Internet Use, Health and Well-being Does social capital play a role?*

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Abstract

This paper investigates the relationship between Internet use and an individual's health and well-being, while exploring whether social capital play a potential mediating role. Using data from the German Family Panel (pairfam), we show that Internet users are more likely to report poor health and lower levels of subjective well-being. Our results therefore suggest that Internet use seems to negatively affect the subjective dimensions of health, whereas no effect is found on more objective measures of physical and mental health. Although Internet use also has an impact on an individual's social capital, by increasing social interactions and social activities, no clear mediating effect is found in the relationship between Internet use and health.

Keywords: Health, Internet, Social Capital.

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1 Introduction

Technological advancements have brought about substantial changes in our daily lives with relevant implications for individuals and their social behaviors. One of the areas in which technology has being playing a crucial role is health-care. Over the last half-century, new technologies and medical techniques have substantially improved prevention and treatment of several diseases, leading to a greater quality of life and higher life expectancy. For instance, in the U.S., the death rate due to heart diseases has dropped by nearly three times, whereas the cancer survival rate has increased by 30 % over the last half century.[1] Similar positive trends are found in Europe, where, despite some heterogeneities by country, the share of people surviving deadly cancers has constantly gone up: 82.8% beat the cancer in 2017, compared with 75.8% at the beginning of the century (Allemani et al., 2018). However, medical advances are not the only technological changes that matter for health. The digital revolution has deeply affected both health and health-care in many other different dimensions, which are still understudied.

With the advent of the Internet, more and more people have access to medical and health-related information, thereby allowing for the search of symptoms, specialists, treatments, and cures on-line. Moreover, health-related smartphone applications are intensively used to assist patients, convey information concerning the delivery of health services, and promote healthy behaviors. Digital therapy platforms provide online therapy sessions focused on patients' specific needs. As a result, Internet access can be assumed to have a strong positive effect on health outcomes, well-being and health behaviors (Guldi et al., 2017; Castellacci and Tveito, 2018). At the same time, Internet access allows individuals to be constantly connected with a broader social network of virtual relationships. Such condition of continuous interactions with the rest of the world has been shown to foster the so called "fear of missing out" (FOMO) and the need to always be up-to-date. All that can lead to a small but reliable increase in depression, due to a raise of health-related anxiety (Bessière et al., 2010), higher perceived digital stress (Lee et al., 2014), and the fear of missing out potential social interactions (Reinecke et al., 2017). Lastly, intensive Internet use may favor a more sedentary lifestyle with a resulting negative effect in terms of physical health and increased body weight both among adolescents (Tsitsika et al., 2016) and adult population (DiNardi et al., 2017). The direction and the magnitude of the effect of Internet on health are therefore theoretically ambiguous and will ultimately be an open empirical question.

In this paper, we study the association betwee Internet use and an individual's mental and physical health, also focusing on the role played by

[1]See, for instance, https://www.cdc.gov/nchs/fastats/heart-disease.htm and https://www.cdc.gov/nchs/fastats/cancer.htm

social capital as a potential mediating factor of this relationship. The contribution of our study on the existing – and still scarce – literature on the effect of Internet on an individual's health is twofold. Firstly, the present paper extends the literature by providing a comprehensive analysis of the association between Internet use and several dimensions of an individual's health, investigating both subjective and objective outcomes, as well as physical and mental ones. Second, our analysis integrates two still independent strands of literature: the first one on the effects of Internet on health, and the other one on the impact of Internet on an individual's social capital. We believe that bringing together these two bodies of research may help shedding further light on the phenomenon of *internetization* (Fortunati, 2005), that is how Internet has been altering social and economic dynamics in our societies as well as individuals' life dimensions, bringing about radical changes in their nature. In order to uncover how an individual's health is affected by the Internet, we therefore also need to understand how the social dimension of one's life is internetized.

In our empirical analysis, we exploit the richness of the German Family Panel (pairfam), a longitudinal panel dataset containing information on a broad set of individuals' socio-economic characteristics in Germany. We find that Internet use has a negative impact on self-rated health and well-being, whereas no evidence of significant effects of Internet on more objective dimensions of physical and mental health is found. At the same time, Internet use seems to increase an individual's social interactions and social activities. That could suggest that an increased availability of social capital brought about by Internet may result in a communication and social interactions overload, which in turn negatively affects the subjective dimensions of health and well-being. However, a specific moderation analysis is unable to confirm such explanatory pathway.

The remainder of the paper is structured as follows. Section 2 briefly presents the conceptual framework of our study. Sections 3 and 4 describe the data and methods, respectively. Section 5 presents the results, and section 6 concludes.

2 Conceptual Framework

Our paper integrates two strands of research: the literature on Internet use and health, and the literature on Internet use and social capital.

While Internet use can improve health by promoting access to information concerning health outcomes and health behaviors, being constantly informed about diseases can lead to increased pessimism, depression and health-related anxiety (Bessière et al., 2010). Moreover, as people spend more time sitting in front of their personal computers, they may reduce time devoted to physical activities, thereby adopting a more sedentary lifestyle. Furthermore, recent empirical evidence also suggests that Internet overuse near bedtime can lead to sleep problems and disorders (Shochat, 2012; Chen and Gau, 2016; Billari et al., 2018), with negative consequences for mental and physical health. We are interested in exploring which dimensions of health are affected by Internet use, also investigating whether the effect of the latter is equally important for subjective (e.g., subjective well-being) and objective health outcomes (e.g., BMI).

The Internet may also influence physical and mental health by affecting an individual's social capital. A growing body of literature shows that social capital is affected by communication and entertainment technologies, such as television and Internet (e.g., La Ferrara et al., 2012; Bauernschuster et al., 2014; Geraci et al., 2018). However, there seems to be no consensus on the direction of this effect. While some studies find a positive impact of communication technologies on social capital, by increasing social interaction and engagement (Bauernschuster et al., 2014), others show that the more time people spend using information technologies for virtual interactions, the less the time devoted to social interactions is worth in terms of well-being (Olkean, 2009; Rotondi et al., 2017; Geraci et al., 2018). In this study, we aim at providing new and further evidence on the relationship between Internet use and social capital, with the idea of also investigating whether changes in the latter due to the former might also partially explain the effect of Internet use on an individual's health.

Social capital represents an important source of social support and, thus, is a key determinant of an individual's health (Fiorillo and Sabatini, 2011, 2015). Existing literature shows that social support has positive effects on mental and physical health. As an example, while participation in social activities is found to improve older adults' ability to perform daily life's activities (Tomioka et al., 2016), perceived social isolation is linked to an increase in the stress hormone cortisol, high blood pressure and inflammation in the body (Cole et al., 2015). Accordingly, loneliness can be related to higher rates of morbidity and mortality (Cacioppo and Cacioppo, 2014), social isolation to increased chance of premature death (Luo et al., 2012), and low social trust to higher rates of psychosomatic symptoms, musculoskeletal pain, and depression (Åslund et al., 2010). While the effect of social capital on mental health is generally robust, few studies report that, although increased access to social capital has been found to be associated with a significantly higher level of quality of life, it had no independent effect on the course of depression (Webber et al., 2011).

This inconclusiveness can be related to the fact that, today, the term "social capital" describes more a strand of the literature than a specific concept.[2] While this paved the way to a genuine interchange among scholars

[2] For a discussion regarding whether the concept of social capital is indeed a good social science concept see Bjrnskov and Snderskov (2013).

from different disciplines, the array of definitions and measurement methods used in the empirical literature has often made it difficult to compare the results of different studies and formulate any general assessment about the effects of social capital (Sobel, 2002).

One of the reasons behind this difficulty is the practice, very common in sociology and economics, to use the label "social capital" to indicate one of its components, thus measuring a part for the whole. Social capital arises from social networks and it is the use that individuals make of them that may produce social capital. Following Bourdieu (1986) and Coleman (1994), social capital is therefore *intangible*. In order to possess social capital, a person must be related to others and it is those others, not himself, who are the actual source of his social capital, as tangible resources (Lin et al., 2001). In fact, the existence of social capital depends on the quality of the networks, on their ability in promoting and socializing trust (Sabatini, 2009), on the actions undertaken by individuals in building trust and reciprocity inside and towards those networks, and on the resources available to their connections (Portes, 2000).

The literature usually defines trust as the *cognitive* component of social capital, while networks are generally referred to as its *structural* component (Burt, 2000). While trust is more linked to individuals' perceptions, and it is therefore more difficult to measure, networks are usually identified through observation of reality (e.g., exchange of resources between individuals, participation in voluntary activities).[3]

In this paper, we focus on the structural component of social capital rather than on its cognitive dimension. Specifically, building on an existing strand of research (Uhlaner, 1989; Gui, 1987), we examine relational goods, i.e., goods that "can only be possessed by mutual agreement that exist, after appropriate joint actions taken by a person and non-arbitrary others"(1989, p. 254). While the primary producers of these goods are family and friends, social events, such as concerts and sport events (Becchetti et al., 2008), or the active engagement in volunteering associations, can also produce them. A few papers to date show that relational goods have a positive effect on well-being (Bruni and Stanca, 2008; Becchetti et al., 2008; Stanca, 2009; Becchetti et al., 2011; Colombo et al., 2017).

We operationalize relational goods as social interactions, social activities and social cohesion. We expect that the increased availability of social relations brought about by Internet can play a two-fold and opposite role for an individuals' health. On the one hand, given that social capital is a source of social support it can play a crucial role as a buffering factor for the negative

[3]The structural and cognitive components of social capital are inextricably linked, either positively or negatively (Sabatini, 2009). Trust, for instance, can confer legitimacy to cooperative behaviors that can result in the formation of networks. These networks, in turn, strengthen trust and reciprocity. Conversely, certain types of networks hamper trust by restricting others, outside the network, in accessing it (Woolcock, 2001).

effect of techno-stress on health (Lee et al., 2014). Conversely, the communication and social interactions overload brought about by over connection might have detrimental effects in terms of health. Such detrimental effect might stem from the so-called Fear of Missing Out (FOMO), that is the pervasive apprehension to miss others' rewarding experiences, which translates to the desire to stay continually connected with what others are doing (Przybylski and Weinstein, 2013; Buglass et al., 2017). Furthermore, the replacement of real relationships with virtual ones generated by the availability of remote connection with people not physically present, and the possibility of carrying out more and more activities without moving from home (think for example to the increasing connectivity of mobile phones) has a negative effect on physical health because it increases a sedentary life.

3 Data

In our empirical analysis, we employ data from the pairfam, a multi-disciplinary longitudinal dataset, which focuses on partnership development, family formation, child-rearing as well as intergenerational relations in Germany. It was first conducted in 2008/2009, and consists of three birth cohorts: 1971-73, 1981-83, and 1991-93. A detailed description of the survey can be found in Huinink et al. (2011).

The pairfam data have a number of unique features that make them particularly attractive for our analysis. First, they contain detailed information on several metrics of physical and mental health. We use this information to construct our main health-related outcomes of interest: a dummy variable equal to one if respondents report their health status to be less than good (and zero otherwise); an indicator of obesity, conventionally defined as BMI greater than or equal to 30. Subjective well-being is measured using the following question "*All in all, how satisfied are you with your life at the moment?*". Possible answers are on a 11-point Likert scale ranging from 0 (very dissatisfied) to 10 (very satisfied). We then use three indicators of mental distress, focusing on measuring an individual's perceived stress, i.e., whether the respondent felt stressed, overburdened, or under pressure during the past four weeks. Such items come from the "Perceived Stress Questionnaire"(Levenstein et al., 1993) and its German Version (Fliege et al., 2001). For ease of interpretation we recoded those variable so as to take value 1 when the variable is greater than the median of the sample.

Second, the pairfam also contains information on how often an individual's engage in various formal and informal social activities and interactions. Exploiting such richness of information, we operationalize social capital along three dimensions: social interactions, defined as meeting with friends; social activities, defined as going to movies, disco, concerts and artistic or musical events; and sport activities, defined as doing any sport. For ease of interpretation, we recode these discrete variables – measured on a 5-point Likert scale ranging from "daily" to "never" – into three separate dummies taking value one when the respondents report to see their friends, do social activities, and practice sport at least once a week. The opportunity to measure social capital along these different dimensions should enable us to uncover whether social relationships and activities are potential channels through which Internet use affects health.

Finally, our dataset provides information on Internet use, our main explanatory variable. Specifically, respondents are asked to report the number of hours spent on personal Internet use during the past week. To assess the robustness of the results, we also recode this continuous variable into a dummy variable taking value one when respondents spent on Internet more hours than the mean of the sample for each year. The latter is a measure of *intensive* Internet use. As a further check, we also consider an alternative threshold, i.e., a dummy variable equal to one when the respondents spent on Internet more hours than the median of the sample in a given year. The results of this exercise are not reported in the paper and are available upon request.

Our longitudinal sample contains 23,349 person-year observations resulting from 12,383 individuals at wave 1.

Table 1 reports descriptive statistics on the main variables used along the empirical analysis. Approximately 12% of individuals in our sample declare to have a poor health-status, and about 11% are obese. Average satisfaction with life is 7.59. Approximately 13% of individuals are intensively stressed, 9% are overburdened, and 11% are intensively under pressure. Moreover, they are 28 years old on average, and they spend about 10.2 hours on Internet per week. As far as social capital outcomes are concerned, 69% of the individuals see their friends, 31% go to movies, disco, concerts and artistic or musical events, and 56% practice sport at least once a week.

4 Empirical Methodology

As previously stated, the focus of this paper is to investigate how Internet use affects health and subjective well-being, while looking at the association between Internet use and social capital, as a potential mediating pathway. To this end, we exploit the panel structure of pairfam data and estimate the following linear fixed effect specification:

$$Y_{ist} = \alpha + \beta Internet_{ist} + \gamma X_{ist} + \theta_i + \mu_t + \eta_s + \lambda_s^1 t + \epsilon_{ist} \tag{1}$$

where the index ist denotes an individual i residing in state s at the year

Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Health					
Not so good/Bad health	0.12	0.33	0	1	58091
BMI	23.56	5.31	11.36	167.65	30362
Obese	0.11	0.31	0	1	30362
Life satisfaction	7.59	1.68	0	10	58053
intensively stressed	0.13	0.34	0	1	28663
intensively overburdened	0.09	0.29	0	1	36485
intensively under pressure	0.11	0.31	0	1	28638
Social capital					
Social interactions	0.69	0.46	0	1	31618
Sport	0.56	0.5	0	1	31606
Social activities	0.31	0.46	0	1	31592
Internet					
Internet hrs	10.23	12.48	0	150	31166
intensive Internet user	0.35	0.48	0	1	31166
intensive Internet user (2)	0.56	0.5	0	1	58091
Has online profile on SNs	0.87	0.34	0	1	10835
Check SNs at least daily	0.68	0.47	0	1	9400
Covariates					
Male	0.48	0.5	0	1	58091
Age	28.4	8.80	14	45	58091
Age sq.	884.07	511.16	196	2025	58091
1st or 2nd gen. immigrant	0.22	0.41	0	1	56779
Never married	0.63	0.48	0	1	57849
Married/civil union	0.32	0.47	0	1	57849
Divorced/dissolved civil union	0.04	0.2	0	1	57849
Widowed/surviving partner in civil union	0	0.04	0	1	57849
Household income (log)	7.77	0.65	0	11.29	46252
Number of children	0.67	1.03	0	10	58086
No degree	0.02	0.12	0	1	58052
Currently enrolled	0.319	0.466	0	1	58052
Lower secondary education (2b)	0.04	0.19	0	1	58052
Lower secondary education (2a)	0.03	0.16	0	1	58052
Upper secondary education vocational	0.29	0.45	0	1	58052
Upper secondary education general	0.02	0.16	0	1	58052
Post-secondary non tertiary education	0.08	0.27	0	1	58052
First stage of tertiary education	0.2	0.4	0	1	58052
Second stage of tertiary education	0.01	0.11	0	1	58052

of interview t. We have a set of outcome variables, Y_{ist}, detailed Section 2: 1) a dummy for poor health; 2) obese; 3) subjective well-being; 4) indicators of mental health; and 5) measures of social capital.

Our variable of interest is $Internet_{ist}$, which is a measure of Internet duration, i.e., how many hours respondents spent on Internet during the past week. Thus, β denotes the effect of Internet use on the outcome of interest. X_{ist} is a vector of time-varying individual controls, including age and age squared, number of children, a set of secondary school track effects (basic, intermediate or academic track), indicators for marital status, and the logarithm of net household income.

We include individual fixed effects (θ_i) and thus control for time-constant differences between individuals, such as differences in unobserved socioeconomic factors, genetics or other characteristics related to initial health. Additionally, model (1) contains survey year fixed effects (μ_t) to account for possible trends in our outcomes. We also include a full set of federal state fixed-effects (η_s) as well as a set of linear state-specific time trends ($\lambda_s^1 t$). The former control for unobservable, time-invariant differences across states that may influence the health and social capital patterns of individuals, the latter for unobserved cross-state differences in health and social capital over time. Finally, ε_{ist} represents an idiosyncratic error term. Throughout the analysis, we cluster the standard errors at the individual level.

Establishing a causal relationship between Internet use and individuals' health may be complicated by the presence of endogeneity due to self-selection and potential reverse causality. While panel data are useful to disentangle the problem of reverse causality, the selection issue still remains difficult to solve. Internet use is likely to be correlated with many unobservable determinants of health, such as, for instance, unobserved socioeconomic factors, time preferences, genetics, and risk aversion. Such correlation may confound our relationship of interest. The inclusion of person specific fixed effects in model (1) allows us to mitigate the omitted variable bias by eliminating the effects of time-invariant counfounders. However, there may still exist some time-varying unobserved factors, which are not captured by the set of controls included in X_{ist}. For this reason, we caution that conclusions regarding the causal effects of Internet use on health and subjective well-being rely on the assumption that these covariates fully capture any remaining confounders.

5 Empirical Results

The discussion of the results is divided into three parts. First, we analyze the association between Internet use and health. We then present some robustness checks. Finally, we investigate the role of social capital as a mediator of the relationship between Internet use and health.

5.1 Internet Use, Health, and Life Satisfaction

Before presenting the results, in Figure 1 we provide a visual analysis of the evolution of the share of respondents' poor health (upper panel) and well-being (lower panel). In particular, we divide the sample into two groups: in one group, individuals who are intensive Internet users; and in the other, those who are not. Overall, the pattern that emerges is that intensive Internet users are more likely to report a lower level of health status and well-being. In what follows, we perform a variety of analyses to further unpack and explain this difference.

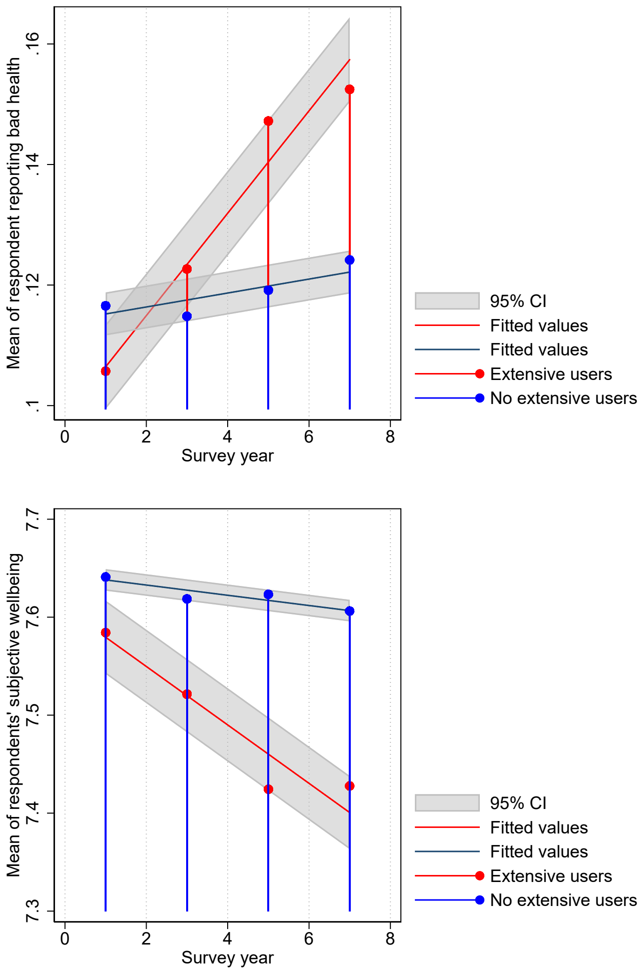
Table 2 reports the panel data fixed effects estimates for the association between the number of hours spent on Internet on physical health, subjective well-being, and mental health. As described in the previous section, in each regression we include a set of individual time-varying controls, individual fixed effects, survey years and state dummies, as well as state-specific time trends. The estimates in columns 1 and 3 suggest that Internet use increases the probability of reporting poor health and reduces subjective well-being. Instead, we find no evidence of significant effects for obesity and mental health outcomes (see columns 2 and 4 to 6).

Table 2: Associations between hours spent on Internet and health: Fixed effect panel data model

	(1)	(2)	(3)	(4)	(5)	(6)
	Not so good/Bad health	Obese	Life satisfaction	Extesively stressed	Extesively overburdened	Extesively under pressure
Internet hrs	0.001***	-0.000	-0.005***	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Age	-0.005	0.010	-0.018	0.050*	0.009	0.028
	(0.012)	(0.009)	(0.047)	(0.028)	(0.016)	(0.027)
Age sq.	-0.000	-0.000***	0.000	-0.000	0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married/civil union	0.018	0.005	0.094	-0.030	0.005	-0.011
	(0.015)	(0.014)	(0.064)	(0.033)	(0.018)	(0.033)
Divorced/dissolved civil union	0.066**	0.000	0.067	-0.034	0.018	0.016
	(0.030)	(0.027)	(0.146)	(0.061)	(0.033)	(0.062)
Widowed/surviving partner in civil union	0.218*	-0.032	-1.612***	-0.038	-0.053	0.200
	(0.120)	(0.101)	(0.597)	(0.041)	(0.194)	(0.208)
Household income (log)	0.004	-0.000	0.165***	0.001	-0.007	0.019
	(0.006)	(0.004)	(0.028)	(0.013)	(0.007)	(0.014)
Number of children	-0.007	0.005	0.007	0.024	0.007	-0.022
	(0.008)	(0.007)	(0.037)	(0.018)	(0.009)	(0.017)
Currently enrolled	-0.053	0.009	0.414	-0.112	-0.035	-0.131
	(0.049)	(0.025)	(0.252)	(0.098)	(0.061)	(0.209)
Lower secondary education (2b)	0.040	0.016	-0.101	-0.060	-0.019	-0.162
	(0.060)	(0.034)	(0.316)	(0.126)	(0.085)	(0.225)
Lower secondary education (2a)	-0.029	0.039	0.122	-0.097	0.002	-0.206
	(0.058)	(0.035)	(0.292)	(0.107)	(0.074)	(0.214)
Upper secondary education vocational (3b)	-0.064	0.029	0.328	-0.153	-0.087	-0.162
	(0.051)	(0.027)	(0.263)	(0.109)	(0.066)	(0.214)
Upper secondary education general (3a)	-0.049	0.005	0.165	-0.197*	-0.022	-0.084
	(0.052)	(0.028)	(0.271)	(0.101)	(0.064)	(0.209)
Post-secondary non tertiary education general (4a)	-0.056	0.056*	0.552**	-0.113	-0.026	-0.183
	(0.054)	(0.029)	(0.269)	(0.108)	(0.067)	(0.215)
First stage of tertiary education (5)	-0.070	0.040	0.467*	-0.236**	-0.001	-0.312
	(0.052)	(0.029)	(0.264)	(0.111)	(0.065)	(0.215)
Second stage of tertiary education (6)	-0.063	0.039	0.493	-0.406**	0.168	-0.453*
	(0.081)	(0.039)	(0.320)	(0.169)	(0.136)	(0.243)
Constant	0.190	0.046	6.024***	-1.397*	-0.168	-0.849
	(0.329)	(0.259)	(1.295)	(0.799)	(0.448)	(0.792)
N.	23349	22622	23344	9404	15345	9402
Mean of dep. var.	0.122	0.118	7.585	0.137	0.097	0.114
S.D. of dep. var	0.327	0.323	1.651	0.344	0.296	0.318

Note: Covariates as described in Table 1. Cluster-robust standard errors reported in brackets. * p<0.10, ** p<0.05, *** p<0.01

Figure 1: Bivariate evidence from Pairfam data



Note: The upper (lower) panel represents the mean of respondents reporting subjective bad health (subjective wellbeing) status by non intensive (blue) and intensive (red use of Internet. For a description of "intensive" internet use see section 3.

Table 3 provides the estimation results when analyzing the association between intensive Internet use, i.e., an indicator for whether respondents spent on Internet more hours than the mean of the sample in a given year, and health outcomes. We continue to find that Internet increases poor health and reduces life satisfaction. The point estimates of the coefficient of interest become considerably larger compared to those obtained using the hours spent on Internet. In particular, the estimate reported in column 1 suggests that intensive Internet use increases the probability of poor health by about 20% relative to the mean outcome, whereas it decreases life satisfaction by about 1%. Due to space constraints in the remainder of the paper we will report only the results obtained when using the dichotomized variable and we will leave the remaining models in the appendix as robustness analysis.

Table 3: Associations between intensive Internet use and health: Fixed effect panel data model

	(1) Not so good/Bad health b/se	(2) Obese b/se	(3) Life satisfaction b/se	(4) Extesively stressed b/se	(5) Extesively overburdened b/se	(6) Extesively under pressure b/se
intensive Internet user	0.025***	-0.007	-0.073**	-0.012	0.003	-0.014
	(0.007)	(0.006)	(0.030)	(0.016)	(0.008)	(0.014)
Age	-0.005	0.010	-0.020	0.050*	0.009	0.027
	(0.012)	(0.009)	(0.047)	(0.028)	(0.016)	(0.027)
Age sq.	-0.000	-0.000***	0.000	-0.000	0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married/civil union	0.018	0.005	0.097	-0.030	0.005	-0.011
	(0.015)	(0.014)	(0.064)	(0.033)	(0.018)	(0.033)
Divorced/dissolved civil union	0.065**	-0.001	0.076	-0.033	0.018	0.014
	(0.030)	(0.027)	(0.146)	(0.060)	(0.033)	(0.061)
Widowed/surviving partner in civil union	0.220*	-0.032	-1.625***	-0.040	-0.051	0.208
	(0.121)	(0.101)	(0.599)	(0.040)	(0.192)	(0.215)
Household income (log)	0.004	-0.000	0.166***	0.002	-0.007	0.019
	(0.006)	(0.004)	(0.028)	(0.013)	(0.007)	(0.014)
Number of children	-0.008	0.005	0.009	0.024	0.007	-0.023
	(0.008)	(0.007)	(0.037)	(0.018)	(0.009)	(0.017)
Currently enrolled	-0.055	0.010	0.427*	-0.110	-0.036	-0.132
	(0.048)	(0.025)	(0.255)	(0.096)	(0.061)	(0.213)
Lower secondary education (2b)	0.041	0.016	-0.108	-0.060	-0.020	-0.164
	(0.060)	(0.034)	(0.318)	(0.126)	(0.085)	(0.228)
Lower secondary education (2a)	-0.029	0.039	0.124	-0.097	0.001	-0.208
	(0.058)	(0.035)	(0.294)	(0.106)	(0.074)	(0.217)
Upper secondary education vocational (3b)	-0.067	0.030	0.341	-0.151	-0.088	-0.160
	(0.051)	(0.027)	(0.266)	(0.108)	(0.066)	(0.218)
Upper secondary education general (3a)	-0.050	0.005	0.172	-0.196*	-0.023	-0.084
	(0.052)	(0.028)	(0.274)	(0.100)	(0.064)	(0.213)
Post-secondary non tertiary education general (4a)	-0.058	0.056*	0.561**	-0.112	-0.026	-0.183
	(0.054)	(0.029)	(0.272)	(0.107)	(0.067)	(0.219)
First stage of tertiary education (5)	-0.073	0.040	0.485*	-0.234**	-0.002	-0.310
	(0.052)	(0.029)	(0.267)	(0.110)	(0.065)	(0.219)
Second stage of tertiary education (6)	-0.069	0.040	0.517	-0.402**	0.167	-0.448*
	(0.081)	(0.039)	(0.323)	(0.167)	(0.136)	(0.246)
Constant	0.184	0.052	6.006***	-1.396*	-0.166	-0.827
	(0.329)	(0.259)	(1.295)	(0.798)	(0.449)	(0.791)
N.	23349.000	22622.000	23344.000	9404.000	15345.000	9402.000
Mean of dep. var.	0.122	0.118	7.585	0.137	0.097	0.114
S.D. of dep. var	0.327	0.323	1.651	0.344	0.296	0.318

Note: Covariates as described in Table 1. (d) indicates discrete change of dummy variable from 0 to 1. Cluster-robust standard errors reported in brackets. * p<0.10, ** p<0.05, *** p<0.01

Assuming that the omitted variables are time-invariant (with time-invariant effects), a fixed effect panel estimator may provide a means for controlling for omitted variable bias. However, if subjects move little, or not at all, across time, a fixed effects model may not be the best model to study the relationship of interest and you would wish to exploit the between-subject variability in the variables. As a result, random effects models would be more suitable. We therefore also consider a random effect model, an estimator that is more efficient and allows to estimate the parameters of time-invariant regressors but it is inconsistent in the presence of unobservable effects correlated with the included controls. The results are reported in Table 4. Unlike what is reported in the previous table, we note that the coefficient for obese turns now out to be positive and significant.

Table 4: Associations between intensive Internet use and health: Random effect panel model

	(1) Not so good/Bad health b/se	(2) Obese b/se	(3) Life satisfaction b/se	(4) Extesively stressed b/se	(5) Extesively overburdened b/se	(6) Extesively under pressure b/se
Intensive Internet user	0.020***	0.016***	-0.131***	-0.010	-0.003	-0.005
	(0.005)	(0.005)	(0.023)	(0.008)	(0.006)	(0.008)
Constant	0.356***	-0.091	5.517***	0.128	0.468***	0.187*
	(0.064)	(0.056)	(0.328)	(0.105)	(0.079)	(0.099)
N.	23349	22622	23344	9404	15345	9402
Mean of dep. var.	0.122	0.118	7.585	0.137	0.097	0.114
S.D. of dep. var	0.327	0.323	1.651	0.344	0.296	0.318

Note: Covariates as described in Table 1. (d) indicates discrete change of dummy variable from 0 to 1. Cluster-robust standard errors reported in brackets. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Overall, the evidence presented above suggests that there are negative, robust, and significant effects of intensive Internet use on subjective measures of health, such as health status and life satisfaction. Instead, less robust effects are detected for a more objective health metric, such as obesity. The results also indicate that there seems to be no association between Internet and indicators of mental health.

Internet use might have differential effects among gender and age groups. In an attempt to disentangle the associations between Internet use and health for males and females, we separately consider samples of males and females. The results by gender are presented in Table 5 in the first two panels. While men and women equally report lower level of self-assessed health when they use Internet extensively, only men show a negative effect on life satisfaction. Such finding might imply that heavy Internet users among men are more subject to a reduction in psychological well-being, although they seem to be less extensively stressed out. It is therefore unclear what is the mechanism at play here, aspect that may be investigated in further research.

The bottom part of Table 5 also provides the estimates by dividing the sample into two age-groups: adolescents (aged 14 to 19), and (young) adults (aged 20 to 45). Here, it is interesting to notice that teenagers who use Internet heavily show lower levels of life satisfaction than older users, who, on the other hand, seem to report higher level of stress due to Internet use.

5.2 Internet Use and Social Capital

What could be the mechanism underlying the negative relationship between Internet use and health? Our proposed interpretation is that Internet increases social interactions. However, while the increased availability of social

Table 5: Associations between intensive Internet use and health: Fixed effect panel model, heterogeneous effects

	(1) Not so good/Bad health	(2) Obese	(3) Life satisfaction	(4) Extesively stressed	(5) Extesively overburdened	(6) Extesively under pressure
Males						
Intensive Internet user	0.026***	-0.006	-0.120***	-0.039*	0.006	0.000
	(0.009)	(0.009)	(0.040)	(0.020)	(0.012)	(0.019)
N.	10950	10818	10946	4389	7234	4390
Mean of dep. var.	0.097	0.164	7.612	0.105	0.106	0.097
S.D. of dep. var	0.295	0.370	1.594	0.307	0.307	0.297
Females						
Intensive Internet user	0.024**	-0.003	-0.024	0.012	-0.001	-0.027
	(0.011)	(0.007)	(0.043)	(0.024)	(0.011)	(0.022)
N.	12399	11804	12398	5015	8111	5012
Mean of dep. var.	0.144	0.076	7.560	0.165	0.090	0.128
S.D. of dep. var	0.351	0.265	1.700	0.371	0.286	0.334
< 20						
Intensive Internet user	0.018*	0.003	-0.090**	0.000	0.040	0.000
N.	8062.000	7753.000	8057.000	810.000	3799.000	811.000
Mean of dep. var.	0.099	0.030	7.891	0.126	0.160	0.126
S.D. of dep. var	0.299	0.170	1.525	0.332	0.366	0.332
>= 20						
Intensive Internet user	0.022***	-0.008	-0.058*	-0.025*	0.001	-0.032**
N.	23100	22193	23089	10320	15079	10315
Mean of dep. var.	0.128	0.133	7.481	0.136	0.090	0.115
S.D. of dep. var	0.334	0.340	1.724	0.342	0.286	0.319

Note: Covariates as described in Table 1. (d) indicates discrete change of dummy variable from 0 to 1. Cluster-robust standard errors reported in brackets. * p<0.10, ** p<0.05, *** p<0.01

contacts may provide a source of social support with a resulting positive effect in terms of health, there is growing evidence that being to much "connected with others" leads to a communication and social interactions overload with negative effect on individuals' health and subjective well-being.

To test this hypothesis, we estimate the same specification as in equation (1), by using three different outcome variables, which measure different dimensions of an individual's social capital, as detailed in Section 3: (a) an indicator variable for social interactions, i.e., when respondents meet up with their friends at least once a week; (b) an indicator variable for social activities, i.e., when respondents go to movies, discos, concerts and artistic or musical events at least once a week; and (c) an indicator variable for sport activities, i.e., when respondents practice sport at least once a week.

The results presented in Tables 6 (and in Table 10 in the appendix) show that there is a positive and significant association between Internet use and social interactions and social activities. Instead, we do not detect any effect in terms of sport activities, which could explain the non-significant effect obtained for obesity.

As a further check on the interpretation of our results, in Table 7 we conduct a falsification test using an alternative dependent variable, defined as the frequency of people reporting to go with their partner to a vacation trip. This outcome variable should not differ for intensive and non intensive Internet users. Consistent with our hypothesis, the coefficient for intensive Internet users reported in column 1 is not statistically significant.

We also investigate the associations between Internet use and social capital, constructing an indicator of net face-to-face interactions, defined as the

Table 6: Associations between Internet use and social capital: Fixed effect panel model

	(1) Social interactions b/se	(2) Sport b/se	(3) Social activities b/se
Intensive Internet user	0.028***	0.014	0.024***
	(0.008)	(0.009)	(0.009)
Age	0.008	-0.036**	0.013
	(0.014)	(0.015)	(0.014)
Age sq.	-0.000	0.001***	-0.000***
	(0.000)	(0.000)	(0.000)
Married/civil union	-0.048**	0.011	-0.102***
	(0.022)	(0.021)	(0.020)
Divorced/dissolved civil union	0.022	-0.004	-0.050
	(0.040)	(0.036)	(0.036)
Widowed/surviving partner in civil union	0.145	-0.238**	0.040
	(0.155)	(0.107)	(0.110)
Household income (log)	-0.022***	0.008	-0.003
	(0.007)	(0.008)	(0.008)
Number of children	-0.059***	-0.059***	-0.059***
	(0.011)	(0.010)	(0.009)
Currently enrolled	0.029	0.105	-0.028
	(0.056)	(0.073)	(0.072)
Lower secondary education (2b)	0.035	0.038	-0.056
	(0.066)	(0.086)	(0.088)
Lower secondary education (2a)	0.050	0.104	-0.048
	(0.067)	(0.085)	(0.084)
Upper secondary education vocational (3b)	0.001	0.126	-0.076
	(0.059)	(0.076)	(0.076)
Upper secondary education general (3a)	0.019	0.109	0.027
	(0.059)	(0.077)	(0.077)
Post-secondary non tertiary education general (4a)	0.044	0.135*	-0.077
	(0.061)	(0.079)	(0.079)
First stage of tertiary education (5)	0.007	0.079	-0.084
	(0.061)	(0.077)	(0.077)
Second stage of tertiary education (6)	0.061	-0.137	-0.078
	(0.166)	(0.136)	(0.139)
Constant	0.903**	0.892**	0.432
	(0.377)	(0.398)	(0.381)
N.	23337	23333	23327
Mean of dep. var.	0.661	0.540	0.294
S.D. of dep. var	0.473	0.498	0.456

Note: Covariates as described in Table 1. (d) indicates discrete change of dummy variable from 0 to 1. Cluster-robust standard errors reported in brackets. * p<0.10, ** p<0.05, *** p<0.01

Table 7: Associations between broadband Internet and social capital: falsification test and interpretation

	(1) Leisure with partner: Vacation trips b/se	(2) Friends -SNs b/se
Intensive Internet user	0.003	0.170***
	(0.039)	(0.031)
Constant	-4.398**	0.146
	(1.758)	(1.578)
N.	11188.000	6010.000
Mean of dep. var.	4.072	0.412
S.D. of dep. var	1.264	0.930

Note: Covariates as described in Table 1. (d) indicates discrete change of dummy variable from 0 to 1. Cluster-robust standard errors reported in brackets. * p<0.10, ** p<0.05, *** p<0.01

difference between social interactions and time spent on online social networks.[4] This alternative indicator enables us to account for real-face-to-face interactions instead of the virtual ones. By taking the difference between those two variables, we can disentangle the relational effect of Internet net of virtual relationships. Reassuringly, the coefficient of interest remains positive and statistically significant (see column 2 of Table 7).

After we have empirically assessed the relationship between Internet use and the three dimensions of social capital, we now explore the role of social capital as a pathway through which Internet use might affect health. To do so, we follow Dave and Kelly (2012) and include the three measures of social capital among the controls in our models. The aim of this exercise is to gauge the extent to which the estimated effect of Internet use on health can be explained by them.

In other words, we condition on social capital, which is influenced by Internet, and, in turn, affects an individuals' health, and examine the change in the estimate of the impact of Internet on health. The results of this exercise are reported in Table 8.

Each column of each panel of Table 8 presents estimates controlling alternatively for the three variables of social capital used in Table 10 (i.e., social interactions, sport, and social activities), whereas column 4 controls for them jointly. Notice that, due to space constraints, we restrict the analysis to the health-related outcomes that turned out to be significantly related to Internet use in the first part of our analysis, i.e., poor health and life satisfaction.

Controlling for any social capital dimension does not significantly change

[4]Notice that we re-scaled this second variable in order to be comparable to the indicator for social interactions.

Table 8: Internet, Social capital and health: pathways

	(1)	(2)	(3)	(4)
Panel 1				
Dep. var.: **Poor health**				
Intensive Internet user	0.026***	0.026***	0.025***	0.026***
Social interactions	-0.005			-0.003
Sport		-0.024***		-0.024***
Social activities			-0.005	-0.003
Panel 2				
Dep. var.: **Life satisfaction**				
Intensive Internet user	-0.073**	-0.071**	-0.071**	-0.076**
Social interactions	0.080**			0.071**
Sport		0.059**		0.048
Social activities			0.042	0.034

Note: Covariates as described in Table 1. (d) indicates discrete change of dummy variable from 0 to 1. Cluster-robust standard errors reported in brackets. * p<0.10, ** p<0.05, *** p<0.01

the estimated coefficient for Internet use.[5] Social capital does not seem to act as a mediating factor underlying the relationship between Internet use and health.

6 Conclusions

The advent and the diffusion of the Internet is a technological shift that shapes an individual's health and social life.

The main contribution of this work was to shed further light on the impact of Internet use on an individual's health, looking at several, different dimensions: physical an mental outcomes; objective and subjective aspects. In doing so, we also investigate whether and how Internet affects an individual's social capital, with the additional aim of examining how changes in an individual's social contacts, social activities and social cohesion brought about by the Internet can shape the Internet-health relationship. Our results suggest that Internet use negatively affects only the subjective dimensions of an individual's health, that is, self-assessed health and subjective well-being, whereas it appears to have no effect on a more objective indicator of health, such as obesity. Although we find a positive association between Internet use and social interactions as well as between the former and social activities, changes in an individual's social capital do not seem to act as a mediator of the negative relationship between Internet use and subjective health, by

[5]Notice that our main results remain qualitatively unchanged when using a Structural Equation Modeling (SEM) approach.

increasing an individual's stress. However, we cannot rule out the hypothesis that other mechanisms, that we are not accounting for in this model, might also be playing a role. For example, Internet can cause a shift in risk preferences, thereby changing the relative cost of healthy behaviors. Similarly, Internet can have an effect on time preference and time allocation, with detrimental effects in terms of health (Shochat, 2012). Due to data limitation, we are not able to fully address these alternative potential pathways.

Nevertheless, the correlations emerging in the analysis point to relevant policy implications.

The Internet revolution permeates our daily life and can be empowering in many respects, for example by providing us with constant, up-to-date information and by making us always "connected". However, the changes brought about by this relatively new technology require a better understanding of the mechanisms through which they occur in our life and how individuals adapt to such changes. Uncovering potential negative effects of the use of this technology on an individual's life and health, it is the first necessary step to then develop effective public and private coping strategies.

Furthermore, although we do not find any significant mediating role of social capital in the Internet-health relationship with our data, we cannot forget that social capital may provide social support, and a sense of belonging. Increasing social relationships may mobilize further human and material resources that can dampen the negative effect of Internet use on an *individual* health. When we conceptualize social capital as relational goods, we implicitly recognize its collective dimension. As a result, we implicitly assume that social capital can be crucial also in terms of *public* health. While this last pattern has not been explored in this paper, it can constitute and interesting extension of our current framework.

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Appendix

Table 9: Effects of hours spent on internet on health: Random effect panel model

	(1) Not so good/Bad health b/se	(2) Obese b/se	(3) Life satisfaction b/se	(4) Extesively stressed b/se	(5) Extesively overburdened b/se	(6) Extesively under pressure b/se
Internet hrs	0.001***	0.001***	-0.007***	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Constant	0.351***	-0.096*	5.532***	0.119	0.464***	0.176*
	(0.064)	(0.056)	(0.328)	(0.105)	(0.079)	(0.099)
N.	23349	22622	23344	9404	15345	9402
Mean of dep. var.	0.122	0.118	7.585	0.137	0.097	0.114
S.D. of dep. var	0.327	0.323	1.651	0.344	0.296	0.318

Note: Covariates as described in Table 1. (d) indicates discrete change of dummy variable from 0 to 1. Cluster-robust standard errors reported in brackets. * p<0.10, ** p<0.05, *** p<0.01

Table 10: Associations between intensive Internet use and health: Fixed effect panel model

	(1) Social interactions b/se	(2) Sport b/se	(3) Social activities b/se
Internet hrs	0.001***	-0.000	0.001***
	(0.000)	(0.000)	(0.000)
Age	0.007	-0.036**	0.012
	(0.014)	(0.015)	(0.014)
Age sq.	-0.000	0.001***	-0.000***
	(0.000)	(0.000)	(0.000)
Married/civil union	-0.048**	0.010	-0.102***
	(0.022)	(0.021)	(0.020)
Divorced/dissolved civil union	0.023	-0.006	-0.049
	(0.040)	(0.036)	(0.036)
Widowed/surviving partner in civil union	0.143	-0.237**	0.038
	(0.156)	(0.107)	(0.110)
Household income (log)	-0.021***	0.008	-0.003
	(0.007)	(0.008)	(0.008)
Number of children	-0.059***	-0.059***	-0.059***
	(0.011)	(0.010)	(0.009)
Currently enrolled	0.032	0.105	-0.025
	(0.056)	(0.072)	(0.072)
Lower secondary education (2b)	0.034	0.038	-0.057
	(0.066)	(0.086)	(0.088)
Lower secondary education (2a)	0.050	0.103	-0.048
	(0.067)	(0.085)	(0.085)
Upper secondary education vocational (3b)	0.004	0.126*	-0.073
	(0.059)	(0.076)	(0.076)
Upper secondary education general (3a)	0.019	0.108	0.028
	(0.059)	(0.077)	(0.077)
Post-secondary non tertiary education general (4a)	0.046	0.135*	-0.075
	(0.062)	(0.079)	(0.079)
First stage of tertiary education (5)	0.009	0.078	-0.081
	(0.061)	(0.077)	(0.077)
Second stage of tertiary education (6)	0.067	-0.136	-0.072
	(0.166)	(0.135)	(0.140)
Constant	0.912**	0.905**	0.435
	(0.377)	(0.398)	(0.381)
N.	23337	23333	23327
Mean of dep. var.	0.661	0.540	0.294
S.D. of dep. var	0.473	0.498	0.456

Note: Covariates as described in Table 1. (d) indicates discrete change of dummy variable from 0 to 1. Cluster-robust standard errors reported in brackets. * p<0.10, ** p<0.05, *** p<0.01