relationship is, indeed, spurious. To this regard, it is possible that one hypothesis holds for a certain group of individuals versus another, thus resulting in null and mixed results. Hence, in line with the person-specific effect approach to the study of media effects (e.g., Valkenburg, 2022; Beyens et al., 2020), we think that it is time to center back the person in the context (Molenaar, 2004; Molenaar & Campbell, 2009), with additional consideration of the temporal dynamics (Marciano et al., 2022), since the use of digital technologies tends to be scattered throughout the day. Also, hypotheses are not always supported across different contexts but in specific contexts and moments. Hence, the effects of a behavior (e.g., Internet use) can be negative, positive, or null, depending on the person and the situation. We suggest that future studies should focus on also delineating how a hypothesis holds in a specific individual by considering the actual context.

Our study is one of the first that considered covariates as contextual factors in the RICLPM. All covariates considered in this study had a significant effect on the intercepts of the included variables, indicating that the use of additional information can complement the picture and give a comprehensive overview. For example, girls were more at risk of developing depressive symptoms than boys. These results are in line with findings from the developmental literature but also with more recent longitudinal analyses of mental health symptoms trajectories in adolescence (e.g., Murray et al., 2020), in which female adolescents showed higher starting internalizing (i.e., depression and anxiety) symptoms at the beginning of the adolescent period, with a further increase from early to middle adolescence (with a peak at 13–14 years of age). Again, it's possible that pubertal hormones commonly augment the likelihood of developing internalizing problems more in female than male adolescents; at the same time, females are more sensitive to social cues (e.g., rejection) conveyed online, and they experience identity issues due to the developmental changes occurring at that age (Rapee et al., 2019). In addition, our results showed that a good family climate could be a protective factor against depression, which is in line with previous literature underlying that parents act as safe guardians (Gunnar & Hostinar, 2015). Adolescents who are in good relations with their family members would spend less time with friends or on the Internet and, thus, more time with family (Faltýnková et al., 2020; Marciano, Schulz, & Camerini, 2020). Finally, device ownership may increase both depression and Internet use, which mirrors previous concerns stating that digital devices can be detrimental to youth well-being (Stein, 2018; Wiederhold, 2019). This finding also adds to the ongoing debate on when to give children and adolescents private access to smartphones or other Internet-enabled devices. While these devices are an inherent part of our everyday life, they need to be introduced with caution and in a context with parental support, for example, in the form of active and secure mediation to protect from adverse outcomes caused by Internet use (Collier et al., 2016).

Finally, levels of depression, Internet use, and social connection with friends augmented over time. At the within-person level, the autoregressive effects for each variable in the model were all positively and significantly associated across the four years, indicating that within-person increases in depression, Internet use, and social connection, predicted within-person increases in the same variable one year later. However, the effect sizes of the betas in the RICLPM, as well as the correlation coefficients, were of small sizes, although the large sample. To note, large-scale studies reported small but adverse effects of digital media use on well-being, with only 1% of explained variation (Przybylski & Weinstein, 2017). Some critical linkages between digital media use and well-being may be overlooked by mixing up different sub-groups and population characteristics. However, also small effects can have practical importance: A small effect experienced by the population at large can lead to outcomes that are costly (e.g., higher depression rates which may turn to higher hospitalizations; negative effects of social comparison in youth may create more diagnosis of eating disorders, higher distractibility and cognitive load, which may turn in lower efficiency at work/school, etc.). That said, *at a large-scale, also small effects matter*.

7. Limitations and future directions

Some methodological limitations should be considered when interpreting our study findings. Given the topical variety of the larger longitudinal study from which the data were taken, we used only two-item indicators to measure general duration of Internet use, which is often criticized as too simplistic. A more detailed assessment with multi-item indicators, covering various aspects of Internet use, such as active and passive social networking, information seeking, online gaming, the frequency of cyberbullying or social support seeking and receiving through social media, would provide further insights on the hypothesized relationships. For example, using the frequency of different types of usage, Dienlin, Masur, and Trepte (2017) found that instant messaging and social media use had a mutually reinforcing effect, and the latter also enhanced life satisfaction over time. Furthermore, the measure of social connection with friends can be further elaborated, including the quality of friendship, self-disclosure, perceived support from friends but also perceptions of social exclusion. Additionally,

change of family relations (which we did not assess) may be another predictor of depression. Also, gender was measured as only male and female, however, future studies should be more inclusive by focusing on the role of online social connectedness and well-being of LGBTQ youth. Eventually, selective missingness and the presence of teachers during questionnaire completion at school could have biased the results, hence, our findings should be interpreted to the limit of our sample characteristics. Similarly, partially significant results in our study should be interpreted more as a tendency of our data, and future studies replicating such results are needed.

The present study lays the grounds for different directions for future research. First, future research should disentangle within- and between-person effects to replicate the findings of this study. For example, considering the results of a recent meta-analysis (Liu et al., 2019), it would be helpful to compare longitudinal data of different media and device use and their impact on well-being. According to the authors, phone calls and texting have been found to improve well-being, while social media, instant messaging, and online gaming would diminish it. Second, the consideration of additional mediating or contextual factors (e.g., physical activity, sleep, or other sedentary behaviors) would complete the picture on the role of Internet use and social connection in depression. Third, moderation analysis would allow testing whether the between and within-person effects that we found in the present study also hold across different adolescent populations. In other words, contextual factors such as gender, device ownership or family climate can become moderators, but such models with three within-person factors measured at multiple times require large sample sizes to reach the necessary statistical power to detect small effects. Eventually, it would be beneficial to introduce *in-situ* assessments of depression, Internet use, and social connection, as the use of multiple short surveys throughout a day over a given timeframe would provide an even more detailed and reliable picture of within-person experiences and bidirectional effects of the concepts investigated in this study (Sequeira et al., 2020).

Authors Contributions

Laura Marciano: Conceptualization, Methodology, Formal Analysis, Writing - Original Draft, Writing - Review & Editing, Funding acquisition. Peter J. Schulz: Conceptualization, Validation, Writing - Review & Editing, Supervision. Anne-Linda Camerini: Writing - Review & Editing, Supervision, Project administration, Funding acquisition.

Data availability

The data and R code are now available at the following link: https://osf.io/bt57j.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chb.2022.107390.

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