The interplay of mobile phone radiation and psychological effects on psychological and somatic health, behavior and cognition

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A sculpture is a sculpture

Marmalade is marmalade

And a sculpture of marmalade is a sculpture

But it isn't marmalade

-

David Tattersall, singer of The Wave Pictures

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Summary

Background

The digital communication in the last 20 years has increased rapidly. In 2016 in Switzerland 99% of adolescents in between 12-19 used their own Smartphone and the age for first adaption of digital devices steadily decreases. At once our daily exposure to radiofrequency electromagnetic fields (RF-EMF) utilized by these wireless communication increased.

RF-EMF radiation may penetrate bodily tissues and if the intensity is high RF-EMF might act detrimentally on health through thermic body heating. However, little is known about potential health effects of low intensity RF-EMF as it is used for wireless communication and data transmission.

In 2011 the World Health Organization (WHO) emphasized the need for epidemiological studies on potential health effects of RF-EMF in children and adolescents. This population may be particularly susceptible to any physiological RF-EMF impact due to their higher cumulative RF-EMF life time exposure and their still developing bodily tissue. Since the RF-EMF exposure is highest during phone calls neurocognitive and behavioral effects are of special concern. Several observational studies until date on this topic could not suggest any strong conclusion.

In parallel to the concerns about potential health effects due to RF-EMF exposure parents and teachers got increasingly worried about the psychosocial consequences of the frequent digital media use of the young generation. A huge body of psychological research has targeted in particular the problematic usage of these devices and their potential impact on emotion, behavior, cognition and physical well-being.

Objectives

The aim of the prospective HERMES cohort was to investigate whether RF-EMF exposure emitted by wireless devices may detrimentally impact on adolescents' health, behavior or cognition. This work is the third thesis on the HERMES cohort study.

This work partly builds on the two preceding thesis. One objective is to update the RF-EMF exposure surrogate developed in HERMES 1 and to investigate the potential effects of modeled RF-EMF brain dose on memory changes in adolescents.

Further the present thesis objectives an in depth investigation of adolescents general and problematic media usage behavior. Both, RF-EMF radiation and the life-style related changes due to device usage might explain a potential effect of media use on health outcomes. In order to address the proper preventive actions or interventions it is important to disentangle these fields from each other

Methods

The prospective HERMES (Health Effects Related to Mobile phone usE in adolescentS) was conducted in two consecutive sampling waves in between the years 2012-2016 in secondary schools (7th to 9th grade) in Central Switzerland and the city of Basel. The baseline investigations started in June 2012 and May 2014, respectively and were each followed-up one year later.

The main study consisted from a questionnaire survey which was conducted directly in school. The questionnaire contained questions on quantitative and qualitative mobile phone and general media use, problematic mobile phone use, psychological and somatic health related quality of life, behavioral problems as well as socio-demographic variables. After completing the questionnaire participants' memory function was tested via computerized cognitive testing. In addition a questionnaire for the parents was distributed to fill in at home.

Further several objective measures were included in the HERMES protocol. Network operator data records were obtained for those adolescents who gave additional written consent (including one of their parents). In addition, personal RF-EMF measurements using portable measurement devices were conducted in a subsample of participants for each 2-3 consecutive days.

The first part of data analysis comprised of an in depth investigation on adolescents' problematic and general media use. In order to obtain a short screening tool for problematic mobile phone use suitable for research in adolescents the Mobile Phone Problematic Usage Scale (MPPUS) was shortened using principal component analysis. To understand general media use in adolescents latent class analysis was applied on the whole baseline sample in order to identify distinct media use patterns on multiple devices amongst adolescents. Further we assessed whether problematic mobile phone use of different media use groups might be associated with health effects in adolescents

The second part of analysis build on previous HERMES1 results and aimed on investigating whether changes in memory performance might be associated with cumulative RF-EMF brain dose in adolescents. In a first step the individual cumulative RF-EMF brain dose was modeled for each participant of the longitudinal HERMES dataset. For this purpose the the exposure surrogate developed in HERMES1 was updated. The RF-EMF modeling used various data sources (objective data from mobile phone operators, personal RF-EMF measurements, questionnaire data and geospatial modeling) in order to obtain a single individual dose estimate for each participant combining near field and a far field exposure. In a second step, multivariate linear regression models were fitted on figural and verbal memory changes over one year and RF-EMF brain dose as well as media usage either related or unrelated (negative exposure controls) to RF-EMF exposure. An additional stratified analysis for right ear vs. left ear/no preference phone callers was conducted since memory functions are known to be lateralized in brain hemispheres. Further we introduced a new approach to control for life-style confounding in stratifying the analysis over different media use groups.

Results

In total 895 adolescents aged between 10 and 17 years were enrolled in the HERMES baseline investigation from which 439 (49.1%) were assessed in the first and 456 (50.9%) in the second sampling period respectively. 843 (94.2%) took part in the follow-up investigation one year later (average time between baseline and follow-up: 12.5 months). At baseline 95.0 % (n=850) and at follow-up 98.1 % (n=827) owned a mobile phone. For 322 participants objectively recorded operator

data was available for at least 6 months between baseline and follow-up and 148 adolescents participated in the personal measurements.

Using the HERMES 1 sample we could develop a screening tool to assess problematic mobile phone use in adolescents. The derived questionnaire MPPUS-10 covers principal symptoms of behavioral addiction like withdrawal, loss of control, craving or negative life consequences and accounts also for a the social communication aspect of mobile phone use. Further, higher scores on the MPPUS-10 were associated with behavioral and emotional symptoms, antisocial behavior and worse health related quality of life.

An in depth investigation of adolescents general media use could reveal five distinct media use groups, differing on 11 media usage variables (Low Use, Medium Use, Gaming, Call Preference and High Social Use). The groups also showed differences in their health related quality of life (HRQOL). Most pronounced were differences between the High Social Use group indicating lowest and the Low Use group indicating highest HRQOL on questionnaire scales measuring affective well-being and relations with parents, family or teachers. In contrast, the High Social Use group was associated with having better peer contacts.

In the longitudinal analysis on memory changes we found a significant decrease in figural but not in verbal memory scores with higher cumulative RF-EMF brain dose in the subsample with operator data and a strong trend for the figural memory decreases in the whole sample. To a smaller extend this result was also seen with media usage related to RF-EMF whereas no association was seen with usage unrelated to RF-EMF. In the laterality analysis the decrease in figural memory scores higher cumulative RF-EMF brain dose was only prominent with right side users. This is in line with right hemispheric lateralization of neurophysiological figural memory processing. The sensitivity analysis over the right head users of the five media use groups showed homogeneous effect estimates; however, residual confounding by media use related life-style might have a weak impact.

Conclusion and Outlook

The HERMES study was the first cohort study in adolescents which used individually modeled RF-EMF dose measures to investigate health effects due to exposure to the environmental agent RF-EMF. Further, we put substantial effort on understanding how differences in media use related life-style of nowadays adolescents' might impact separately or mutually on health.

We found associations with both. The life-style related media use including problematic mobile phone use differed amongst various behavioral and emotional symptoms and health related quality of life whereas higher RF-EMF brain dose was associated with figural memory decreases. The life-style related media use did not seem to have a major impact on this latter finding. Further the results of the laterality analysis are in favor of an RF-EMF impact on high exposed brain areas.

The figural memory processing takes place predominantly in the right temporal lobe. Future studies on RF-EMF might take this into account and focus even more on alterations in neurophysiological outcomes located in high exposed brain areas like for example social emotions or conduct problems.

List of abbreviations and definitions

ADHD	Attention deficit hyperactivity disorder
APC	Adaptive power control
CEFALO	A case-control study of brain tumors in children and adolescents and mobile phone use
CI	Confidence Interval
DAB	Digital audio broadcast
DECT	Digital enhanced cordless telecommunications
DNBC	Danish National Birth Cohort; cohort study on maternal mobile phone use and health in children
DVB-T	Television broadcast
EEG	Electroencephalogram
ELF-EMF	Extremely low frequency electromagnetic fields
ExPOSURE	Australian cohort study in children and mobile and cordless phone use
FM	Frequency modulation
GSM	Global system for mobile communications standard; 2nd generation of mobile phone networks
HRQOL	Health related quality of life
IARC	International Agency for Research on Cancer
ICNIRP	International Commission on Non-Ionizing Radiation Protection
INTERPHONE	A case-control study of brain tumors in adults and mobile phone use
IQR	Interquartile range
IST	Intelligenz-Struktur Test
KIDSCREEN	Questionnaire to measure health related quality of life
LTE	Long Term Evolution; 4th generation of mobile phone networks
MOrPHeUS	Australian cohort study in adolescents and mobile and cordless phone use
RF-EMF	Radiofrequency electromagnetic fields
SAR	Specific Absorption Rate
TV	Television
SDQ	Strengths and Difficulties Questionnaire; questionnaire to measure behavioral problems

UMTS	Universal mobile telecommunications system; 3rd generation of mobile phone networks
WHO	World Health Organization
WiFi	Wireless local area networking technology

Units

eV	Electron Volt; unit of the photonic energy
Hz	Hertz; unit of the frequency
kHz	Kilohertz; 10^3 Hz
MHz	Megahertz; 10^6 Hz
GHz	Gigahertz; 10^9 Hz
THz	Terahertz; 10^{12} Hz
PHz	Petahertz; 10^{15} Hz

Definitions

Downlink	Communication of signals from a RF base station to mobile phone handset
Uplink	Communication of signals from mobile phone handset to a RF base station

1. Introduction and background

The public health relevance of a specific risk factor depends mainly on two things: the strength of an effect attributable to the risk factor and the fraction of the whole population exposed to the risk factor. Entering the digital age, the penetration of information and communication technologies is constantly augmenting in particular in the younger generation: in Switzerland 99 % of adolescents use a smartphone(Waller et al. 2016). Although most people appreciate the benefits going along with this technological evolution, it is also targeted by researchers evaluating potential physiological and psychological health effects of the still new phenomena.

Children and adolescents born between 2000 and 2017, the digital natives, are the first generation of early users of wireless devices. Consequently, they might be a more susceptible population to the potential hazardous effects related to radiofrequency electromagnetic fields (RF-EMFs) emitted by those devices. The WHO thus emphasized the need to gather better knowledge on potential detrimental health effects of RF-EMF, particularly in children and adolescents.

The biggest challenge in epidemiological research on potential health effects of wireless devices is the ambiguous exposure situation. One major challenge is to quantify exposure to RF-EMFs in observational studies since the exposure in real life depends on many hardly measurable factors. Further, wireless media use might not only be a physical hazard in terms of RF-EMF emissions but also as a risk factor for behavioral changes and psychological and somatic well-being through the device use per se. However, while the RF-EMF exposure is addressed by environmental epidemiologists, psychological researchers focus on the life-style changes due to (wireless) media use. Studies linking both fields are missing despite the common association of life-style changes and RF-EMF exposure with wireless device use and health.

The present work is interested in both potential hazardous aspects of wireless media use: the RF-EMF exposure and the psychological life-style changes. Disentangling these fields is particularly challenging since they are both in constant change due to the rapidly developing media environment.

1.1. The electromagnetic spectrum

1.1.1. Brief history and characterization

While electricity and magnetism have been known and used earlier, the story of electromagnetic radiation initiated only in the second half of the 19th century. It was during the 1860s when James Maxwell published his ground-braking equations predicting an infinite number of frequencies carrying electromagnetic radiation. The ensuing development of an apparatus to prove the existence of these frequency waves designed in 1886 by Heinrich Hertz and gave rise to a unique physical and technological revolution. Starting with simple radio transmitters, electromagnetic radiation finally started to connect the whole world via wireless portable communication devices and an entire new world wide web.

When talking about the electromagnetic spectrum today, we classify all electromagnetic radiation using wavelength, frequency, or photonic energy. The wavelength is the spatial dimension of a wave and defined as the distance between two consecutive points of the same phase e.g. zero crossings. The frequency is measured in Hertz (Hz) and refers to the timely dimension of a wave/radiation which is measured by the number of oscillations occurring in a defined time- usually per second. Given the fact that all electromagnetic waves travel at the same speed, the speed of light, frequency and wavelength are inversely related, the higher the frequency the shorter the wavelength whereby the photonic energy increases with higher frequencies.

An overview over the used frequencies and corresponding wavelengths of the electromagnetic spectrum as well as emitting sources and biological effects is displayed in Figure 1-1.

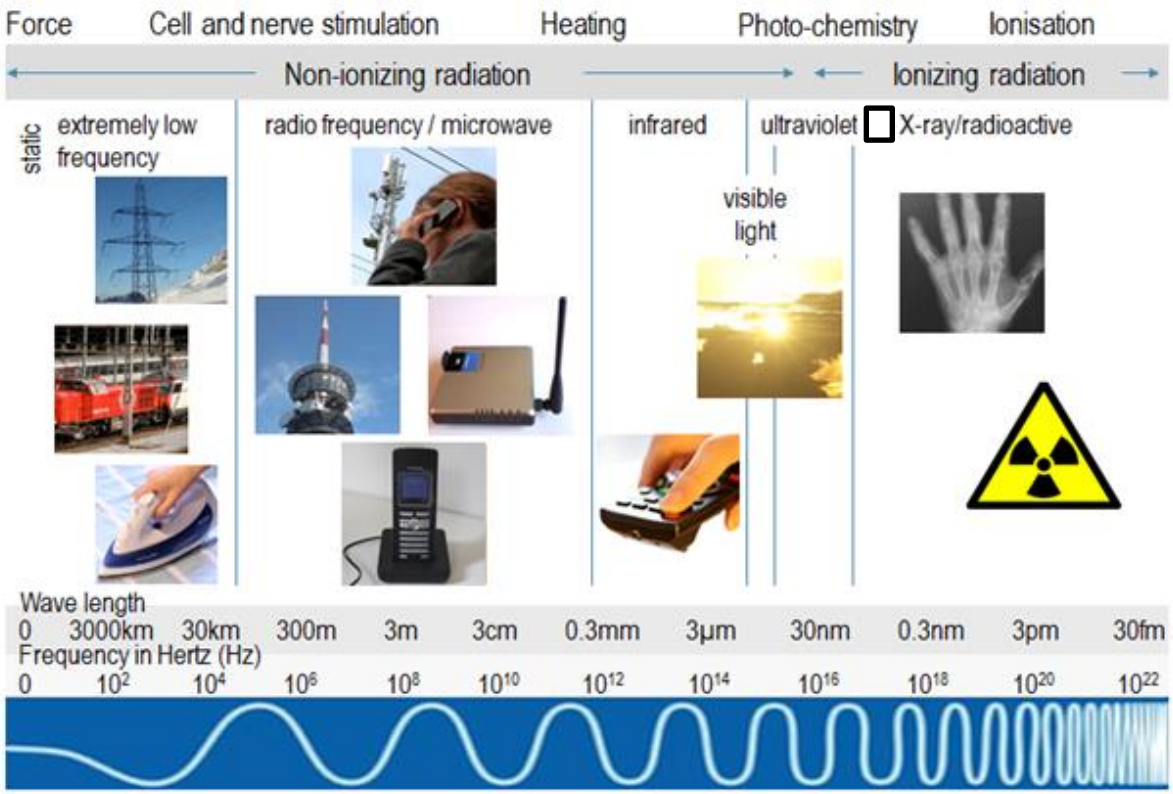

Figure 1-1: The electromagnetic spectrum

The electromagnetic spectrum can be further divided into non-ionizing and ionizing radiation. The threshold to ionizing radiation is based on the capability of a single photon with an energy of 10eV (electron Volt (eV): 1eV = $1.6*10^{-19}$ Joule) or above to liberate electrons from atoms. This energy level is reached with ultraviolet radiation and higher frequency radiation like x-rays and gamma-rays which are well known to directly impact detrimentally on living organisms. Despite its hazardous impact on human health, ionizing radiation is still used by humans e.g. to generate energy through the weak decay of gamma rays in nuclear power plants or x-rays in medical diagnostics.

Radiation below the threshold of 10eV, non-ionizing radiation, has become ubiquitous in nowadays environments. Apart from visible light on the upper and the earth static magnetic field on the lower end, sources of non-ionizing radiation are usually manmade. Depending on their physical properties we separate – with increasing frequency and photonic energy- static fields (0Hz), extremely low frequency electromagnetic fields (ELF-EMF; 3-3000 Hz), intermediate frequency (300 Hz- 10 MHz) radiofrequency electromagnetic fields (RF-EMF; 100kHz – 300 GHz), microwave radiation (300 GHz – 300 MHz) and above this terahertz radiation and infrared light (300 GHz - 30 THz), visible light (430 THz – 790 THz) and ultraviolet light (790 THz- 30 PHz).

While ionizing radiation is used only under the highest safety standards, ELF-EMF and RF-EMF are emitted by various sources in daily environments. ELF-EMFs occur with running current. This can be

either a plugged in household device like a hair-dryer, but also a train connected to its overhead electrical circuit or the power lines supplying remote areas with current. RF-EMF frequencies instead are used for “wireless” signal transmission which is facilitated through their higher photonic energy; the electric and magnetic field get uncoupled at shorter distances from the emitting source, which enables propagation of waves over the distances desired for telecommunication. .

1.2. Daily exposure to radiofrequency electromagnetic fields

Although invisible, nowadays exposure to RF-EMFs is ubiquitous due to the worldwide use of information and telecommunication technologies (ICTs). These technologies require electromagnetic waves in the RF range for wireless information transmission. Table 1-1 gives an overview over the most commonly used frequencies in European environments for the different RF-EMF emitting sources.

RF-EMF Source		Frequency (MHz)
FM radio broadcast		88-108
Digital video (TV) and dîgital audio broadcast (DAB)		174-230
Television broadcast (DVB-T)		470-790
Mobile phone handset (Uplink)*		
	GSM (2G)	832-862
		880-915
	UMTS (3G)	1710-1785
		1920- 1980
	LTE (4G)	2500-2570
RF base station		
	(GSM, UMTS, LTE)	791-821
		925-960
		1805-1880
		2110-2170
		2620-2690
DECT cordless phones		1880-1900
W-LAN		2400-2500
		5150-5350
		5470-5795
		5815-5875

* Allocation of the mobile phone network frequencies are flexible. The indicated allocation refers to the most commonly used frequency for the respective networks

Table 1-1: overview over the most commonly used frequencies in European environments for RF-EMF sources (adapted from Frei and Röösli (2014))

1.2.1. Far field vs. near field exposure

Based on the distance to the emitting source we separate far field (distance to the source above one wave length) from near field (distance to the source up to one wave length). Exposure to near field

exposure is generally higher due to a rapid decrease in RF-EMF field strength with increasing distance following an inverse or inverse-square law.

The far field exposure is the “steady” environmental background exposure originating from remote sources like broadcast transmitters (radio, TV) outside a city or mobile phone base stations located on roof tops. But also sources at home or at work like WiFi or cordless phone base stations account for our far field exposure; so do the mobile phone signals of surrounding people which account for more than 60 % of daily far field exposure(Roser et al. 2017).

To measure the environmental far field RF-EMF exposure intensity, two different units are commonly used. The electric field strength E describes the force of radiation and is measured in Volt per meter (V/m). The other unit is the power flux density S which is a measure for the amount of energy passing through a vertical reference area in a certain amount of time. The unit here is Watt per square meter (W/m2) and bears the advantage that it is additive compared to the non-additive V/m. However, both are measures for RF-EMF intensity and are easily convertible into each other.

Near field exposure originates from RF-EMF emissions of close-to-body sources which basically subsume our daily personal use of wireless communication devices like mobile and cordless phones, laptops or tablet PCs. In contrast to the far field exposure near field exposure is strongly dependent on personal wireless device use.

The intensity of the near field exposure is complex to assess. It is measured by the specific absorption rate (SAR) in Watt per kilogram (W/kg) which refers to the amount of energy absorbed by a specific body tissue. It depends on the sources’ frequency (the lower the RF-EMF frequency the deeper the potential for penetration in the body), the physiological properties of the bodily tissue and the field strength. In particular the exposure assessment of mobile phone RF-EMF emissions is challenging due to various frequency bands used and a high variability in the field strength.

1.2.2. Mobile Phone Radiation

Mobile phone telecommunication networks underwent rapid changes during the last 25 years, due to the continuously redefined technological standards of mobile phones and later smartphones. Up to now four network generations have been developed and the fifth generation will be launched end of 2017. Since the first generation (1G) already expired at the moment there are three different network generations used: the global system for mobile communications standard (GSM or 2G) which was introduced in the early 90s, the universal mobile telecommunications system (UMTS or 3G), launched in the early 2000s and the long-term evolution network (LTE or 4G) developed only a few years later. Each new network generation is capable of transmitting a higher amount of data

more efficiently. Further, the different network generations differ on their exposure strength and their allocated frequencies although these allocations got more flexible with the launch of LTE.

Still the exposure strength differs considerably amongst the network generations. In particular, signal strength of the pulse modulated GSM might lead to a factor 100 – 1000 higher exposure compared to later network generations. This is mainly due to a different output power control within the networks. GSM uses adaptive power control (APC). APC is a technical mobile phone signal standard starting with the maximum output power of the mobile phone and consecutive reduction to the minimum out power needed for sufficient connection. However when switching the connecting base station (so called location updates) the power gets back up to the maximum level and has to be down regulated again. In contrast the UMTS signal starts with the minimum output power needed and keeps balance on the lowest threshold during the whole connection.

In measurement studies the GSM mobile phone call fraction contributed by far highest to the average individual near field exposure (+/- 80%). The near field exposure in turn accounted for about 95% of total exposure (Roser et al. 2017). However, these proportions are in constant change due to more devices using newer network generations and the expansion of nationwide network supply. It is likely, that nowadays the average near field exposure is considerably lower than only a few years ago and the far field fraction of total exposure thus gets more important (Joseph et al. 2010).

1.3. Wireless communication and health

1.3.1. The radiation perspective

Electromagnetic radiation in several frequency ranges is known to impact detrimentally on animal and human health. The carcinogen effects of ionizing radiation are widely known and also high doses of ELF-EMF were found to heighten the risk of childhood leukemia. More ambiguity exists regarding potential health effects due to the relatively new RF-EMF exposure.

Safety standards and risk communication

RF-EMF is known to impact on human body tissue through thermal heating. Since this might have a detrimental effect on health, the International Council for Non-Ionizing Radiation Protection (ICNIRP) has set safety limits in terms of SAR values in order to prevent detrimental effects on physiological functions (ICNIRP 2010). The allowed SAR values for human bodies refer to a maximal thermal increase of 1° Celsius and were adopted in more than 30 countries worldwide. In addition some countries, amongst them Switzerland, have implied further precautionary limits which are far below the ICNIRP standards. However, it remains unclear if RF-EMF might impact on the human body also below these thresholds. The exposure route hereby remains unclear and several hypothesis are discussed; amongst them induction of oxidative stress responses and release of free radicals (Bilgici

et al. 2013; Consales et al. 2012; Jiang et al. 2016; Lantow et al. 2006; Megha et al. 2015; Tkalec et al. 2013).

In order to define health outcomes populations at risk to target in terms of RF-EMF exposure the WHO has stated in their 2010 research agenda on radiofrequency electromagnetic fields the need of *prospective cohort studies of children and adolescents with outcomes including behavioural and neurological disorders and cancer*: This implies two major assumptions about

1. **A population at risk.** Children and adolescents might be at elevated risk due to a higher cumulated life-time exposure to RF-EMF. Further their still developing brain and body might be particularly susceptible to environmental agents.
2. **Relevant health outcomes.** The exposure to RF-EMF depends from the type of use**.** Although surrounded by numerous different wireless devices the accompanying irradiation is highest while conducting phone calls when the device is usually held close to the head. Thus the brain tissue, higher exposed than the rest of the body, might particularly be at risk regarding a potential impact of RF-EMF.

Considering exposure to the head many studies targeted brain tumors. The large-scale case-control Interphone study collected data from 13 countries and showed a slightly increased risk for brain tumors in the highest 10% of self-reported cell phone users (INTERPHONE 2010). Interestingly, this result was laterality specific: the risk was only elevated if the tumor location was on the same side where the device was usually held while calling. These findings led the International Agency for Research on Cancer (IARC) to the classification of RF-EMF as possibly carcinogenic to humans (Group 2B) (IARC 2013). However, the CEFALO study of similar design in children and adolescents reported no elevated risk due to mobile phone use(Aydin et al. 2011b).

Behavioral and neurological impact of RF-EMF

Little is known about the potential effect of RF-EMF on non-carcinogenic behavioral and neurological alterations. In particular sleeping problems, behavioral problems or cognitive performance have been studied. Most studies used experimental setups and acute exposure to mobile-phone like signals (either GSM or UMTS).

Experimental studies

Most consistent are the effects on sleep physiology. Several experimental studies found non-REM sleep alpha activity altered by mobile phone signals during nocturnal RF-EMF exposure in adults (Croft et al. 2010; Lustenberger et al. 2013; Regel et al. 2007b; Schmid et al. 2012; Wagner et al. 1998). Yet the clinical significance of these findings is still not understood since subjective sleep quality was not affected. However, some evidence that sleep mediated RF-EMF exposure might have

an effect on long-term memory acquisition was found in the study of Lustenberger and colleagues (2013) where sleep-dependent performance improvement in a motoric learning task was smaller in RF-EMF exposed compared to non-exposed adults.

The results of experimental studies using acute RF-EMF exposure to assess cognitive performance are more controversial and inconsistent. Only very few studies were conducted in adolescents. One study found less accurate answers in a working memory task in adolescents during acute RF-EMF exposure (Leung et al. 2011) and one reported slightly non-significant decreased reaction times (Preece et al. 2005). Similarly, some studies in adults found impaired cognitive performance (Koivisto et al. 2000; Regel et al. 2006) and others reported improvements (Keetley et al. 2006). However, most studies did not find any effect (Haarala et al. 2003; C. Haarala et al. 2005; Haarala et al. 2007; Regel et al. 2006; Sauter et al. 2011; Unterlechner et al. 2008).

Although these studies all using experimentally controlled RF-EMF exposure setups which might give indications on potential physiological effects, they also bear several disadvantages. Apart from their small sample sizes they are limited to acute short term effects on physiological markers or cognitive performance assessed via test batteries. Further, they are hardly comparable to real-life conditions where the individual near-field exposure is subject to huge variability and far field conditions are constantly changing.

Observational studies: cognitive effects

Only few observational studies have been conducted focusing on exposure to RF-EMF and cognitive Two Australian cohort studies MoRPhEUs (Mobile Radiofrequency Phone Exposed Users' Study) and ExPOSURE (Examination of Psychological Outcomes in Students using Radiofrequency dEvices) were the first to address cognitive outcomes in adolescents and children, respectively. However their results were somewhat contradictive. The cross-sectional analysis of the MOrPHEuS data found less accurate answers and reduced reaction times in two different tasks related to self-reported mobile phone call frequency (Abramson et al. 2009); changes in reaction times was also seen in the longitudinal analysis (Thomas et al. 2010a). The ExPOSURE study in primary school children found little evidence for decreased memory performance in 5 out of 78 statistical comparisons for the children with the highest number of mobile phone or cordless phone calls.

Results of the previous investigation phase of the present HERMES cohort

Decreases in figural memory performance over one year with higher cumulative RF-EMF dose measures were found (Schoeni et al. 2015a). The effect was only prominent in right side callers. This is in line with a right hemispheric lateralization for neurophysiological processing of figural memory (Schoeni et al. 2015a).

A cross-sectional association of higher cumulative RF-EMF brain dose with lower concentration capacity. However, these results could not be confirmed in a longitudinal analysis (Roser et al. 2016b).

Observational studies: behavioral and emotional symptoms

Behavioral problems were associated with different postnatal and prenatal maternal mobile phone use in the Danish National Birth Cohort (DNBC)(Divan et al. 2008; Divan et al. 2012). In the most recent prospective analysis of the DNBC prenatal and postnatal exposure assessed at age 7 were associated with a higher risk of behavioral and emotional problems at age 11 (Sudan et al. 2016).

In the German cohort study personal measurements were conducted in a sample of 1498 children and 1524 adolescents. Conduct problems were associated with higher RF-EMF exposure in adolescents but not in children (Thomas et al. 2008).

Results of the previous investigation phase of the present HERMES cohort

A cross-sectional association of RF-EMF brain dose with behavioral problems. The results could not be replicated in a longitudinal analysis.

However, most observational studies on RF-EMF have not found an effect on health, behavior or cognition in relation to RF-EMF (Calvente et al. 2016; Guxens et al. 2013; Heinrich et al. 2010).

1.3.2. Challenges in epidemiological RF-EMF research

RF-EMF exposure assessment in observational studies is a challenge. Most of the studies referred to use the self-reported call duration as a proxy for exposure. Although this measure might be well correlated with RF-EMF exposure (Cardis et al. 2011; Erdreich et al. 2007), this approach bears several problems. In particular in children and adolescents recall bias might be of concern. Self-reported duration of mobile phone calls has been found to be overestimated by 120 % in the CEFALO brain tumor study in adolescents (Aydin et al. 2011b). Further, the actual RF-EMF exposure does depend from many factors not linearly associated with the duration of device use. Amongst them, two factors might be of special importance:

1. The physical distance to the device since the RF-EMF exposure decreases rapidly with increasing distance to the device.
2. The network used for calling. GSM calls have been found to account for the largest proportion of individual RF-EMF exposure whereas the exposure due to calls executed on the UMTS networks is negligible.

While the physical distance may still be controlled via self-reported headset use valid information about the network used while calling may only be obtained by objective sources like the network operators or smartphone application tuned to measure determinants of individual mobile phone use.

A further issue which is mostly overlooked in RF-EMF health research is the confounding effect of the device use per se. Apart from its RF-EMF emission, wireless device use is known to impact on behavior, cognition and emotion through its accompanying changes on life-style and behavior. Thus life-style and RF-EMF exposure are associated through the device use; a methodological challenging situation which has not been sufficiently addressed by any study. To disentangle the interplay between the biological RF-EMF exposure and the psychological life-style changes a profound knowledge of both perspectives is key.

1.3.3. The psychological perspective

Problematic mobile phone use

Parents and teachers are increasingly worried about the mobile phone use of children and adolescents. One frequent concern driven by the incremented device use is whether the youngsters are addicted from their mobile phones. Addressing this concern psychological research on problematic mobile phone use has gained considerable attention during the last years. If embedded in the conceptual framework of behavioral addiction mobile phone use might be regarded problematic if the device use is maintained despite its negative consequences. Similar to substance abuse disorders the main symptoms of behavioral addictions include loss of control, withdrawal, craving or negative life consequences and thus cause harm to the individual (Grant et al. 2010; Young 1998).

Health effects associated with problematic mobile phone use are often overlapping with those targeted by studies on RF-EMF. Amongst others negative effects on cognitive performance, (Hartanto and Yang 2016) sleep and behavioral or emotional symptoms like hyperactivity, impulsivity, affectivity were found (Billieux 2012; Elhai et al. 2017; Hadlington 2015; Hartanto and Yang 2016; Kim et al. 2016; Schoeni et al. 2015b). Further, psychological studies often emphasize the societal and individual dimension of media usage and link the adoption of different usages to family, peers, socioeconomic status and personality factors whereby the results are often contradicting. Low

financial resources, problems within families and in school and higher levels of social anxiety were found to be prevalent with higher mobile phone use (Chiu 2014; Ehrenberg et al. 2008; Enez Darcin et al. 2016; Hawi and Samaha 2016; Samaha and Hawi 2016); in other studies instead, problematic higher mobile phone use was also positively related to individual social capital, high family economy, good peer relations and more outgoing personality traits like extraversion or approval motivation (Bian and Leung 2015; Bianchi and Phillips 2005; Sánchez-Martínez and Otero 2009; Takao et al. 2009).

General media use in adolescents

Nowadays, mobile phones are not only used for communication. The Smartphone bears many more use applications. Moreover, media use of multiple devices in parallel has become usual in nowadays adolescents (Waller et al. 2016). From a public health perspective it is thus important to not only assess health effects of problematic device usages but also media use in general. However, until date, studies mostly focus on only single devices or applications. A more profound knowledge on adolescents general media use and health effects is urgently needed.

2. Methods and Objectives

2.1. Study population: the HERMES cohort

The study population of the present thesis is the Swiss adolescent HERMES cohort (Health Effects Related to Mobile phone usE in adolescentS). The HERMES cohort contributes to the epidemiological workpackage 1 (*EMF and health and development of children and adolescents – exploiting (large-scale) prospective cohorts*) of the multicenter EU-funded GERoNiMO project (Generalized EMF research using Novel MethOds) which aims on integrating research on electromagnetic fields from different research branches to evaluate the potential impact of EMF on health.

The prospective HERMES cohort study was investigated during the years 2012-2016 in Swiss school classes in the 7th - 9th grade. Different types of data were collected as summarized in the list below. An arbitrary timeline is displayed in figure 1-2.

School survey: Baseline investigation and Follow Up approximately one year later in the whole sample consisting from:

- wireless and general media use
- health-related factors
  - health related quality of life (HRQOL): KIDSCREEN
  - behavioral and emotional problems: Strengths and Difficulties Questionnaire (SDQ)
- Mobile phone problematic use
- life-style and socio-demographic factors

- Computerized cognitive testing
  - Figural and Verbal Memory: two subscales of the Intelligenz-Struktur-Test (IST)
- Parents questionnaire

Personal RF-EMF measurements: subsample recruited from participants of the school survey. Measurements were conducted for 2-3 consecutive days and consisted from:

- Records of personal far field RF-EMF exposure to various frequency bands.
- Data from a simultaneously filled in activity diary App

Data records from mobile phone network operators: Obtained for participants of the school survey who gave additional written consent (including parent consent). Data from the three Swiss network operators (swisscom, sunrise and salt) was obtained for at least 6 months preceding the baseline investigation until the date of follow-up investigation and included daily records of:

- Mobile phone call duration including the network used for calling
- Volume of data traffic
- Number of SMS

Geospatial modeling of far field RF-EMF exposure: Obtained for all participants of the school survey. Average incidence fields of far field exposure for different frequency bands were modeled using the NISMap Software. Separate values were obtained for

- Place of residence, daytime average
- Place of residence, nighttime average
- Place of school, daytime average

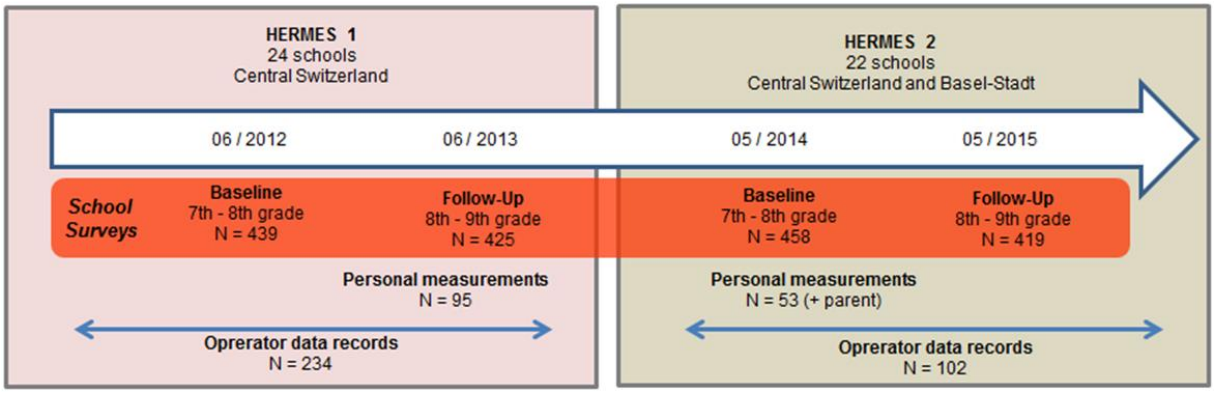

Figure 1-2: Timeline of the HERMES cohort study.

2.2. Objectives

The present work is the third and last thesis on the HERMES cohort. In one of the preceding works Katharina Roser developed a RF-EMF exposure surrogate based on the various data collected during the HERMES 1 sampling wave (Roser et al. 2015). The exposure surrogate was applied multiple times in previous analysis of the HERMES 1 data (Roser et al. 2016b; Schoeni et al. 2015a) and will be used in a modified version also in the present thesis. The second thesis of Anna Schoeni investigated effects of mobile phone use on sleep and cognitive functions.

The previous works on the HERMES1 data mainly focused on RF-EMF exposure and its potential health effects. The present thesis proposes a more integrative view of health effects due to wireless media use which might be either due to RF-EMF emitted by the devices or psychological life-style changes. A main aim is thus to disentangle their interplay in order to get a clearer picture on wireless media and adolescents health using the complete HERMES dataset.

Objective 1: To investigate problematic mobile phone use and potential health effects in Swiss adolescents.

Since problematic mobile phone use might be a frequent issue in adolescents we aimed on deriving a short questionnaire to be used as screening tool in epidemiological studies. Principal component analysis was applied in order to shorten the Mobile Phone Problematic Use Scale (MPPUS) consisting from 27 items using the HERMES 1 dataset. We derived the MPPUS-10, a 10 item screening tool for quick assessment of problematic mobile phone in adolescents based on symptoms of behavioral addiction.

The results are illustrated in article 1.

Further we assessed whether problematic mobile phone use is associated with behavioral problems and health related quality of life in Swiss adolescents. Multivariable regression models controlled for mobile phone use via self-reported text messages were used to investigate the relationships between the MPPUS-10 and the SDQ (Strength and Difficulties Questionnaire) and KIDSCREEN questionnaire.

The results are illustrated in article 2.

Objective 2: An in depth investigation of general media use in Swiss adolescents.

Swiss adolescents tend to use multiple media devices and applications simultaneously. However, research usually focus on single devices or a single type of use (e.g. gaming, texting, social network use) to investigate potential health effects. In order to characterize the general media use of adolescents latent class analysis on 11 different media use variables was applied. Five different media use patterns were obtained which were further differently associated to health related quality of life.

The results are illustrated in article 3.

The media use patterns might not only help to get a better understanding of adolescents media use but were also planned to act as control for life-style confounding in RF-EMF studies.

Objective 3: To update the RF-EMF dose measure used in the previous HERMES1 study for use in the whole sample.

The RF-EMF exposure surrogate developed for the HERMES1 sample was updated using more recent information to calculate new SAR values for adolescents' brain gray matter and whole body dose. Further we aimed on reducing recall bias from self-reported mobile phone use in estimating the individual call duration on the basis of the available operator data recorded call duration. Further the estimated model parameters were slightly revised in order to better fit the data (improved R^2).

Objective 4: To apply the RF-EMF dose measure in order to investigate a potential effect of RF-EMF dose on changes in adolescents' memory performance over one year.

We aimed on replicating the findings of an analysis conducted in the HERMES 1 sample which found some indications for decreases in figural memory performance with cumulative RF-EMF dose measures over one year. Linear exposure-response models were fitted in order to investigate the association of RF-EMF brain dose as well as RF-EMF related media usage (mobile phone calls, cordless phone calls, mobile data traffic) on verbal and figural memory changes. Additional models were fitted for negative exposure control variables (gaming, text messages) unrelated to RF-EMF exposure in order to compare estimates for RF-EMF related and unrelated exposure measures.

Objective 5: To try a new approach to control for life-style confounding in epidemiological research on RF-EMF.

To address life-style confounding due to general media usage in our sample the media use patterns derived by latent class analysis (article 3) were used to determine whether residual confounding by media use might be an issue in our analysis of RF-EMF dose and changes in memory performance.

The results of objectives 3 – 5 are illustrated in article 4.

3. Problematic mobile phone use

3.1. Article 1: Problematic mobile phone use in adolescents: derivation of a short scale MPPUS-10

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ORIGINAL ARTICLE

Problematic mobile phone use in adolescents: derivation of a short scale MPPUS-10

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Abstract
Objectives Our aim was to derive a short version of the Mobile Phone Problem Use Scale (MPPUS) using data from 412 adolescents of the Swiss HERMES (Health Effects Related to Mobile phonE use in adolescentS) cohort.
Methods A German version of the original MPPUS consisting of 27 items was shortened by principal component analysis (PCA) using baseline data collected in 2012. For confirmation, the PCA was carried out again with follow-up data 1 year later.
Results PCA revealed four factors related to symptoms of addiction (*Loss of Control, Withdrawal, Negative Life Consequences* and *Craving*) and a fifth factor reflecting the social component of mobile phone use (*Peer Dependence*). The shortened scale (MPPUS-10) highly reflects the original MPPUS (Kendalls' Tau: 0.80 with 90% concordant pairs). Internal consistency of MPPUS-10 was good with Cronbach's alpha: 0.85. The results were confirmed using the follow-up data.
Conclusions The MPPUS-10 is a suitable instrument for research in adolescents. It will help to further clarify the definition of problematic mobile phone use in adolescents and explore similarities and differences to other technological addictions.

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Keywords Mobile phone use · Problematic mobile phone use · MPPUS · Technological addictions · Adolescents

Introduction

Since the mid-90s and the public availability of the internet and mobile phones, the use of electronic media devices rapidly increased. According to the International Telecommunication Union (ITU), the amount of mobile phone subscriptions has grown from 2.2 billion in 2005 to 6.9 billion in 2014 (ITU 2014). Despite the facilitating effects of mobile phones like the ease of accessibility or useful applications, for example in health care (Boulos et al. 2011), concerns about adverse effects on social communication patterns and health due to new information technologies have arisen (Kowall et al. 2012; Schreier et al. 2006; Srivastava 2005). In 2014, 98 % of adolescents own a mobile phone in Switzerland (thereof 97 % a smartphone) (Willemse et al. 2014). Problematic mobile phone use (also known as mobile phone addiction, compulsive mobile phone use) has been documented for adolescents and young adults, whereby affected persons experience unpleasant symptoms of withdrawal when switching off their mobile phone or being out of range (Campbell 2005; Walsh et al. 2007). In addition, a variety of adverse health effects such as depression, social anxiety, insomnia, hyperactivity or conduct problems have been associated with different forms of technology overuse (Canan 2013; Cheung and Wong 2011; Jenaro et al. 2007; Morgan and Cotten 2003; Thomée et al. 2011). Behavioural addictions are like drug addictions characterized through maintaining abuse despite of its adverse consequences. While in drug addictions, short-term rewards, the so-called "highs", are gained from and

necessarily need chemical substance intake; in behavioural addictions, similar effects, neurologically and emotionally, are reached through engaging in specific behaviours (Clark and Limbrick-Oldfield 2013). The primary diagnostic symptoms of substance abuse include withdrawal, loss of control, tolerance or craving and are featured by behavioural addictions as well. Those symptoms cause major negative life consequences in the affected person like impaired health or deprived social functioning (Park 2005).

One major problem in research on problematic mobile phone use is the inconsistency in its definition and assessment. Bianchi and Phillips have introduced a 27-item Mobile Phone Problem Use Scale (in the following referred to as MPPUS-27) which addresses different aspects of addiction (Bianchi and Phillips 2005). Particularly, the aspects of *Tolerance, Escape from other Problems, Withdrawal, Craving* and *Negative Life Consequences* are emphasized by the authors. The MPPUS-27 is frequently used in research on problematic mobile phone use (Izdebski and Kotyśko 2013; Lopez-Fernandez et al. 2011, 2014; Richardson 2012). The scale shows excellent internal consistency (Cronbach's $\alpha > 0.9$) and is validated in an adult sample through comparison with general mobile phone usage behaviour and the Addiction Potential Scale (APS) of the Minnesota Multiphasic Personality Inventory (MMPI-2). Despite of those strengths, it is long and tends to be somewhat redundant which may be a problem for research in adolescents. This may elevate the risk to upset the study participants and may lead to blindfold answers on similar items. Further, it has not yet been evaluated in adolescent research. For that reason, we aimed at developing a short MPPUS suitable for adolescents using data from the ongoing HERMES (Health Effects Related to Mobile phonE use in adolescentS) study.

Methods

Study population

The HERMES study aims to investigate effects of mobile phone use on health and behaviour of adolescents. The study population consists of 7th, 8th and 9th grade students (12–17 years) attending secondary schools in Central Switzerland. The baseline investigation took place from June 2012 until March 2013, and each school was visited 1 year later for a follow-up investigation with the same study participants. Participating adolescents were recruited through initial phone contact with the head of the school and a subsequent informational visit in the respective classes. Participation was voluntary and had to be preceded by informed consent of the adolescents and a parent. The investigation took place in school during school time and was led by two study managers. It consisted of filling in a paper and pencil questionnaire on various aspects such as mobile phone use, behavioural aspects, health-related quality of life, socio-economic factors and other covariates. Student's mobile phone use was assessed through questionnaire including questions about frequency and duration of calls, frequency of outgoing text messages (text messages sent by mobile phone network referred as SMS as well as other text messages sent by internet-based applications like *WhatsApp*), duration of data traffic on the mobile phone and about the usage of the mobile phone for other purposes. Objective mobile phone use traffic data were provided from the three mobile phone operators in Switzerland for the participants who gave informed consent together with their parents to collect these data. These operator data included the amount of outgoing and incoming calls and SMS, the duration of calls and the amount and the volume of data traffic sessions for up to 6 months prior to the investigation. Only participants reporting to own a mobile phone were included in analysis.

Ethical approval for the conduct of the study was received from the ethical committee of Lucerne, Switzerland on 9 May 2012 (EK 12025).

Mobile phone problem use scale (MPPUS)

The MPPUS-27 consists of 27 items covering the addictive symptoms *Tolerance, Escape from other Problems, Withdrawal, Craving* and *Negative Life Consequences* (Bianchi and Phillips 2005) (see Table 1). The 27 items have to be answered on a 10-point Likert scale ranging from 1 ("not true at all") to 10 ("extremely true") resulting in a final sum score with a theoretical maximum range of 27–270 points. The English version was translated into German by the study managers using a back translation procedure.

Statistical analysis

Principal component analysis

We applied principal component analysis (PCA) to derive a short version of the MPPUS for adolescents. The PCA was conducted with data from participants that had no missing in the MPPUS-27 (35 participants (8.5 %) with at least one missing value; $n = 377$). Prior to the analysis, we tested the data to be suitable assessing the Kaiser–Meyer–Olkin measure and Bartlett's test for sphericity. Furthermore, an item analysis of the MPPUS-27 items was executed including item-test correlations, item-rest correlations and average inter-item correlations. Additionally the mean and the standard deviation of each item were calculated to evaluate the discriminatory power of the items. Based on those results, the less conservative Kaiser-Criterion was chosen for factor

Table 1 The 27-item Mobile Phone Problem Use Scale (MPPUS-27)

For each item, please mark the box which fits best for you from 1 "Not true at all" to 10 "Extremely true"	
1	I can never spend enough time on my mobile phone
2	I have used my mobile phone to make myself feel better when I was feeling down
3	I find myself occupied on my mobile phone when I should be doing other things, and it causes problems
4	All my friends own a mobile phone
5	I have tried to hide from others how much time I spend on my mobile phone
6	I lose sleep due to the time I spend on my mobile phone
7	I have received mobile phone bills I could not afford to pay
8	When out of range for some time, I become preoccupied with the thought of missing a call
9	Sometimes, when I am on the mobile phone and I am doing other things, I get carried away with the conversation and I don't pay attention to what I am doing
10	The time I spend on the mobile phone has increased over the last 12 months
11	I have used my mobile phone to talk to others when I was feeling isolated
12	I have attempted to spend less time on my mobile phone but am unable to
13	I find it difficult to switch off my mobile phone
14	I feel anxious if I have not checked for messages or switched on my mobile phone for some time
15	I have frequent dreams about the mobile phone
16	My friends and family complain about my use of the mobile phone
17	If I do not have a mobile phone, my friends would find it hard to get in touch with me
18	My productivity has decreased as a direct result of the time I spend on the mobile phone
19	I have aches and pains that are associated with my mobile phone use
20	I find myself engaged on the mobile phone for longer periods of time than intended
21	There are times when I would rather use the mobile phone than deal with other more pressing issues
22	I am often late for appointments because I am engaged on the mobile phone when I should not be
23	I become irritable if I have to switch off my mobile phone for meetings, dinner engagements, or at the movies
24	I have been told that I spend too much time on my mobile phone
25	More than once I have been in trouble because my mobile phone has gone off during a meeting, lecture, or in a theatre
26	My friends do not like it when my mobile phone is switched off
27	I feel lost without my mobile phone

extraction which allows factors with eigenvalues above one to be included. Varimax rotation was used to maximize factor loadings. The number of items per factor included in the shortened questionnaire was decided based on the explained variance of each factor. A main criterion for choosing a specific item was its load on the corresponding factor. Further, we preferred items which tend to have stronger discriminatory power. And additionally, we wanted items with face validity for adolescents. Since this cannot be guaranteed by looking at the factor loadings and item analysis only, we did the final item selection manually. PCA was executed again with the follow-up data 1 year later.

Missing items

To do all further reliability analyses and comparisons with the full sample, missing items of the shortened MPPUS-scale (referred to as MPPUS-10) were imputed using a linear regression imputation taking into account the remaining items of the MPPUS-10. From the 35 participants with missing values in the MPPUS-27 only 13 participants had at least one to maximum four missing values in the MPPUS-10 items. The same computations were executed with the follow-up data one year later (10 participants with one missing item each in the follow-up MPPUS-10 score).

Reliability measures

To test the internal consistency of the questionnaire, Cronbach's alpha was assessed for the derived shortened MPPUS-10 as well as for the MPPUS-27. The retest reliability for the MPPUS-10 between the baseline and follow-up measures was calculated using Pearson's correlation for continual variables.

MPPUS-27 vs. MPPUS-10 relations

To investigate how well the sum score of the MPPUS-10 reflects the original score, the Pearson's correlation

between the MPPUS-27 and the MPPUS-10 was calculated. Since this approach overestimates the correlation because the MPPUS-10 score is part of the MPPUS-27 score, we also calculated the correlation between the MPPUS-10 and the 17 remaining items of the MPPUS-27. This shows to what extent the 10 final items are reflected by the remaining 17 items only. In addition, to test the concordance of both scales Kendall's Tau was calculated. The proportion of persons assigned to the same rank amongst all participants according to both questionnaire scores was obtained by the following formula: Percentage of concordant pairs $= 0.5 \times (\tau + 1) \times 100$.

Subjective and objective mobile phone use data

Pearson's correlations were calculated for the MPPUS-10 versus subjectively (questionnaire data) and objectively recorded (operator data) quantitative mobile phone use data including frequency of calls per day, outgoing text messages/SMS per day and daily duration of internet use/data traffic volume.

Statistical analyses were carried out using STATA version 12.1 (StataCorp, College Station, TX, USA).

Results

In total, 439 adolescents participated in the baseline investigation of the HERMES study. Thereof, 27 (6.2 %) reported not to own a mobile phone and were therefore excluded from the data analysis. Thus, data from 412 (93.8 %) participants owning a mobile phone were included in the baseline data analysis. Of the mobile phone users, 319 (77.4 %) were smartphone users.

253 (61.4 %) of the 412 participants were female and 159 (38.6 %) male with a mean age of 14.0 years (min = 12.1 years, max = 17.0 years). A majority (67.6 %) were 8th grade students, and 317 participants (76.9 %) went to secondary school and 95 participants (23.1 %) attended a gymnasium. 79.6 % of the participants were Swiss.

The study participants reported to use their mobile phone on average for 1.3 calls (standard deviation: 1.5; maximum: 8.6) and for 44.9 min of data traffic (SD 41.4; 103.6) per day. 151 participants (36.7 %) reported to send up to 5 messages per day, 50 (12.1 %) 6–15 messages per day, 90 (21.8 %) 16–40 messages per day and 121 participants (29.4 %) reported to send more than 40 messages per day. According to objectively recorded operator data available from 234 (56.8 %) participants, they used their mobile phone for 0.8 calls (SD 1.7; maximum: 8.5), sending 2.8 short text messages (SMS) (SD 5.0; 40.2) per day, and the daily data traffic volume exchanged was 3.9 MB (SD 9.3; 50.5). Note that operator data include only messages sent by short message services (SMS) but not by internet-based applications, whereas self-reported messages refer to both type of messages.

Principal component analysis

PCA was performed using complete MPPUS-27 questionnaires of 377 (91.5 %) participants. Because test scores were left skewed data were z-standardized prior to analysis. In order to test the data to be suitable for PCA, we assessed the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy which was 0.909 (rejection if KMO <0.5). We tested the data for multicollinearity using Bartlett's test for sphericity which tests the null hypothesis if the correlation matrix is an identity matrix. With suitable data, this test should be significant, and we obtained $\chi = 4{,}317.3$, $df = 351$; $p < 0.001$. The PCA revealed five factors with eigenvalues above one (see Table 2). Factor interpretation was based on the clinical diagnostic symptoms of addiction and the theoretical considerations of the authors of the MPPUS-27 (Bianchi and Phillips 2005). The factors extracted were named *Loss of Control* (explanation of 15.9 % of total variance), *Withdrawal* (12.5 %), *Negative Life Consequences* (11.8 %), *Craving* (8.8 %) and *Peer Dependence* (7.1 %). After factor rotation, the five factors explained 56.1 % of the total variance. Although the eigenvalues of factor 4 (subsequently named *Craving*) and factor 5 (*Peer Dependence*) were close to one, we decided to keep them as single factors because our major consideration was to keep as much content as possible of the original MPPUS. Eigenvalues, the proportion of explained variance as well as the cumulative proportion of explained variance of the factors, are displayed in Table 2.

Item selection

The higher the variance explained by a factor, the more items were included in the MPPUS-10. Three items loading on the factors *Loss of Control* and *Withdrawal* and two from the factor *Negative Life Consequences* were chosen, respectively. One single item was chosen loading on the factors *Craving* and *Peer Dependence* since the variance explained by these factors and their eigenvalues were considerably lower compared to the others (see Table 3).

We preferred items with a mean value close to the average of the item scores with additionally high standard deviations since they tend to have stronger discriminatory power (see Table 4).

After all we wanted items to be suitable for adolescents thus to be short, easy to understand, unambiguous and non-redundant in their content. Thus, despite high factor load item 11, item 15, item 23 and item 26 were not considered

Table 2 Eigenvalues, proportion of explained variance (%) and the cumulative proportion of explained variance (%) after factor rotation of the factors

Factor	Eigenvalue	Proportion of explained variance (%)	Cumulative proportion of explained variance (%)
Factor 1 (subsequently named *Loss of Control*)	8.91	15.90	15.90
Factor 2 (*Withdrawal*)	2.38	12.47	28.37
Factor 3 (*Negative Life Consequences*)	1.63	11.81	40.18
Factor 4 (*Craving*)	1.15	8.83	49.01
Factor 5 (*Peer Dependence*)	1.07	7.07	56.08

Subsequently chosen names in italic brackets. Factors with eigenvalues below one are omitted

Table 3 Factor loadings of the 27 items of the original Mobile Phone Problem Use Scale (MPPUS-27) on each factor after factor rotation

Factor	Loss of Control	Withdrawal	Negative Life Consequences	Craving	Peer Dependence
Item					
Item 1	0.10	0.18	−0.08	0.24	0.03
Item 2	*0.01*	*−0.02*	*0.03*	***0.49***	*0.05*
Item 3	0.26	0.05	−0.01	0.07	0.10
Item 4	0.01	0.24	−0.29	−0.27	0.28
Item 5	0.00	0.01	0.19	0.28	−0.04
Item 6	0.16	0.09	0.02	0.21	−0.09
Item 7	*0.09*	*−0.04*	***0.33***	*−0.07*	*0.12*
Item 8	*−0.02*	***0.45***	*0.00*	*0.06*	*−0.13*
Item 9	0.10	0.33	0.01	−0.08	−0.03
Item 10	0.26	0.07	−0.14	0.00	0.13
Item 11	−0.09	0.01	−0.04	0.52	0.14
Item 12	0.26	0.07	0.08	0.07	−0.07
Item 13	*0.07*	***0.35***	*−0.02*	*0.00*	*0.02*
Item 14	*0.05*	***0.32***	*−0.07*	*0.18*	*−0.02*
Item 15	−0.16	0.10	0.43	0.00	0.02
Item 16	***0.48***	*−0.12*	*0.02*	*−0.03*	*−0.07*
Item 17	*0.06*	*−0.03*	*0.03*	*0.01*	***0.57***
Item 18	0.13	−0.10	0.27	0.07	0.12
Item 19	0.04	0.05	0.38	−0.01	−0.16
Item 20	***0.38***	*0.06*	*−0.01*	*−0.03*	*−0.02*
Item 21	0.27	0.07	−0.01	−0.01	0.10
Item 22	*−0.01*	*−0.02*	***0.46***	*0.03*	*0.01*
Item 23	−0.08	0.40	0.18	−0.11	−0.02
Item 24	***0.47***	*−0.12*	*0.06*	*−0.03*	*−0.09*
Item 25	0.01	0.18	0.26	−0.34	0.20
Item 26	−0.03	−0.11	0.07	0.05	0.60
Item 27	−0.05	0.28	−0.01	0.17	0.18

Item numbers relate to the MPPUS-27 questionnaire displayed in Table 1. The chosen items for the short version Mobile Phone Problem Use Scale-10 (MPPUS-10) are marked in italics. The factor loadings of the chosen items for the particular factor are marked in bold

for the factors *Craving, Negative Life Consequences, Withdrawal* and *Peer Dependence*, respectively. The final short version MPPUS-10 with the chosen items is displayed in Table 5.

The PCA was executed again with the follow-up data including data from 378 adolescents owning a mobile phone and filled in all MPPUS-27 items at follow-up to replicate the extracted five factor structure found through the PCA with the baseline data. The analysis with the follow-up data (Table 6) did not noticeably differ from the baseline analysis (Table 3).

Reliability of the MPPUS-10

The mean of the MPPUS-27 was $m = 80.5$ (SD 34.5; min = 32, max = 239) with a theoretical achievable

Table 4 Number of observations (*N*), results of item analysis (item-test, item-rest and average inter-item correlation coefficients), means and standard deviations (SD) for each item of the Mobile Phone Problem Use Scale prior to shortening (MPPUS-27)

	N	Item-test correlation[a]	Item-rest correlation[b]	Average inter-item correlation[c]	Mean[d]	SD[e]
Item 1	410	0.66	0.63	0.29	3.46	2.53
Item 2	*410*	*0.65*	*0.60*	*0.29*	*3.84*	*2.88*
Item 3	409	0.67	0.63	0.29	3.71	2.68
Item 4	409	0.12	0.06	0.32	8.68	2.20
Item 5	409	0.55	0.50	0.30	1.95	1.97
Item 6	410	0.64	0.60	0.29	2.47	2.23
Item 7	*411*	*0.53*	*0.48*	*0.30*	*1.37*	*1.40*
Item 8	*410*	*0.64*	*0.60*	*0.29*	*2.20*	*2.07*
Item 9	410	0.58	0.53	0.29	2.69	2.21
Item 10	409	0.52	0.47	0.30	4.90	3.23
Item 11	412	0.53	0.48	0.30	3.95	3.03
Item 12	412	0.67	0.63	0.29	2.38	2.16
Item 13	*411*	*0.67*	*0.63*	*0.29*	*2.56*	*2.58*
Item 14	*412*	*0.69*	*0.65*	*0.29*	*2.74*	*2.47*
Item 15	412	0.41	0.36	0.30	1.25	1.10
Item 16	*412*	*0.62*	*0.57*	*0.29*	*2.98*	*2.62*
Item 17	*407*	*0.54*	*0.49*	*0.30*	*4.94*	*3.13*
Item 18	411	0.59	0.54	0.29	2.09	1.65
Item 19	409	0.47	0.42	0.30	1.43	1.30
Item 20	*409*	*0.70*	*0.66*	*0.29*	*3.30*	*2.53*
Item 21	405	0.63	0.58	0.29	4.14	2.84
Item 22	*410*	*0.56*	*0.52*	*0.30*	*1.45*	*1.14*
Item 23	409	0.59	0.54	0.29	1.62	1.42
Item 24	*410*	*0.64*	*0.59*	*0.29*	*2.86*	*2.68*
Item 25	408	0.38	0.32	0.30	1.90	1.93
Item 26	401	0.40	0.34	0.30	3.02	2.60
Item 27	407	0.69	0.65	0.29	2.95	2.63
Mean	409	0.57	0.52	0.30	2.98	2.26

Item numbers relate to the MPPUS-27 displayed in Table 1. Chosen items are in italics

[a] Item-test correlation: correlation between the item score *i* and the total test score

[b] Item-rest correlation: correlation between the item score *i* and the sum of the other item scores excluding item score *i*

[c] Average inter-item correlation: average of the correlation between the item score *i* and the other item scores

[d] Mean: mean of the item score *i*

[e] SD: standard deviation of the item score *i*

maximum range of 27–270. The MPPUS-10 had a mean of $m = 28.2$ (SD 15.6; min = 10, max = 96) with a theoretic maximum range of 10–100. Cronbach's alpha measuring the internal consistence was good with alpha = 0.85 for the MPPUS-10 (Nunnally et al. 1967). In our adolescent sample for the MPPUS-27, alpha was 0.92 which is similar to the internal consistency assessed by Bianchi et al. in an adult sample (0.93). The retest reliability of the MPPUS-10 after 1 year assessed through Pearson's correlation between baseline and follow-up data was relatively low ($r = 0.40$, $p < 0.001$).

MPPUS-27 vs. MPPUS-10 relations

The Pearson's correlation between the MPPUS-10 and the MPPUS-27 was $r = 0.95$, $p < 0.001$ (Fig. 1), and the Pearson's correlation between the MPPUS-10 and the remaining 17 items of the MPPUS-27 was $r = 0.86$, $p < 0.001$. Assuming that the first measure overestimates the correlation and the second should rather underestimate it, the true correlation is still quite high. Kendall's Tau for the MPPUS-10 vs. MPPUS-27 was 0.80, $p < 0.001$ with a corresponding proportion of concordant ranks among the participants of 90 %.

MPPUS-10 vs. quantitative mobile phone use

The Pearson's correlation between the MPPUS-10 and the self-reported frequency of phone calls was $r = 0.31$ ($p < 0.001$). The correlation of the MPPUS-10 with self-reported number of outgoing messages was $r = 0.53$ ($p < 0.001$), and for self-reported duration of mobile internet use, we found $r = 0.41$ ($p < 0.001$). For objectively recorded operator data, the Pearson's correlation with the MPPUS-10 score was $r = 0.30$ ($p < 0.001$) for phone calls, $r = 0.34$ ($p < 0.001$) for frequency of SMS and $r = 0.42$ ($p < 0.001$) for the data traffic volume.

Table 5 The Mobile Phone Problem Use Scale-10 (MPPUS-10) items with the original item number of the original scale, the number of observations (*N*), factor loadings after rotation, means and standard deviations (SD)

Item	Original item	*N*	Factor loading	Mean	SD
For each item, please mark the box which fits best for you from 1 "Not true at all" to 10 "Extremely true"					
I have used my mobile phone to make myself feel better when I was feeling down. (*Craving*)	2	410	0.49	3.84	2.89
When out of range for some time, I become preoccupied with the thought of missing a call. (*Withdrawal*)	8	410	0.45	2.20	2.07
If I don't have a mobile phone, my friends would find it hard to get in touch with me. (*Peer Dependence*)	17	407	0.57	4.94	3.13
I feel anxious if I have not checked for messages or switched on my mobile phone for some time. (*Withdrawal*)	14	412	0.32	2.74	2.47
My friends and family complain about my use of the mobile phone. (*Loss of Control*)	16	412	0.48	2.98	2.62
I find myself engaged on the mobile phone for longer periods of time than intended. (*Loss of Control*)	20	409	0.38	3.30	2.53
I am often late for appointments because I'm engaged on the mobile phone when I shouldn't be. (*Negative Life Consequences*)	22	410	0.46	1.45	1.14
I find it difficult to switch off my mobile phone. (*Withdrawal*)	13	411	0.36	2.56	2.58
I have been told that I spend too much time on my mobile phone. (*Loss of Control*)	24	410	0.47	2.86	2.68
I have received mobile phone bills I could not afford to pay. (*Negative Life Consequences*)	7	411	0.33	1.37	1.40

Respective factor classification can be found in italic brackets after each item

Discussion

The derived short scale using 10 items to measure problematic mobile phone use among adolescents showed a good internal consistency and was highly correlated with the original 27-item scale. A large majority of 90 % of participants had the same rank measured by both scores.

Assessment of problematic mobile phone use

The assessment and definition of problematic mobile phone use differs in studies on this topic resulting in inconsistency in prevalence rates and cut-off scores. In an Italian study using the Mobile Addiction Test (MAT), 6.3 % of adolescents were classified as dependent from their mobile phones (Martinotti et al. 2011). In another study on British adolescents using the MPPUS, the 90th percentile was chosen to classify at-risk use according to a statistical classification they prompted to have found in pathological gambling assessment (Lopez-Fernandez et al. 2014). High prevalence rates of about 30 % were reported in studies assessing addictive behaviour through a single questionnaire item ("perceived dependence") (Billieux et al. 2007) or through choosing the 70th percentile as arbitrary questionnaire cut-off value (Ha et al. 2008). In our study, we did not find an obvious threshold for differentiating between problematic and non-problematic mobile phone uses, which supports the idea that problematic mobile phone use is a continuum, and the higher the score on the MPPUS-10, the more likely mobile phone use is problematic in adolescent. A linear association without a threshold for detrimental effects is also supported by our analysis on behavioural and personal factors as well as health symptoms in relation to problematic mobile phone use as measured by the MPPUS-10 (Roser et al., submitted).

Problematic mobile phone use in the context of behavioural addictions

The PCA of the MPPUS revealed five factors. In line with the theoretical construction of the MPPUS, four of them were strongly related to addiction theory and thus were named *Loss of Control, Withdrawal, Negative Life Consequences* and *Craving*. The factors show considerable overlap with the symptoms that have been proposed from the authors of the original MPPUS-27 (including also *Withdrawal, Negative Life Consequences* and *Craving*). *Loss of control*, which was described as *Tolerance* by Bianchi and Phillips (Bianchi and Phillips 2005), deals with the growing time spent with the mobile phone even if not intended. The importance of this factor is also displayed in the correlation between the MPPUS score and quantitative mobile phone use. *Withdrawal* refers to the mental occupation with the device, i.e. anxious or stressful feelings if being out of range. *Negative Life Consequences* due to a mobile phone might either directly result from the first and second factor or may be due to financial, occupational or school issues. *Craving* gets obvious if one needs his mobile phone to relieve himself from negative feelings.

Table 6 Replication of the principal component analysis with the follow-up data: factor loadings of the 27 items of the original Mobile Phone Problem Use Scale (MPPUS-27) on each factor after factor rotation

Factor	Loss of Control	Withdrawal	Negative Life Consequences	Craving	Peer Dependence
Item					
Item 1	0.14	0.23	−0.08	0.12	−0.06
Item 2	*0.06*	*0.04*	*−0.02*	***0.51***	*−0.02*
Item 3	0.30	0.06	−0.03	0.07	−0.01
Item 4	0.17	0.07	−0.37	−0.12	0.03
Item 5	−0.01	−0.09	0.31	0.33	−0.06
Item 6	0.16	0.10	0.16	0.00	−0.06
Item 7	*0.00*	*−0.01*	***0.32***	*0.03*	*0.08*
Item 8	*−0.07*	***0.42***	*0.03*	*−0.03*	*0.10*
Item 9	−0.02	0.20	0.13	0.19	−0.06
Item 10	0.18	0.13	−0.10	0.09	−0.21
Item 11	0.05	−0.05	−0.03	0.56	0.08
Item 12	0.22	0.14	0.04	0.04	−0.20
Item 13	*0.13*	***0.36***	*−0.02*	*−0.14*	*−0.04*
Item 14	*0.00*	***0.47***	*−0.12*	*−0.02*	*−0.05*
Item 15	−0.09	0.06	0.40	0.00	0.03
Item 16	***0.48***	*−0.13*	*0.06*	*−0.21*	*0.03*
Item 17	*0.14*	*−0.03*	*−0.12*	*0.14*	***0.53***
Item 18	0.21	0.02	0.23	−0.01	−0.11
Item 19	0.06	0.02	0.39	−0.08	−0.04
Item 20	0.31	−0.01	−0.03	0.19	−0.01
Item 21	0.34	−0.03	−0.04	0.06	0.08
Item 22	*0.09*	*−0.05*	***0.37***	*−0.05*	*0.04*
Item 23	−0.07	0.37	0.19	−0.11	−0.02
Item 24	***0.43***	*−0.06*	*0.05*	*−0.11*	*0.04*
Item 25	0.07	0.05	0.16	−0.24	0.41
Item 26	−0.03	0.10	0.02	0.06	0.63
Item 27	−0.05	0.36	−0.01	0.14	0.09

Item numbers relate to the MPPUS-27 questionnaire displayed in Table 1. The chosen items for the short version Mobile Phone Problem Use Scale-10 (MPPUS-10) are marked in italics. The factor loadings of the chosen items for the particular factor are marked in bold

As a fifth factor, *Peer Dependence* was identified. This factor was not described by the authors of the original MPPUS-27. Although peer dependence is not a primary symptom of addictive behaviour, it might be important in the development of problematic mobile phone use in adolescents since the mobile phone is mostly used for social communication purposes, and peer influence is particularly prevalent in adolescent years (Steinberg and Monahan 2007; Steinberg and Silverberg 1986).

Although these symptoms suit the concept of behavioural addictions, it is important to critically reflect, if problematic mobile phone use may be considered a nosological entity. Whereas few years ago mobile phones were solely used for calling and somewhat later for texting, nowadays with the rapid spreading of smartphones, the boundaries between problematic mobile phone use and other technological addictions get blurred due to the various purposes a smartphone may be used for. Problematic mobile phone use may thus involve a combination of various known reinforcing mechanisms of technological addictions such as Online Gaming Disorder (OGD) and Internet-Addiction (IA).

In online gaming, reinforcement is gained through in-game rewards and the ease to escape daily life (Hilgard et al. 2013), and similarly, a prominent motive for excessive internet use is diversion (Song et al. 2004). Both gaming and surfing the web are possible with smartphone use, and in our study a higher MPPUS-10 score is correlated with more time spend online and a higher amount of data traffic via mobile phone. Using various applications as well as the perceived satisfaction involved was found to predict compulsive smartphone use (Park and Lee 2011; Salehan and Negahban 2013) and leisure boredom as well as sensation seeking were found as motives in adolescents with higher addictive mobile phone use tendencies (Leung 2008). Distraction through technology may be a mechanism which is common for compulsive gaming, surfing or smartphone use.

A different and more distinct motive for problematic mobile phone use might be the need for social

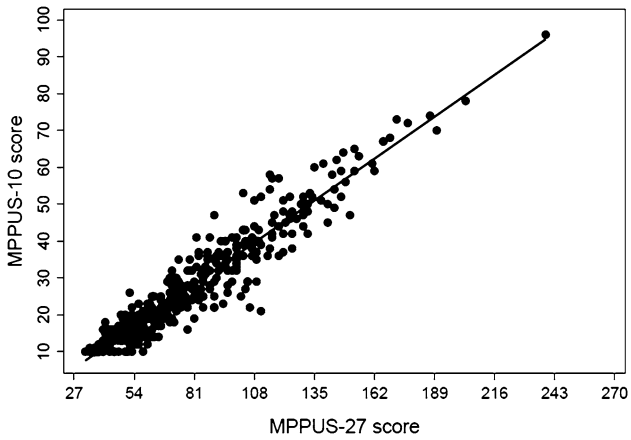

Fig. 1 Correlation of the original 27-item Mobile Phone Problem Use Scale (MPPUS-27) score and the shortened 10-item Mobile Phone Problem Use Scale (MPPUS-10) score. Pearson's correlation was r 0.95, $p < 0.001$. Each *dot* displays a single participants MPPUS-27 score on the x axis (range from 27 to 270) and the corresponding MPPUS-10 score on the y axis (range from 10 to 100 units)

communication, which in our results is underlined by the high quantity of outgoing text messages per day and the highest correlations of the MPPUS-10 with this kind of self-reported mobile phone use (0.53 vs. ≤0.41 for calling and data exchange). Peer influence, social relationships and the need for belongingness are important factors in adolescents life and to interconnect via mobile phones helps adolescents to satisfy their needs (Gardner and Steinberg 2005; Walsh et al. 2009). The urge to be accessible all the time and feelings of fear and loneliness, if they are out of range have been reported by adolescent heavy users being asked about their mobile phones (Campbell 2005). Studies focussing on personality and emotional impact factors on problematic mobile phone use (messaging and phone calls) emphasize high feelings of loneliness, low self-esteem as well as extraversion being prevalent in high users (Augner and Hacker 2012; Butt and Phillips 2008; Reid and Reid 2007; Roser et al., submitted).

Thus, we suggest two different patterns of problematic mobile phone use. One relates to media entertainment which a few years before required being at home. Nowadays, smartphones enable a person to surf the internet and playing online games everywhere, and the use of various applications provides even more possibilities of distraction. This form of problematic mobile phone use may be rather seen as media addiction with the portable smartphone providing the highest accessibility to entertainment. The other form of problematic mobile phone use emphasizes the need for social interconnectivity and relates to the mobile phone used as a communication device. Since the underlying motives and personality factors leading to both forms of problematic mobile phone use differ, it is thinkable that they also lead to distinct health effects.

Strengths and limitations

A particular strength of the HERMES study is the objective data on quantitative mobile phone use provided by the Swiss network operators that minimizes recall bias and allows a more robust evaluation between MPPUS-10 and actual mobile phone use. As a limitation, we did not have data from a second-independent sample, and we did not perform a confirmatory factor analysis with the MPPUS-10. However, at least we conducted the PCA again with the follow-up data to replicate its factorial structure. Of note, the relatively low retest coefficient ($r = 0.40$) may indicate that problematic mobile phone use is not a stable attribute in adolescence, at least during the years of uptake of mobile phone use. The test–retest period of 1 year is long considering the developmental changes which study participants might have undergone in this timespan. Furthermore, a part of the mobile phone users (17.7 %) in our sample switched to using smartphones during this period, which is likely to have a major impact on the usage pattern.

Another limitation is that the MPPUS-10 score was calculated after PCA by summing up the 10 corresponding items of the MPPUS-27. That means, in our study, the MPPUS-10 was an artificial questionnaire that was not filled in by the participants. This procedure might have led to overestimations in correlations between the MPPUS-10 and MPPUS-27. To deal with this shortcoming, the MPPUS-10 is currently distributed in a second sample of adolescents.

Conclusion

The MPPUS-10 showed considerable overlap with the original MPPUS-27. Thus, we suggest using the shorter MPPUS-10 in future research. It is clearly more convenient since it consists only of 10 items which saves time and is likely to reduce the number of missing items. Our item selection criteria focussed particularly on creating a questionnaire suitable for research in adolescents, which is important considering the high amount of mobile phone use stated for this age group in different studies using different methods for assessment (Ha et al. 2008; Lopez-Fernandez et al. 2014; Martinotti et al. 2011).

Future research in adolescents should focus on disentangling two different patterns of problematic mobile phone use. On the one hand, a smartphone may be excessively used for personal entertainment, which may be similar to other technological addictions (e.g. internet use).

On the other hand, a strong need for social interconnectivity may result in problematic mobile phone use as well.

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3.2. Article 2: Problematic mobile phone use of Swiss adolescents: is it linked with mental health or behaviour?

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ORIGINAL ARTICLE

Problematic mobile phone use of Swiss adolescents: is it linked with mental health or behaviour?

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Abstract
Objectives To investigate the associations between problematic mobile phone use and mental health and behavioural problems in 412 Swiss adolescents owning a mobile phone while controlling for amount of mobile phone use.
Methods Problematic mobile phone use was determined by the MPPUS-10 (Mobile Phone Problem Use Scale) and related to health and behavioural problems by means of multivariable regression modelling.
Results MPPUS-10 was 4.7 (95 % CI 1.8, 7.6) units higher in girls than in boys, increased significantly with age and was significantly decreased with increasing educational level of the parents. Furthermore, problematic mobile phone use was associated with impaired psychological well-being, impaired parent and school relationships and more behavioural problems but was not related to peer support and social acceptance.
Conclusions Our study indicates that problematic mobile phone use is associated with external factors such as worse home and school environment and internal factors such as impaired mental health and behavioural problems of the adolescents and thus problematic mobile phone use should be addressed, in particular when dealing with adolescents showing behavioural or emotional problems.

Keywords Mobile phone use · Problematic mobile phone use · MPPUS · Health · Behaviour · Adolescents · Addiction

Introduction

Nowadays mobile phones are omnipresent in everyday life and adolescents are among the heaviest mobile phone users. A recent representative survey in more than 1000 adolescents aged 12–19 years in Switzerland revealed that 98 % of the adolescents own a mobile phone and 97 % of these devices are smartphones (Willemse et al. 2014). Smartphones are multifunctional devices often used by adolescents for gaming, browsing the internet and exchanging text messages. For instance, 94 % of the Swiss adolescents surveyed used their mobile phone daily or several times per week for exchanging text messages via internet-based applications, 87 % for browsing the internet, 53 % for gaming and 61 % for checking their e-mails (Willemse et al. 2014). This frequent use may have a negative impact on daily life and thus may be problematic. However, to date it is not clear what aspects of mobile phone use, if any, are problematic and what this means for mental health and behaviour of adolescents.

On the basis of the lack of a theoretical framework for problematic mobile phone use, Billieux (2012) proposed an integrative model describing four pathways leading to problematic mobile phone use (Billieux 2012), an impulsive pathway, a relationship maintenance pathway, an extraversion pathway and a cyber-addiction pathway. The first three pathways describe a link of problematic mobile

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phone use and personality traits found in previous studies (Augner and Hacker 2012; Bianchi and Phillips 2005; Takao et al. 2009). The cyber-addiction pathway is related to and inspired by research about problematic internet use, since nowadays most adolescents own a smartphone and, therefore, have internet access on their mobile phone. Along that line, Bianchi and Phillips (2005) have introduced a 27-item Mobile Phone Problem Use Scale (MPPUS) to measure problematic use. The scale addresses different aspects of addiction such as tolerance, escape from other problems, withdrawal, craving and negative life consequences.

Strikingly, little research has quantified the impact of problematic mobile phone use on mental health and behaviour of adolescents. A cross-sectional survey in 196 young adults living in Austria observed increased chronic stress, increased extraversion, increased depression and decreased emotional stability to be related to problematic mobile phone use (Augner and Hacker 2012). In this study, problematic mobile phone use was more common among women than men. In an Australian survey of 195 adults, prevalence of problematic mobile phone use was not different between men and women, but also related to increased extraversion and low self-esteem (Bianchi and Phillips 2005). In a cross-sectional study including more than 10,000 Taiwanese adolescents, depressive symptoms were related to problematic mobile phone use (Yen et al. 2009). Additionally, adolescents showing symptoms of problematic use showed impairment in daily life such as poor relationship with friends and family, problems in financial affairs or poor academic performance. Another study in the same adolescents observed that those adolescents with problematic use were more likely to be aggressive, be victims of aggression and to have low self-esteem (Yang et al. 2010). Furthermore, they found higher prevalence of problematic mobile phone use in girls and in older adolescents. A South Korean study dividing mostly male adolescents in an excessive user group and a comparison group found more depressive symptoms, more difficulty in expression of emotions, higher anxiety and lower self-esteem in the excessive mobile phone users (Ha et al. 2008).

To better understand the consequences of problematic mobile phone use for the life of adolescents, potential associations with physical well-being and behaviour need to be evaluated. However, this was not done so far, although impaired well-being (Byun et al. 2013a; Redmayne et al. 2013) and attention deficit hyperactivity disorder (ADHD) symptoms (Byun et al. 2013b) were linked to amount of mobile phone use in children and adolescents. Thus, it remains unclear, if these adverse effects in adolescents may be attributed to problematic use of the mobile phone or amount of mobile phone use.

In this explorative study, we aim at obtaining a better understanding on how problematic mobile phone use is related to health-related quality of life (HRQOL) including mental health and behavioural problems in adolescents while controlling for amount of mobile phone use. These findings are relevant to assess the impact of problematic mobile phone use for adolescents and to contribute to a better understanding of behavioural and emotional problems in adolescents.

Methods

Study population

The Health Effects Related to Mobile PhonE use in adolescentS study (HERMES) population consists of 7th, 8th and 9th grade students attending secondary schools in Central Switzerland. The baseline investigation took place from June 2012 until March 2013. Participating adolescents were recruited through initial phone contact with the head of the school and a subsequent informational visit in the respective class. Participation was voluntary and had to be preceded by informed consent of the adolescents and a parent. The investigation took place in school during school time and was led by two study managers. It consisted of filling in a paper and pencil questionnaire. An additional paper and pencil questionnaire for the parents was distributed, filled in at home and sent back to the study managers.

Questionnaire

The adolescents' questionnaire included questions about mobile phone use, age, sex, nationality, school level, the German adaptation of the self-report version of the standardized Strengths and Difficulties Questionnaire (SDQ) (Goodman 1997) (referred to as *Adolescents SDQ*) measuring behavioural and affective problems of adolescents and the KIDSCREEN-52 (Ravens-Sieberer et al. 2008; The KIDSCREEN Group Europe 2006) measuring HRQOL. The parents' questionnaire included a question about the educational level of the parents and the German adaptation of the informant-rated version of the SDQ (referred to as *Parents SDQ*) measuring adolescents' behavioural and affective problems.

Problematic mobile phone use measured by the MPPUS-10

We used a shortened 10-item version (MPPUS-10 (Foerster et al. 2015); Table S1 in Electronic Supplementary Mate-

rial) of the MPPUS, which addresses different issues of problematic mobile phone use by means of a 27-item questionnaire (Bianchi and Phillips 2005). The five factors covered by the MPPUS-10 are loss of control, withdrawal, negative life consequences, craving and peer dependence. The first four factors are strongly related to addiction theory, the fifth factor *peer dependence* was considered important especially in adolescents (Foerster et al. 2015). The items have to be answered on a 10-point Likert scale ranging from 1 ("not true at all") to 10 ("extremely true"). Internal consistency of the MPPUS-10 measured by Cronbach's alpha was 0.84 in our study sample.

Amount of mobile phone use

To capture various aspects of mobile phone use, we collected different usage measures which were either self-reported or recorded by the mobile phone operators. Adolescents' self-reported mobile phone use included frequency of outgoing and incoming calls, frequency of outgoing text messages [text messages sent by mobile phone network (SMS) as well as text messages sent by internet-based applications] and duration of data traffic on the mobile phone. Objective mobile phone use data were provided from the three mobile phone operators in Switzerland for the participants who gave informed consent together with their parents to collect these data. These operator data included frequency of outgoing and incoming calls and outgoing SMS and the volume of data traffic for up to 6 months prior to the investigation.

Behaviour measured by the SDQ

The *Adolescents SDQ* in the questionnaire of the adolescents and the *Parents SDQ* in the parents' questionnaire score self-reported and parent-rated behavioural and affective problems of adolescents, respectively. They consist of five scales assessing *Emotional symptoms*, *Conduct problems*, *Hyperactivity*, *Peer problems* and *Prosocial behaviour* on five items answered on a 3-point Likert scale, respectively. A *Total Difficulties Score* can be calculated by summing up the scores for *Emotional symptoms*, *Conduct problems*, *Hyperactivity* and *Peer problems*. Internal consistency of the five scales measured by Cronbach's alpha ranged from 0.51 to 0.74 in our study sample and was comparable to a nationwide British study sample of children and adolescents (0.41–0.77) (Goodman 2001). Furthermore, the scales of the SDQ were associated with relevant diagnoses (Goodman 2001). An overview from Klasen et al. (2003) concluded that the German SDQ is just as useful and valid as the English original scale in terms of similar factorial structure, reliability and validation of the scales (Klasen et al. 2003).

HRQOL measured by the KIDSCREEN

The KIDSCREEN-52 (Ravens-Sieberer et al. 2008; The KIDSCREEN Group Europe 2006) is a standardized questionnaire measuring health-related quality of adolescents' life on ten dimensions named *Physical well-being* (5 items), *Psychological well-being* (6 items), *Moods and emotions* (7 items), *Self-perception* (5 items), *Autonomy* (5 items), *Parent relations and home life* (6 items), *Social support and peers* (6 items), *School environment* (6 items), *Social acceptance* (3 items) and *Financial resources* (3 items) answered on a 5-point Likert scale. Internal consistency of the ten dimensions ranged from 0.77 to 0.88 in our study sample and was comparable to a representative sample of children and adolescents from 13 European countries (0.77–0.89) (Ravens-Sieberer et al. 2008).

Statistical analyses

The associations of problematic mobile phone use (MPPUS-10) with behaviour (Adolescents SDQ, Parents SDQ) and HRQOL (KIDSCREEN) of the adolescents were investigated by multivariable linear regression models. Nonparametric bootstrapping was used to estimate the coefficients to account for non-normal data distribution. MPPUS-10 was included either as continuous score or as categorical variable since no cutoff point dividing mobile phone use into non-problematic and problematic is proposed. The four categories of MPPUS-10 were defined a priori using the 30th, the 60th and the 90th percentile of the distribution of the MPPUS-10 as cutoff points. All models were adjusted for age, sex, nationality (Swiss, mixed or foreign), school level (college preparatory high school or high school), educational level of the parents (six categories: no education, mandatory school, training school, college preparatory high school, college of higher education, university) and self-reported frequency of outgoing text messages as a proxy for amount of mobile phone use. Sensitivity analyses were conducted with operator-recorded frequency of outgoing text messages instead of self-reported frequency of text messages as well as without any adjustment for amount of mobile phone use. Missing items in the MPPUS-10 were imputed using a linear regression imputation taking into account the available items of the MPPUS-10 (13 participants with four or less missing values in the MPPUS-10 items). Missing values in the confounder variables were imputed using imputation of the most common category "training school" for education of the parents (71 missing values) and mean of the available answers for self-reported frequency of outgoing text messages (1 missing value).

Statistical analyses were carried out using STATA version 12.1 (StataCorp, College Station, TX, USA).

Figures were made with the software R using version R for Windows 3.0.1.

Results

HERMES study

In total, 439 adolescents participated in the HERMES study. Participation rate for adolescents was 36.8 % and 89.5 % of their parents returned the questionnaire. 27 (6.2 %) of the adolescents reported not to own a mobile phone and were, therefore, excluded for this analysis. Out of the remaining 412 participants, 319 (77.4 %) indicated to own a smartphone. Participants had a mean age of 14.0 years (ranging from 12.1 to 17.0 years) and 253 (61.4 %) of the participants were female (Table 1). The majority of the adolescents (66.8 %) were 8th grade students.

The average MPPUS-10 score was 28.2 (SD 15.6). Score was higher in smartphone users than in non-smartphone users (mean of 30.6 (SD 16.1) vs. 20.0 (SD 10.0)). The 30th, 60th and 90th percentile of the MPPUS-10 corresponded to MPPUS-10 scores of 17, 29 and 51 units, respectively. All participants in the highest MPPUS-10 category reported to own a smartphone.

According to multivariable regression modelling, problematic mobile phone use score was 4.7 (95 % CI 1.8, 7.6) units higher in girls than in boys and increased significantly with age (2.1 units increase per 1 year ageing, $p = 0.031$) (Table 1). Problematic mobile phone use score was significantly decreased with increasing educational level of the parents ($p = 0.004$). Problematic mobile phone use score tended to be higher in adolescents with mixed nationality compared to Swiss nationality ($p = 0.107$) and tended to be lower for participants attending college preparatory high school compared to participants from high schools ($p = 0.222$).

Amount of mobile phone use

Self-reported mobile phone use data were available for all 412 participating mobile phone users (1 missing value each for frequency of outgoing text messages and duration of data traffic), operator-recorded data were available for a subsample of 233 (56.6 %) participants. Spearman correlation coefficients of self-reported and operator-recorded mobile phone use were 0.48 ($p < 0.001$) for frequency of calls, 0.56 ($p < 0.001$) for frequency of outgoing text messages and 0.50 ($p < 0.001$) for data traffic on the mobile phone.

There was a clear trend of increasing mobile phone use across the four MPPUS-10 categories (Table S2 and Figure S1 in Electronic Supplementary Material). The participants in the highest MPPUS-10 category reported to use their mobile phone on average for 2.7 calls, for sending 44.8 text messages (SMS and text messages sent by internet-based applications) and for 84.3 min of data traffic per day. According to objectively recorded operator data they used their mobile phone for 1.8 calls, sending 6.8 SMS (only SMS were recorded but not text messages sent by internet-based applications) and their mobile phone transmitted 13.9 MB data traffic volume per day.

Table 1 Personal and social factors of the HERMES study participants and change in the Mobile Phone Problem Use Scale-10 score per unit increase in factors, the corresponding 95 % confidence intervals and *p* values, HERMES study, Switzerland, 2012

Personal and social factors		MPPUS-10 score			
		Coefficient		95 % CI	*p* value
Age (in years)	14.0 (12.1–17.0)	Per year	2.09	(0.19, 4.00)	0.031
Sex: female	253 (61.4 %)	Compared to male	4.71	(1.78, 7.64)	0.002
Nationality					
Swiss	328 (79.6 %)				
Mixed	56 (13.6 %)	Compared to Swiss	4.10	(−0.89, 9.10)	0.107
Foreign	28 (6.8 %)	Compared to Swiss	−0.76	(−6.98, 5.47)	0.811
School level: college preparatory high school	95 (23.1 %)	Compared to high school	−2.12	(−5.52, 1.28)	0.222
Highest educational level parents		Per category	−1.80	(−3.05, −0.56)	0.004
No education	3 (0.7 %)				
Mandatory school	12 (2.9 %)				
Training school	212 (51.5 %)				
College preparatory high school	30 (7.3 %)				
College of higher education	122 (29.6 %)				
University	33 (8.0 %)				

The strongest Spearman correlation of problematic mobile phone use score with amount of mobile phone use was observed for self-reported frequency of outgoing text messages with $\rho = 0.59$ ($p < 0.001$). Other types of use were only fairly to moderately correlated [self-reported frequency of calls: 0.32 ($p < 0.001$), self-reported duration of data traffic: 0.42 ($p < 0.001$), objectively recorded frequency of calls: 0.35 ($p < 0.001$), objectively recorded frequency of outgoing SMS: 0.41 ($p < 0.001$), objectively recorded volume of data traffic: 0.39 ($p < 0.001$)].

Behaviour

Problematic mobile phone use was significantly positively associated with overall behavioural problems [adjusted coefficient 0.96 (95 % CI 0.58, 1.35) units increase in the *Total Difficulties Score* per 10 units increase in the MPPUS-10 score] (Table 2). Among the specific behavioural problems, most pronounced association was observed for *Hyperactivity* [0.42 (0.26, 0.57)], followed by *Conduct problems* [0.30 (0.19, 0.41)] and *Emotional symptoms* [0.17 (0.02, 0.32)]. *Prosocial behaviour* was significantly negatively associated with problematic mobile phone use [−0.14 (−0.25, −0.04)], whereas *Peer problems* was not related to problematic mobile phone use. Results were similar for continuous and categorical analysis. Behavioural problems rated by the parents based on 344 questionnaires showed a similar pattern although coefficients were lower and associations with *Emotional symptoms* and *Prosocial behaviour* did not reach statistical significance (Table S3 in Electronic Supplementary Material).

Estimated coefficients and the corresponding 95 % confidence intervals did not much change if adjustment for self-reported or operator-recorded frequency of outgoing text messages was dropped (Tables S4 and S5 in Electronic Supplementary Material).

HRQOL

Six out of the ten HRQOL dimensions were significantly decreased (*Moods and emotions*, *Self-perception*, *Autonomy*, *Parent relations and home life*, *Financial resources* and *School environment*) for increasing problematic mobile phone use score (Table 2). Not related to problematic mobile phone use were the dimensions *Social support and Peers* and *Social acceptance*. *Physical well-being* and *Psychological well-being* were significantly decreased in the 10 % of adolescents in the highest MPPUS-10 category, but the associations were only borderline or not significant according to the test for trend and the continuous analysis. Again, results were similar for continuous and categorical analysis. Adjustment for self-reported or operator-recorded frequency of outgoing text messages as a proxy for amount of mobile phone use had little impact on the results (Tables S4 and S5 in Electronic Supplementary Material).

Discussion

Overall, problematic mobile phone use, expressed by a higher MPPUS-10 score, was associated with increased amount of mobile phone use, impaired psychological well-being, decreased mood and more behavioural problems whereas no association with social relationships with peers was observed. Our categorical analysis indicates that there is no common threshold above which mobile phone use becomes problematic for mental health, instead we observed a fairly linear relation between the problematic mobile phone use score and various mental health outcomes.

Problematic mobile phone use and amount of mobile phone use

Problematic mobile phone use score was associated with amount of calls, text messages and data traffic. Nevertheless, Spearman correlations were modest indicating that problematic mobile phone use as measured by the MPPUS-10 does not only reflect amount of mobile phone use but also other aspects such as loss of control, withdrawal symptoms, craving and peer dependence which are problematic. As a consequence even extensive amount of mobile phone use did not result in a high problematic mobile phone use score in some study participants and vice versa high problematic mobile phone use score occurred in participants with low to modest amount of mobile phone use. Strikingly, the coefficients of all models with mental health outcomes did not change noticeably if models were not adjusted for amount of mobile phone use. This indicates that the observed associations are independently related to problematic aspects of use and not to the amount of mobile phone use itself. Thus, amount and problematic aspects of mobile phone use should be considered separately in future studies in adolescents.

Personal and social factors related to problematic mobile phone use

Significant increases of problematic mobile phone use score were found for being female, age and low educational level of the parents. These findings are in line with other studies (Augner and Hacker 2012; Bianchi and Phillips 2005; Byun et al. 2013a; Sanchez-Martinez and Otero 2009; Yang et al. 2010) although, to the best of our

Table 2 Change in the Adolescents Strengths and Difficulties Questionnaire scores and KIDSCREEN dimensions per 10 unit increase in the Mobile Phone Problem Use Scale-10 score and per Mobile Phone Problem Use Scale-10 category and the corresponding 95 % confidence intervals and *p* values for the test for trend in the Mobile Phone Problem Use Scale-10 categories, HERMES study, Switzerland, 2012

Adolescents SDQ	*n*	MPPUS-10 score				MPPUS-10 categories**								Test for trend***
		Crude		Adjusted*		<30th (*n* = 125)		30th–60th (n = 120)		60th–90th (*n* = 125)		≥90th (*n* = 42)		
		Coefficient	95 % CI	Coefficient	95 % CI			Coefficient	95 % CI	Coefficient	95 % CI	Coefficient	95 % CI	*p* value
Total Difficulties Score	412	0.80	(0.48, 1.12)	0.96	(0.58, 1.35)	0	(reference)	1.17	(0.07, 2.27)	2.36	(1.22, 3.49)	4.99	(2.94, 7.03)	<0.001
Emotional symptoms	412	0.20	(0.07, 0.34)	0.17	(0.02, 0.32)	0	(reference)	0.04	(−0.46, 0.53)	0.26	(−0.24, 0.76)	0.73	(−0.12, 1.57)	0.075
Conduct problems	412	0.26	(0.17, 0.35)	0.30	(0.19, 0.41)	0	(reference)	0.52	(0.17, 0.86)	0.88	(0.5, 1.25)	1.52	(0.89, 2.14)	<0.001
Hyperactivity	412	0.38	(0.24, 0.51)	0.42	(0.26, 0.57)	0	(reference)	0.55	(0.04, 1.05)	1.13	(0.63, 1.63)	2.33	(1.52, 3.15)	<0.001
Peer problems	412	−0.05	(−0.15, 0.05)	0.08	(−0.05, 0.21)	0	(reference)	0.07	(−0.39, 0.53)	0.09	(−0.38, 0.56)	0.41	(−0.34, 1.16)	0.371
Prosocial behaviour	412	−0.05	(−0.15, 0.05)	−0.14	(−0.25, −0.04)	0	(reference)	−0.38	(−0.81, 0.05)	−0.25	(−0.69, 0.2)	−0.88	(−1.48, −0.28)	0.039
KIDSCREEN														
Physical well-being	411	−0.44	(−1.02, 0.14)	−0.66	(−1.53, 0.21)	0	(reference)	−0.02	(−2.28, 2.23)	−1.24	(−3.91, 1.44)	−5.07	(−9.02, −1.13)	0.036
Psychological well-being	412	−0.74	(−1.33, −0.16)	−0.62	(−1.39, 0.14)	0	(reference)	−0.90	(−3.22, 1.41)	−0.80	(−3.22, 1.62)	−5.00	(−9.23, −0.78)	0.063
Moods and emotions	412	−2.00	(−2.70, −1.30)	−1.73	(−2.64, −0.82)	0	(reference)	−2.25	(−4.98, 0.48)	−5.87	(−8.59, −3.14)	−8.65	(−12.94, −4.36)	<0.001
Self-perception	412	−1.12	(−1.68, −0.57)	−0.90	(−1.66, −0.15)	0	(reference)	−1.41	(−3.8, 0.98)	−4.23	(−6.61, −1.84)	−3.90	(−7.46, −0.33)	0.001
Autonomy	409	−0.62	(−1.12, −0.12)	−0.67	(−1.28, −0.06)	0	(reference)	−2.05	(−4.17, 0.07)	−1.62	(−3.94, 0.7)	−4.61	(−7.87, −1.34)	0.026
Parent relations and home life	408	−1.39	(−1.87, −0.90)	−1.50	(−2.09, −0.91)	0	(reference)	−2.58	(−4.92, −0.23)	−5.15	(−7.52, −2.77)	−5.82	(−9.36, −2.28)	<0.001
Financial resources	405	−1.15	(−1.63, −0.68)	−1.51	(−2.03, −0.99)	0	(reference)	−1.85	(−3.78, 0.08)	−4.47	(−6.46, −2.47)	−6.15	(−9.1, −3.21)	<0.001
Social support and peers	412	0.46	(−0.03, 0.94)	−0.11	(−0.72, 0.50)	0	(reference)	−1.95	(−4.09, 0.2)	−0.38	(−2.84, 2.09)	−2.08	(−5.34, 1.17)	0.551
School environment	407	−1.08	(−1.51, −0.65)	−0.97	(−1.54, −0.41)	0	(reference)	−2.62	(−4.66, −0.59)	−3.51	(−5.58, −1.44)	−5.34	(−8.1, −2.58)	<0.001
Social acceptance	409	−0.04	(−0.66, 0.57)	−0.60	(−1.36, 0.16)	0	(reference)	−0.09	(−2.72, 2.53)	−1.07	(−3.87, 1.73)	−2.19	(−6.38, 2.00)	0.266

* Models adjusted for age, sex, nationality, school level, education of the parents and self-reported frequency of outgoing text messages

** MPPUS-10 categories correspond to MPPUS-10 scores of 10–17 (<30th percentile), 18–28 (30th–60th percentile), 29–50 (60th–90th percentile) and 51–100 (≥90th percentile), respectively

*** *p* value of the ordinal variable of the four MPPUS-10 categories <30th percentile, 30th–60th percentile, 60th–90th percentile and ≥90th percentile ranging from 1 to 4 in adjusted regression models

knowledge, parents' education was not reported to be associated with problematic mobile phone use before. It is conceivable that parents with higher educational background are more aware of problematic aspects of their children's mobile phone use and thus consider these aspects in their education. Furthermore, the school environment also plays an important role, as indicated by our results on the corresponding KIDSCREEN dimensions (*Parent relations and home life* and *School environment*). These findings also support the relevance of the social background for developing addictive behaviours. Particularly, good family functioning and good communication between parents and adolescents may help prevent problematic mobile phone use in adolescents as it was observed for pathological internet use (Wartberg et al. 2015). A possible explanation could be that rules for media use controlled by parents prevent problematic use. Education of media use in school in combination with adolescents feeling comfortable in school may play a similar role.

HRQOL and problematic mobile phone use

Our results indicate decreased mood and psychological well-being to be associated with problematic mobile phone use. Similar findings come from recent studies linking symptoms of mental ill health, depression and anxiety to problematic mobile phone use (Augner and Hacker 2012; Ha et al. 2008; Yen et al. 2009), to problematic internet use (Kaess et al. 2014; Ko et al. 2012) and to amount of mobile phone use which is expected to partly reflect problematic use (Ikeda and Nakamura 2014; Thomée et al. 2011). Similar to these studies, our cross-sectional study cannot clarify the direction of these associations. Either problematic mobile phone use could be the consequence of decreased mood, psychological well-being and negative self-perception or the other way around. For both pathways there are plausible arguments. Negative self-perception is linked to depression (Lewinsohn et al. 1980) and individuals with negative self-perception may use the mobile phone to elevate their self-perception by spending time on social networks (Steinfield et al. 2008). Mobile phones might thus be used to escape from negative feelings, which in the long run may act as an amplifier of such feelings because the underlying problems are not approached. Or mobile phones may be used to seek for social support in times of depressed feeling. In line of the latter hypothesis, decreased depressive symptoms have been observed for increased instant messenger and social network use (Morgan and Cotten 2003). On the other hand, decreased mood and psychological well-being may be a consequence of problematic mobile phone use thinking of the overwhelming possibilities the mobile phone and the internet provide nowadays and the accompanying stress of being accessible all the time. This hypothesis is in agreement with the finding of Thomée et al. (2011) of high mobile phone use being a risk factor for reporting symptoms for depression 1 year later with the risk being greatest among those participants who reported to perceive stress because of the high accessibility via mobile phone (Thomée et al. 2011). Another possibility is that there is not a pathway pointing in one direction but a reinforcing spiral leading to the associations between problematic mobile phone use and health and behavioural factors as it is proposed for media effects in general (Slater 2007).

Behaviour and problematic mobile phone use

We found a strong association between *Hyperactivity* and problematic mobile phone use, which, to the best of our knowledge, has not been examined so far. Previous studies found hyperactivity and ADHD associated with problematic internet use (Kaess et al. 2014; Ko et al. 2012; Kormas et al. 2011; Ozturk et al. 2013) and using the mobile phone for entertainment (playing games, internet) (Byun et al. 2013b; Zheng et al. 2014). Hyperactive adolescents are easily distracted, show problems in sustaining attention and are less capable of impulse control (Douglas 1972). Thus, hyperactive adolescents may be prone to develop problematic mobile phone use through the countless possibilities of a mobile phone to drift away, find excitement and escape from boredom. At the same time, we found *Conduct problems* to be associated with problematic mobile phone use, which is in line with the finding of Kaess et al. (2014) of problematic internet use being related to conduct problems in adolescents. Adolescents with conduct problems are often impulsive and pathological internet use is considered to be an impulse-control disorder.

Strengths and limitations

A particular strength of this study is that we could rely on both self-reported and objectively recorded mobile phone use data from mobile phone operators. It is well established that adolescents tend to overestimate their mobile phone use (Aydin et al. 2011; Inyang et al. 2009). This especially holds for duration of mobile phone calls and less pronounced for frequency of calls. However, since results were similar for self-reported and operator-recorded amount of mobile phone use, recall or reporting bias is not expected to affect our study results. We adjusted our analyses for self-reported and operator-recorded frequency of outgoing text messages. We think that daily frequency of outgoing text messages is a valuable proxy for all types of activity on the mobile phone. Note that analyses with adjustment for data traffic or call frequency yielded similar results.

We were able to investigate a variety of external as well as internal factors found in the literature and possibly related to problematic mobile phone use in one study sample at the same time. An inherent limitation of our study is that problematic mobile phone use, HRQOL and behaviour are self-reported. However, we had additionally parent-rated behaviour available and SDQ and KIDSCREEN are widely used and validated scales.

Conclusion

Our study indicates that problematic mobile phone use in adolescents is associated with external factors such as worse home and school environment, and internal factors such as impaired HRQOL and behavioural problems. Future longitudinal studies should clarify whether problematic mobile phone use is the consequence of unfavourable conditions or whether and to what extent problematic mobile phone use reinforces behavioural problems as well as decreased mood and psychological well-being. In the meantime, problematic mobile phone use in adolescents should be addressed, in particular when dealing with adolescents showing behavioural or emotional problems.

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Compliance with ethical standards

Ethical standard Ethical approval for the conduct of the study was received from the ethical committee of Lucerne, Switzerland on May 9, 2012 (Ref. Nr. EK 12025).

Conflict of interest The authors declare that they have no conflict of interest.

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4. General media use in adolescents

4.1. Article 3: A latent class analysis on adolescents media use and associations with health related quality of life

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A latent class analysis on adolescents media use and associations with health related quality of life

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ABSTRACT

Purpose: Recent studies linked adolescents' media use to a variety of physical, psychological and social impairments. However, research neglected that adolescents' media use is complex and includes various combinations of activities such as mobile internet browsing, calling, online gaming or use of social network sites.
Methods: The aim of this study is to use latent class analysis in a sample 895 Swiss adolescents to classify different media usage types based on eleven media use variables. Subsequently, associations of these classes with health related quality of life (HRQoL) as measured by the KIDSCREEN-52 questionnaire were assessed using multivariable regression models adjusted for relevant confounding factors.
Results: Five distinct media use classes could be identified: Low Use, Medium Use, Gaming, Call Preference and High Social Use. The Low Use class reported highest and the High Social Use class lowest HRQoL on the KIDSCREEN scales *Moods and Emotions* (mean adjusted scores: 55.1 (95%CI: 53.8; 57.0) vs. 49.1 (47.5; 50.7)), *Self-Perception* (51.8 (50.3; 53.3) vs. 48.0 (46.7; 49.28), *Parents and Home Life* (53.3 (51.7; 54.9) vs. 48.6 (47.2; 50.0)) and *School Environment* (52.7 (51.3; 54.0) vs. 49.3 (48.2; 50.7)). On the subscale *Social Support and Peers* the pattern was reversed. The Low Use class indicated least and the High Social Use class most well-being (48.5 (47.0; 50.0) vs. 53.8 (52.4; 55.3)).
Conclusions: Latent class analyses is a fruitful approach to differentiate between various media usage types and is expected to better characterize and evaluate potential causal associations between media use and HRQoL.

1. Introduction

According to the International Telecommunication Union (ITU) in 2015 the penetration rate of mobile phone subscriptions in developed countries worldwide exceeded 120%. In Switzerland the rate was even higher with 140 mobile phone subscriptions per 100 inhabitants. Coincidentally with the vast increase in prevalence, the age of owning the first mobile phone is decreasing. In a recent representative survey of 6–13 year old children in Switzerland 52% stated to own a mobile phone. In a related study investigating over 1000 12–19 year old adolescents the penetration rate was 99% (Suter et al., 2015; Waller, Willemse, Genner, Suter, & Süss, 2016). Of those devices 97% were smartphones, which allow the user to access the internet from everywhere and additionally ease mobile communication through the use of various applications ("Apps") such as Facetime or WhatsApp. But frequent use of media devices is not restricted to Smartphones. In the same survey over 76% of the adolescents stated to possess an own PC or laptop, about 53% of the adolescents also used an MP3 player, 45% owned a portable game console and 44% a digital camera.

Although one could assume that "digital natives" who grow up surrounded by new media technologies should have adopted to this rapid technological change more easily than "digital immigrants" (Prensky, 2001), adverse health effects have been associated with the use of new media in young people.

A growing body of research focuses on frequent media use defined as problematic behavior which causes harm to the

Abbreviations: HRQoL, Health related quality of life; HERMES, Health Effects Related to Mobile phone usE in adolescentS; Swiss cohort study, MPPUS-10; Mobile phone problematic usage scale, short version; SABIC, sample size adjusted Bayesian information criterion; AIC, Akaike's information criterion; CAIC, consistent Akaike's information criterion, Bozdogan's criterion; MP, mobile phone.

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individual. Several questionnaires have been developed to assess addictive use of online gaming, the internet, social network sites or Smartphones (Andreassen, Torsheim, Brunborg, & Pallesen, 2012; Foerster, Roser, Schoeni, & Röösli, 2015; Wölfling, Müller, & Beutel, 2011; Young, 1998). One of these constructs, Internet Gaming Disorder (IGD) has even gained sufficient attention by clinicians to be included in the appendix of the DSM-5 manual for mental disorders as a research category. Like other behavioral addictions IGD is defined as maintaining a behavior despite its negative social and individual consequences. Excessive online gaming has been linked to impulsive, aggressive and ADHD-like behavior, depressive tendencies, sleep problems or anxiety (Ding et al., 2014; Lam, 2014; Mehroof and Griffiths, 2010; Stetina, Kothgassner, Lehenbauer, & Kryspin-Exner, 2011). Interestingly, similar symptoms have been linked to problematic mobile phone use (Billieux, Van der Linden, & Rochat, 2008; Demirci, Akgönül, & Akpinar, 2015; Lee et al., 2015; Lemola, Perkinson-Gloor, Brand, Dewald-Kaufmann, & Grob, 2014; Roser, Schoeni, Foerster, & Röösli, 2015, 2016), Internet (Ko et al., 2014; Ko, Yen, Yen, Chen, & Chen, 2012; Ostovar et al., 2016; Young and Rogers, 1998) and social network use (Banyai et al., 2017; Feinstein et al., 2013; Hong, Huang, Lin, & Chiu, 2014; Schou Andreassen et al., 2016; Tandoc, Ferrucci, & Duffy, 2015). However, due to the qualitatively different contents media technologies may be used for (e.g. texting, calling, social network platforms, surfing, gaming …) there might be reasonable doubt that they all relate to the same health impairments. And indeed, it is heavily discussed if addictions to different kind of media should be regarded as one or separated concepts (Billieux, Maurage, et al., 2015; Choi et al., 2015; Király et al., 2014; Pontes and Griffiths, 2014).

Differences amongst types of media use are emphasized by studies focusing on the social implications of media use types. (Online) social communication facilitated through mobile phones and social media was found to be related to the need to belong, higher levels of loneliness (Abeele & Roe, 2013; Bian & Leung, 2015), female gender (Bianchi and Phillips, 2005) and has been accompanied by social stress and low self-regulation (van Deursen, Bolle, Hegner, & Kommers, 2015). Still, benefits of social network use have also been highlighted. In a longitudinal study of Steinfield and colleagues Facebook use increased social capital and well-being through building and maintaining social relationships. This effect was even more pronounced for persons with initial low self-esteem and less life-satisfaction (Steinfield, Ellison, & Lampe, 2008). In contrast, online gaming is more prevalent in male and was found to go along with hostile cognitions, to decrease the quality of interpersonal relationships and heighten social anxiety (Choo et al., 2010; Kuss & Griffiths, 2012; Lo, Wang, & Fang, 2005).

Similarly, studies on media users' personality propose differences between media types. In a German study comparing a sample of 115 individuals diagnosed with Internet Gaming Disorder to non-addicted controls pathological online gamers showed higher neuroticism, decreased conscientiousness and low extraversion applying the NEO FFI questionnaire based on the BIG-5 personality dimensions (Müller, Beutel, Egloff, & Wölfling, 2013). Differently, high extraversion, narcissism and openness to experiences was found in high social network (Correa et al., 2010; Ong et al., 2011; Wang, Ho, Chan, & Tse, 2015) and extraversion, low self-esteem and trait social anxiety in high mobile phone users (Bianchi and Phillips, 2005; Ehrenberg, Juckes, White, & Walsh, 2008).

Despite these various attempts to understand the impact of media use on well-being by linking it to personality and social factors the picture remains blurred. The main problems might lie in the usually limited focus on single types of media use or applications and the restriction to their problematic uses. This design does not account for the nowadays habitual combined use of many media devices and applications in parallel and might over-pathologize sociological changes. Thus, in particular adolescents' complex media use - including not only a number of different devices but also the way they handle them - remains poorly understood. In our opinion this limited view is likely to produce confounded results through the high intercorrelation amongst the variables and might lead to exposure misclassification.

Studies looking at media use as interplay of different usage domains are rare. Two recent studies focusing on the relation between problematic internet and problematic smartphone use introduced latent class analysis as an effective method for identifying different media usage groups among Asian adolescents and college students respectively (Kim, Nam, Oh, & Kang, 2016; Mok et al., 2014). Mok et al. identified in each of two gender-separated analysis three classes (high, medium and low) of internet and smartphone addiction levels simultaneously whereas Kim et al. found three additional user groups by cross-secting amount of smartphone and internet use (e.g. low smartphone but high internet use). As a shortcoming, both studies were restricted to the problematic use of only two variables to identify the classes neither taking into account different types and motives of habitual media use nor the implicit differences amongst both media, e.g. the higher accessibility to online social communication via the portable smartphone.

Hypothesizing individual media use being a more complex composition of use variables (such as preferences for messaging, calling, gaming, surfing or using social network sites) we conducted a latent class analysis in an adolescent sample from Switzerland aiming at identifying more distinct user profiles. Since knowledge regarding general media use in adolescents is scarce the study is of exploratory nature and no predictions were made concerning the latent structure. Furthermore we assessed the relationship of the obtained profiles with health related quality of life for a better understanding of media use in adolescents' life.

2. Methods

2.1. Study population

The HERMES cohort (Health Effects Related to Mobile phone usE in adolescentS) consists of adolescents attending 7th to 9th grade in Switzerland. Here we report about the baseline investigations, which were conducted in two waves in 2012/2013 and 2014/2015 in Central Switzerland and Basel. Participating adolescents were recruited through initial phone contact with the head of the school and a subsequent informational visit in the respective classes. Participation was voluntary and had to be preceded by informed consent of the adolescents and a parent. The investigation took place in school during school time. During the investigation students filled out a paper and pencil questionnaire.

Ethical approval for the conduct of the study was received from the ethical committee of Lucerne, Switzerland on May 9, 2012.

2.2. Material

2.2.1. Mobile phone and general media use

Student's media use was assessed through questionnaire and included detailed questions about their quantitative use of mobile phones and other media devices, as well as questions on different use possibilities like social media use or online gaming. The questions entering the latent class analysis were mostly rated via 4–6 hierarchic categories separately for weekend and weekdays. The duration of time spent on the Internet using the mobile phone, subsequently referred to as *Online (M*P), for example was assessed via the item "How much time do you spend actively online using

your mobile phone?" and rated on five categories. The lowest category hereby was "never or less than 10 min per day" and the highest "more than 1.5 h per day". In addition, some of the question were based on a self-estimated duration like playing games *(Gaming)* which was asked about with the item "For how long do you engage in PC/online games or video console playing per day?" followed by a free space in which the participant could write down an open answer in minutes per day. The complete list of included items and their answering schemes is displayed in the first two columns of Table 1.

2.2.2. Problematic mobile phone use

To measure addictive tendencies regarding mobile phone use the MPPUS-10 was administered (Foerster et al., 2015). The questionnaire consists of 10 items using a ten point Likert-scale covering different aspects of problematic device use namely loss of control, withdrawal, craving, negative life consequences and peer dependence. Internal consistency of the questionnaire is good (Cronbach's Alpha = 0.85). The questionnaire score was used as variable entering the latent class analysis *(MPPUS-10).*

2.2.3. KIDSCREEN

The KIDSCREEN-52 (Ravens-Sieberer et al., 2008; The KIDSCREEN Group Europe, 2006) is a standardized questionnaire measuring the health related quality of adolescents' life on ten dimensions named *Physical Well-being* (5 items), *Psychological Well-being* (6 items), *Moods and Emotions* (7 items), *Self-Perception* (5 items), *Autonomy* (5 items), *Parent Relation and Home Life* (6 items), *Social Support and Peers* (6 items), *School Environment* (6 items), *Social Acceptance* (3 items) and *Financial Resources* (3 items) answered on 5-point Likert scales. For easier interpretation of the results the subscale scores are transferred into T-values with mean values of 50 and standard deviations of 10. Transformation is conducted via an algorithm derived from the original European KIDSCREEN sample of children and adolescents from 13 European countries. Higher values indicate more well-being on the respective scale (Ravens-Sieberer et al., 2008). In the same sample the internal consistency measured with Cronbach's alpha ranged from 0.77 to 0.89 and the test-retest stability ranged from 0.56 to 0.77 for the ten dimensions. The internal consistency in the HERMES sample for the ten scales was comparable with alpha values ranging between 0.77 (*Self-Perception*) and 0.89 (*Psychological Well-Being*).

3. Statistical analysis

Data analysis consisted of two steps. First a latent class analysis was performed to identify subgroups of media use patterns. Afterwards associations between the identified classes and the KIDSCREEN subscales were investigated applying multivariable linear regression models.

3.1. Latent class analysis

Latent class analysis is a method to classify a population into meaningful subgroups showing distinct patterns of item response probabilities on a set of predefined variables. For each individual (observation) a posterior probability for belonging to one class is provided.

Table 1
Overview over the questionnaire items entering the latent class analysis and their original scoring scheme (Columns one and two). For latent class analysis the variables had to be categorized. Columns three to five show the number of participants in the respective category and their respective mean value on the numeric score derived by the original questionnaire items.

Use type *Original questionnaire item*	Original scoring	Category	N	Mean (SD)
Calls (MP)[a]	Open answer	Low	281	1.3 (1.2)
"For how long do you use your mobile phone for calling per day?"	*(minutes/day)*	Medium	278	8.1 (2.9)
		High	284	46.2 (44.8)
Text messages[a]	6 hierarchical categories	Low	161	2.1 (1.5)
"How many short messages do you sent per day via mobile phone?"	*(frequency/day)*	Medium	274	17.5 (10.2)
(separately for SMS and. Instant messenger apps)		High	411	55.2 (9.2)
Online on MP[a]	5 hierarchical categories	Low	243	5.5 (9.0)
"How much time do you spend actively online on your mobile phone?"	*(minutes/day)*	Medium	303	50.0 (26.5)
		High	302	103.1 (11.6)
Calls (landline)[a]	5 hierarchical categories	Low	450	2.1 (0.9)
"How long on average are you conducting phone calls via a cordless	*(minutes/day)*	Medium	143	5.6 (1.5)
phone at home?"		High	257	17.6 (11.3)
Gaming[a]	Open answer	Low	242	0.0 (0.0)
"How much time on average do you spend gaming on a PC	*(minutes/day)*	Medium	398	22.0 (15.8)
Laptop/tablet/TV(video console)"		High	206	122.7 (52.9)
Music	5 hierarchical categories	Low	198	2.8 (2.5)
"Do you use your mobile phone for listening to music?"	*(minutes/day)*	Medium	308	35.0 (0.0)
		High	302	122.7 (52.9)
Social Network Sites	5 hierarchical categories	Low	150	0.0 (0.0)
"Do you have an account at the social network X? If yes,	*(login/day)*	Medium	372	0.9 (0.5)
how frequently do you log in?"		High	317	6.1 (2.8)
(separately for X = 6 social network platforms)				
MPPUS-10	Questionnaire score	Low	270	15.3 (3.6)
Screening tool for problematic mobile phone use in adolescents.	*(range10-100)*	Medium	273	28.3 (4.0)
10 questions based on symptoms of behavioral addictions.		High	305	48.7 (11.0)
PC Use	Open answer	Low	273	10.9 (7.4)
"How much time do you spend using device X per day"	*(minutes/day)*	Medium	291	45.0 (12.7)
(separately for three devices X = PC, Table, Laptop)		High	283	159.2 (99.2)
MP expenses	6 hierarchical categories	Low	316	5.5 (0.0)
"How high are your monthly expenses for your mobile phone	*(CHF/month)*	Medium	224	20.5 (5.0)
(if you have a fixed contract expenses should include the basic fee)?"		High	231	46.5 (9.9)
MP at night	4 hierarchical categories	On	414	
"Do you switch off your mobile phone during night?"	*(never to always)*	Off	427	

[a] Questions asked separately for weekdays end weekend.

Identifying the number of classes is the critical step of the analysis. In this study we considered models consisting of one to seven latent classes. The overall fit of the models was compared via the sample-size adjusted Bayesian Information Criterion (SABIC), the Akaike's information criterion (AIC) and the Bozdogan's criterion (consistent Akaike's information criterion; CAIC). Since the SABIC is a trustworthy criterion of model fit it was our primary goodness of fit index for determining the number of classes (Nylund, Asparouhov, & Muthén, 2007; Tofighi & Enders, 2008). However, an equally important criterion is that the final model-solution consists of theoretically meaningful classes.

After model selection covariates (e.g. gender) may be included in the analysis. If so, the posterior probabilities are conditioned on their values (being female/male). We decided to include two covariates, gender and belonging to one of the two subsamples (subsequently referred to as *sample 2012/2013* and *sample 2014/2015*, respectively) because both might strongly impact media use in adolescents.

Finally, a post-hoc analysis of the final class solution was conducted regarding their ability to classify individuals with posterior probabilities of at least 80% and 90%.

The eleven variables included in the LCA are presented in more detail in section 2.2.1 and displayed in Table 1. Since latent class analysis cannot be applied to numeric variables, the variables were categorized into low, medium and high. An exception was the variable *MP at night* which was dichotomized ("switched off" vs. "switched on") LCA was executed using the Penn State University Methodology Center LCA Stata Plugin.

3.2. Multivariable linear regression models

To investigate the associations of the class-memberships and health related quality of life, multivariable linear regression models were computed using the KIDSCREEN subscale scores as outcome variables. The class affiliation derived by the LCA was included as categorical explanatory variable with the class showing the lowest use as reference category. Coefficients were obtained via non-parametric bootstrapping (resampling rate: 1000) to account for the non-normal data distribution. All models were adjusted for sex, age, nationality, school-level and education of the parents. Missing values in the variable educational level of the parents (240 missing values) were imputed using the most common education level stratified over adolescents' school level.

Statistical analyses were carried out using STATA version 14.0 (StataCorp, College Station, TX, USA).

4. Results

4.1. Sample

A total of 895 adolescents participated in the study from which 439 (49.1%) were assessed in the first and 456 (50.9%) in the second sampling period respectively. 45 (5.0%) reported not to own a mobile phone and were therefore excluded from the analysis. Of the remaining 850 participants 753 (88.6%) were smartphone users. The mean age was 14.1 years (ranging from 10.4 to 17.0) and more girls (484; 56.9%) than boys (366; 43.1%) participated in the study.

4.2. Latent class analysis

The fit indices for model comparison up to the seven-class solution based on the ML-algorithm are displayed in Table 2.

The three-class and the five-class solution were considered as the final model. The three-class solution showed the lowest CAIC but the SABIC goodness of fit indicator favoured the five-class solution, we preferred this final model (Nylund et al., 2007; Tofighi & Enders, 2008). Except of the fit indices this decision was based on our aim to explore qualitatively different classes of use and not to divide the sample simply into high, medium and low use as suggested by a three class solution. The three class solution split the sample in groups containing 50.1% (medium use), 27.7% (high use) and 22.2% (low use) (data not shown), the five-class solution in 28.3%, 9.8%, 19.6%, 15.3% and 27.1% of the participants, respectively. The main difference of the five-class solution was the split of medium use into three smaller classes leading to more distinct use patterns.

Table 2
Goodness of fit indices AIC (Akaike's Information Criterion), SABIC (sample-size adjusted Bayesian Information Criterion) and CAIC (Bozdogan's Criterion) for the one to seven class solutions. Note that lower values indicate better model fit.

Class	AIC	SABIC	CAIC
1	7977.836	8010.796	8098.486
2	6915.921	6983.411	7162.967
3	6678.418	6780.438	7051.859
4	6605.126	6741.979	7104.962
5	6560.872	**6731.951**	7187.103
6	6530.433	6736.041	7283.058
7	6513.931	6754.069	7392.952

The best model fit according to the SABIC is highlighted in bold letters.

After inclusion of the covariates sample and gender the five classes identified were named *Gaming*, *Medium Use*, *Low Use*, *Call Preference* and *High Social Use*. The naming was based on the item response probabilities of the respective classes. The *Gaming* class for example had a particular high probability to score in the category "high" for the variables Gaming and PC-use. A complete overview of the item response probabilities is displayed in Table 3.

The post-hoc analysis of the class membership probabilities affirmed 66.9% of individuals being assigned to a certain class with a certainty of >0.9 and 78.8% with >0.8, respectively for the five class solution (data not shown). For further analysis all participants were assigned to the class for which they showed the highest individual membership probability.

Inclusion of the covariates gender and sample revealed that participants' class membership was highly dependent on being male or female and belonging to sample 2012/2013 or sample 2014/2015. Table 4 shows the distributions of the five classes on the covariates and demographic variables.

4.2.1. Latent class media use profiles

A graphical illustration of the five media use patterns is displayed in Fig. 1.

The *Low Use* class showed the least frequent media use. More than 70% of the class members scored in the lowest category for eight (calls (MP), calls (landline), text messages, online on MP, music, MPPUS-10 and MP expenses, MP at night) out of the eleven use variables. Further, the penetration rate of smartphones was low in that group (51.8% compared to 97.8% in the remaining sample). Interestingly, almost the whole group belonged to sample 2012/2013.

The *Medium Use* class showed a rather average pattern of media use. In most of the smartphone related use variables the major part of the group scored in the medium category. In contrast to the *Low Use* class, they had a higher rate of participants of sample 2014/2015.

96% of the *Gaming* class which consisted almost exclusively of boys reported high use on the variable gaming. Their actual mean gaming duration was three times higher than in the sample overall. In addition they spent twice as much time on PC or tablet.

Table 3
Item response probabilities for the different categories of the 10 media use variables and of MP at night in the five latent classes.

Type of Use	Category	Class				
		Low Use	Medium Use	Gaming	Call Preference	High Social Use
Calls (MP)	Low	0.54	0.41	0.41	0.09	0.18
	Medium	0.34	0.41	0.35	0.23	0.29
	High	0.12	0.17	0.24	0.68	0.53
Text messages	Low	0.80	0.02	0.00	0.13	0.01
	Medium	0.20	0.55	0.49	0.44	0.01
	High	0.00	0.42	0.50	0.42	0.99
Online on MP	Low	0.77	0.26	0.22	0.21	0.00
	Medium	0.10	0.51	0.53	0.35	0.32
	High	0.13	0.23	0.26	0.44	0.68
Calls (landline)	Low	0.48	0.61	0.71	0.24	0.58
	Medium	0.22	0.17	0.15	0.19	0.12
	High	0.30	0.22	0.15	0.57	0.30
Gaming	Low	0.22	0.38	0.00	0.21	0.42
	Medium	0.56	0.62	0.04	0.53	0.40
	High	0.23	0.00	0.96	0.26	0.18
Music	Low	0.70	0.21	0.11	0.11	0.00
	Medium	0.22	0.50	0.53	0.34	0.26
	High	0.08	0.29	0.35	0.55	0.74
Social networks	Low	0.38	0.20	0.16	0.10	0.04
	Medium	0.60	0.49	0.34	0.81	0.06
	High	0.03	0.32	0.49	0.08	0.90
MPPUS-10	Low	0.78	0.35	0.27	0.15	0.03
	Medium	0.16	0.46	0.46	0.36	0.21
	High	0.06	0.19	0.27	0.49	0.76
PC use	Low	0.25	0.53	0.14	0.09	0.38
	Medium	0.44	0.33	0.22	0.42	0.29
	High	0.31	0.14	0.64	0.48	0.33
MP expenses	Low	0.72	0.40	0.31	0.17	0.20
	Medium	0.18	0.27	0.29	0.40	0.23
	High	0.10	0.33	0.40	0.43	0.57
MP at night	switched off	0.65	0.62	0.55	0.29	0.31
	switched on	0.35	0.38	0.45	0.71	0.69

Table 4
Descriptive statistics of the total sample and the five classes on the demographic variables adjusted for in the multivariable regression models.

	Total	Low Use	Medium Use	Gaming	Call Preference	High Social Use
Total	850	171 (20%)	237 (28%)	99 (12%)	125 (15%)	218 (25%%)
Gender						
Female	484 (56.9%)	103 (60.2%)	127 (53.6%)	1 (1.0%)	92 (73.6%)	161 (73.9%)
Male	366 (43.1%)	68 (39.8%)	110 (46.4%)	98 (99.0%)	33 (26.4%)	57 (26.1%)
Sample						
Sample 1 (2012–2013)	412 (48.5%)	168 (98.3%)	53 (22.4%)	40 (40.4%)	124 (99.2%)	27 (12.4%)
Sample 2 (2014–2015)	438 (51.5%)	3 (1.7%)	184 (77.6%)	59 (59.6%)	1 (0.8%)	191 (87.6%)
Age in years (min-max)	14.1	13.7 (12.1–18.8)	13.9 (10.4–17.0)	14.1 (12.2–16.4)	14.1 (12.3–16.7)	14.2 (12.5–16.8)
Nationality						
Swiss	642 (75.8%)	144 (84.2%)	189 (79.7%)	76 (77.6%)	92 (73.6%)	141 (65.3%)
Swiss and foreign	118 (13.9%)	19 (11.1%)	31 (13.1%)	10 (10.2%)	21 (16.8%)	37 (17.1%)
Foreign	87 (10.3%)	8 (4.7%)	17 (7.2%)	12 (12.2%)	12 (9.6%)	38 (17.6%)
Schoollevel						
Secondary school level C	169 (20.1%)	21 (12.5%)	33 (13.9%)	24 (24.2%)	36 (29.5%)	55 (25.4%)
Secondary school level B	237 (28.1%)	32 (19.0%)	71 (30.0%)	36 (36.4%)	30 (24.6%)	68 (31.3%)
Secondary school level A	265 (31.4%)	63 (37.5%)	76 (32.1%)	20 (20.2%)	40 (32.8%)	66 (30.4%)
High school level	172 (20.4%)	52 (31.0%)	57 (24.0%)	19 (19.2%)	16 (13.1%)	28 (12.9%)
Highest education of the parents						
Training School	387 (45.5%)	69 (40.4%)	95 (40.1%)	47 (47.5%)	95 (40.1%)	111 (50.9%)
High School	176 (20.7%)	18 (10.5%)	60 (25.3%)	18 (18.2%)	60 (25.3%)	65 (29.8%)
University/college	287 (33.8%)	84 (49.1%)	82 (34.6%)	34 (34.3%)	82 (34.6%)	42 (19.3%)

Otherwise their media use was low to average for different usage variables.

The *Call Preference* class showed a rather high media use except use of social networks. Unlike the other classes, the group seemed to favor phone calls (on mobile phone as well as landline phone) over texting. The majority of the class scored high in both call variables. Similarly to the *Low Use* class the fourth class consisted mainly of participants investigated in sample 2012/2013 but the proportion of smartphone users was still high (93.6%).

The *High Social Use* class consisted mainly of girls from sample 2014/2015. Compared to the other classes the group showed the highest use of all variables related to social communication purposes on a smartphone such as use of social network sites, text messages or time spent online on the device. The class also showed the highest values on the MPPUS-10. The only variable below average was gaming.

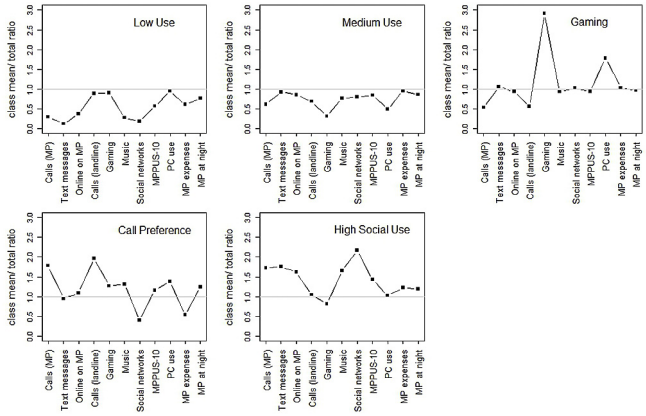

Fig. 1. Mean values of the eleven different item scores expressed as a fraction of the respective overall mean across the five latent classes. The class mean/total ratio was calculated on the real values of the non-categorized variables by dividing the class mean by the simple mean.

4.3. Multivariable regression models

After adjustment for various confounders, significant differences in the scores of six out of ten KIDSCREEN health related quality of life subscales were found among the five classes (Table 5).

In general, two classes appeared to diverge most amongst the scores. The *Low Use* class and the *High Social Use* class were on the upper and lower extremes, respectively, of the subscales *Moods and Emotions* (mean adjusted scores: 55.1 (95%CI: 53.8; 57.0) vs. 49.1 (47.5; 50.7)), *Self-Perception* (51.8 (50.3; 53.3) vs. 48.0 (46.7; 49.28), *Parent Relation and Home Life* (53.3 (51.7; 54.9) vs. 48.6 (47.2; 50.0)) and *School Environment* (52.7 (51.3; 54.0) vs. 49.3 (48.2; 50.7)). Thus, of all classes, the *High Social Use* class reported lowest levels of positive feelings, self-esteem and most problems at home and in school whereas the Low Use class felt most comfortable in those domains. However, the picture was reversed on the subscale *Social Support and Peers*. Here the *High Social Use* class showed the highest and the *Low Use* class the lowest score (53.8 (52.4; 55.3) vs. 48.5 (47.0; 50.0)).

In addition, the *Medium Use* class scored highest on the *Physical Well-being* subscale while the *Low Use* class showed the lowest score on that scale (52.0 (50.8; 53.2) vs. 48.1 (46.4; 49.8)). For the other four scales (*Psychological Well-being, Autonomy, Financial Resources, Social Acceptance*) no significant differences between the classes were found.

5. Discussion

5.1. Latent class media use profiles

Through the latent class analysis five distinct groups differing amongst eleven different media use variables were identified. The inclusion of gender and the subsample as covariates showed meaningful differences between the classes.

Male gender was most prominent in the *Gaming* group which is in line with previous research on (online) gaming (Kuss & Griffiths, 2012). Interestingly the *Gaming* group was most equally distributed amongst the two subsamples. The reason for this might be that online gaming has evolved long before Smartphones and so the class might not have been affected by recent technological changes in the telecommunication industry.

The *Medium Use* class and the *Low Use* class showed the lowest but somehow diverging levels of media use. The *Medium Use* class used mainly the mobile phone for social communication while *Low Use* rather engaged in gaming or used other media. Most of the *Medium Use* class was part of sample 2014/2015. In contrast almost the whole *Low Use* class was investigated in sample 2012/2013. At that time Smartphones were less frequently used. Indeed, the smartphone penetration was lowest in the *Low Use* class (51.8% compared to 97.8% in the remaining sample). It seems likely that these two classes depict to some extend the technological switch from "old fashioned" mobile phones to Smartphones in between the sampling times.

A clear effect of both covariates was observed in the two classes going along with rather high media use, *Call Preference* and *High Social Use*. Both groups consisted from a far higher proportion of girls which is in line with previous knowledge (Nesi & Prinstein, 2015; Shin, Yoon, & Choi, 2015; van Deursen et al., 2015). While *Call Preference* recruited its members mainly from sample 2012/2013 *High Social Users* were more likely to belong to sample 2014/2015. *Call Preference* was mainly characterized by higher levels of calling (mobile phone and landline) while *High Social Use* was marked by heavy use of texting and social networks. This might mirror the more easy and cheap use of web based social messenger application in sample 2014/2015 through the broader availability of WiFi and data flat rates included in mobile phone contracts.

5.2. Associations with the KIDSCREEN

In general, health related quality of life differed most amongst the *High Social Use* class and the *Low Use* class whereby the *High Social Use* class showed less well-being on most of the scales but the

Table 5
Adjusted mean scores and 95% confidence intervals for the five classes on the 10 KIDSCREEN scales.

KIDSCREEN subscale	N	chi2	p-value[b]	Low Use		Medium Use		Gaming		Call Preference		High Social Use	
				score[a]	95% CI	score[a]	95% CI	score[a]	95% CI	score[a]	95% CI	score[a]	95% CI
Physical Well-being	838	18.77	**0.002**	48.1	(46.4; 49.8)	52.0	(50.8; 53.2)	49.2	(47.2; 51.3)	47.8	(45.9; 49.6)	50.3	(48.8; 51.7)
Psychological Well-being	837	3.92	0.561	52.1	(50.4; 53.8)	52.7	(51.4; 54.0)	51.4	(49.4; 53.4)	51.8	(45.0; 53.7)	52.4	(50.8; 53.9)
Moods and Emotions	835	30.03	>**0.001**	55.1	(53.3; 57.0)	52.1	(50.7; 53.4)	51.9	(49.7; 54.2)	51.3	(49.5; 50.7)	49.1	(47.5; 50.7)
Self-Perception	837	21.41	>**0.001**	51.8	(50.3; 53.3)	50.8	(49.7; 52.0)	49.4	(47.4; 51.4)	49.9	(48.2; 51.5)	48.0	(46.7; 49.3)
Autonomy	835	7.27	0.201	50.8	(49.4; 52.3)	50.2	(48.9; 51.4)	49.4	(47.5; 51.3)	51.0	(49.2; 52.8)	50.2	(48.9; 51.6)
Parent Relations and Home Life	833	21.13	>**0.001**	53.3	(51.7; 54.9)	51.9	(50.7; 53.1)	50.4	(48.4; 52.3)	52.4	(50.5; 54.3)	48.6	(47.2; 50.0)
Financial Resources	820	8.51	0.130	55.4	(54.1; 56.8)	55.4	(54.4; 56.3)	54.6	(54.0; 56.2)	54.2	(52.6; 55.8)	53.6	(52.4; 54.9)
Social Support and Peers	835	27.78	>**0.001**	48.5	(46.9; 50.0)	51.5	(50.3; 52.8)	49.0	(47.1; 50.8)	51.5	(49.6; 53.4)	53.8	(52.4; 55.3)
School Environment	833	16.01	**0.007**	52.7	(51.3; 54.0)	51.8	(50.7; 52.8)	51.0	(49.3; 52.7)	50.9	(49.4; 52.5)	49.3	(48.2; 50.5)
Social Acceptance	835	3.15	0.677	51.3	(49.6; 53.0)	51.6	(50.3; 52.9)	50.8	(48.8; 52.8)	52.1	(50.0; 54.1)	51.7	(50.2; 53.2)

Significant differences among the classes on the KIDSCREEN subscales are highlighted in bold (p-value < 0.05).
[a] All scores adjusted for gender, age, investigation phase, nationality, school level and education of the parents.
[b] p-value for group differences calculated by likelihood ratio test.

best connections with peers. The *Call Preference* and *Gaming* class lied between these two extreme categories but also explained part of the outcome variances.

5.2.1. Negative affectivity, self-perception and adolescents media use

The *High Social Use* class differed most from the *Low Use* class in the KIDSCREEN subscales *Moods and Emotions* and *Self-Perception.* These findings are supported by recent studies linking online social communication to depressive symptoms and low self-esteem (Demirci et al., 2015; Ehrenberg et al., 2008; Thomée, Härenstam, & Hagberg, 2012; Yen et al., 2009). The question of causality here is still discussed and for both directions there are reasonable arguments. On the one hand, individuals with initial high levels of depression and/or low levels of self-esteem may perceive online social communication via social network sites or instant messengers as a possibility to gain social support on a lower threshold and to relief themselves from negative feelings through the ease of online self-disclosure (Dolev-Cohen & Barak, 2013; Ellison, Steinfield, & Lampe, 2007; Oh, Ozkaya, & LaRose, 2014; Selfhout, Branje, Delsing, ter Bogt, & Meeus, 2009; Steinfield et al., 2008; Zhang, Tang, & Leung, 2011). On the opposite using social network sites and instant messengers might heighten levels of depression and lessen life satisfaction and self-esteem. Usually, this is explained by dysfunctional social comparisons on social media platforms (Feinstein et al., 2013; Tandoc et al., 2015).

5.2.2. A poststructuralist integration of online social communication

Another possible mechanism which was not yet examined to the best of our knowledge relates to language perception as well as adolescents' psychosocial development and implicit learning processes. Poststructuralists like Foucault claim that the oral and written speech one is surrounded by determines how one perceives his or her environment (Foucault, 2002). Besides, our emotional and intellectual perception of speech is socioculturally determined (Barrett, Lindquist, & Gendron, 2007) even influencing related neurological processes (Wager et al., 2008). The individual perception of the environment is thus dependent from the linguistic frame this individual is moving in.

We can apply this thought to adolescents' media use. Online social communication facilitates self-disclosure via web forums, on online social media platforms via private postings or through the heavy use of instant messaging applications like WhatsApp to rapidly exchange short messages transporting delicate emotional contents (Trepte & Reinecke, 2013). These processes of frequent verbal expression of private emotional contents might often be additionally positively affirmed by "likes" leading to implicit learning processes (Kisyovska, Krönung, & Eckhardt, 2015).

From a poststructuralist view, permanent exposition to and composing of emotional posts and messages may determine how media-prone adolescents perceive, think about and act within their social environment. It is thinkable that the higher exposure to private linguistically transmitted emotional contents in a young age might have an impact on the individual psychosexual development fostering earlier mature and "adult-like" behavior. In our sample such processes would mainly be seen in the *High Social Use* class. The high scores on the *Moods and Emotions* scale could then be partly an artifact due to an ongoing paradigmatic change to think and perceive emotions facilitated by the frequent use of social networks and instant messengers.

Subsuming both ideas more research should be done on the emotional contents of online communication, reinforcement processes and their potential to influence the speech and perception of adolescents. Neuropsychological studies on emotional affectivity and learning could shed light onto those complex interactions.

5.2.3. Social environment, (online) social capital and media use

It is known that adolescents' health is strongly dependent from their social status within society and their proximal social environment. Amongst the most protective factors are safe and supportive families and schools as well as positive and supportive peers (Viner et al., 2012). The *High Social Use* class showed least satisfaction at home (*Parent Relation and Home Life*) and less connectedness to school and teachers (*School Environment)* both particularly contrasted by the Low Use class. Nevertheless, the *High Social Use* class seemed to have better relationships to peers (*Social Support and Peers*) than the *Low Use* class.

These findings indicate that media use might be a mediating factor in the psychosexual development during adolescence there one struggles in defining an own social and yet individual identity in society (Erikson, 1994). These processes are accompanied by social comparisons, the need for belonging, an increasing sensitivity for one's own feelings and emotions and the urge to gain autonomy from parents. In adolescents, the use of smartphones and social network platforms for social communication bear several advantages compared to face-to-face interaction. In a qualitative approach Irish teenagers emphasized staying in intimate contact and sharing the best kept secrets with friends, hiding from the parents, finding help for emotional struggles on a lower threshold or the increased control over written compared to spoken language as motives for online communication (Rice, 2013). In this way media use increases adolescents' social capital which is known as a positive resource resulting from sociability and interpersonal relationships (Bourdieu, 2011) and has been linked to online social communication (Bian & Leung, 2015; Ellison et al., 2007; Steinfield et al., 2008).

Although social capital is known as a protective factor in terms of mental and physical health it remains unclear if its positive effects are comparable if gained through online versus face-to-face interactions. In addition, adolescents' perception of meaningful peer contacts might be biased by social desirability and the wish of self-enhancement. Apart from this positive resource, media use could foster social separation through group formations whereby the messaging frequency or the number of Facebook friends might be important social ranking indicators. That might produce sublime feelings of oneself and the in-group through the perception of being popular and the degradation of others. The wish to belong to the "cool" kids in this way might coincidentally trigger compulsive or even risky smartphone and online behavior like Cyberbullying or Sexting.

Nevertheless, it seems likely that nowadays children "naturally" increase their smartphone and social media use while turning towards adolescence. The use of smartphones and the internet for social communication might help them to approach the challenges in their psychosexual development they have to go through until conquering adulthood (e.g. gaining autonomy from parents, dealing with intimate thoughts etc.). In our results, this link of media use with development is supported by the fact that the *High Social Use* group was characterized by the highest average age and the highest percentage of girls of all groups. In contrast, the *Low Use* group had the lowest age.

Integrating the results in the current discussion on problematic media use, the classes *Call Preference* and *High Social Use* scored slightly above average on the MPPUS-10. This might be an indication that the need for social communication could drive problematic use to some extent. Still, none of the classes generally showed an extremely high score suggesting that high media use per se should not be a priori being considered problematic.

Regarding its clinical implications the results suggest that

treatment for excessive media use in adolescents should build on the differences in psychosexual development, qualitative use preferences and its underlying motives. In this way this study supports the view that more tailored approaches are needed to address problematic media use in adolescents (Billieux, Schimmenti, et al., 2015; Schimmenti et al., 2015).

6. Strengths and limitations

A limitation of the study is the lack of longitudinal data so the direction of associations with the KIDSCREEN scales cannot be clarified. Thus the interpretation of any association has to be regarded with caution. The study had an unusual two stage sampling design which had high impact on the LCA. In both sampling stages there was one class with rather low and one with rather high media use predominant. The classes *Low Use* and *Call Preference* were highly prevalent in the sample 2012/2013 (98.3% and 73.6% of the class members, respectively) whereas two other classes, *Medium Use* and *High Social Use* consisted mainly from participants belonging to sample 2014/2015 (77.6% and 87.6%). Thus it seems likely that the differences in use patterns between *Low Use/Medium Use* and *Call Preference/High Social Use* depict the rapid development in media technologies within two years which was additionally paced by more affordable prices for flat rates included in smartphone subscriptions. Indeed, if we compare pairwise *Medium Use* with *Low Use* and separately *High Social Use* with *Call Preference* the classes more prevalent in sample 2014/2015 (*Medium Use* and *High Social Use*, respectively) showed the higher values on all variables related particularly to smartphone use (online on MP, text messages, social networks, music).

In this way, a multiple stage sampling design is an opportunity for assessing the rapid technology change and its accompanying effects.

7. Conclusion

Using latent class analysis is a fruitful approach to monitor specific patterns of media use on a population level. This approach could shed light onto the frequent but vague concerns of health effects due to media use in linking specific application use to specific outcomes. Nevertheless, appropriate research is challenging since mobile phones are an integral part in adolescents' life to gain independence. Additionally, communication technology and media use patterns are changing rapidly. Using latent class analyses to differentiate various usage types may be an appropriate way to better characterize and evaluate potential causal associations between media use and health related quality of life in adolescents.

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Conflicts of interest

The authors declare that there are no conflicts of interest. Milena Foerster wrote the first draft of the manuscript.

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5. RF-EMF exposure and memory functions

5.1. Article 4:A Prospective Cohort Study of Adolescents' Memory Performance and Individual Brain Dose of Microwave Radiation from Wireless Communication

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A Prospective Cohort Study of Adolescents' Memory Performance and Individual Brain Dose of Microwave Radiation from Wireless Communication

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Background: The potential impact of microwave radiofrequency electromagnetic fields (RF-EMF) emitted by wireless communication devices on neurocognitive functions of adolescents is controversial. In a previous analysis, we found changes in figural memory scores associated with a higher cumulative RF-EMF brain dose in adolescents.

Objective: We aimed to follow-up our previous results using a new study population, dose estimation, and approach to controlling for confounding from media usage itself.

Methods: RF-EMF brain dose for each participant was modeled. Multivariable linear regression models were fitted on verbal and figural memory score changes over 1 y and on estimated cumulative brain dose and RF-EMF related and unrelated media usage ($n = 669$–676). Because of the hemispheric lateralization of memory, we conducted a laterality analysis for phone call ear preference. To control for the confounding of media use behaviors, a stratified analysis for different media usage groups was also conducted.

Results: We found decreased figural memory scores in association with an interquartile range (IQR) increase in estimated cumulative RF-EMF brain dose scores: −0.22 (95% CI: −0.47, 0.03; IQR: 953 mJ/kg per day) in the whole sample, −0.39 (95% CI: −0.67, −0.10; IQR: 953 mJ/kg per day) in right-side users ($n = 532$), and −0.26 (95% CI: −0.42, −0.10; IQR: 341 mJ/kg per day) when recorded network operator data were used for RF-EMF dose estimation ($n = 274$). Media usage unrelated to RF-EMF did not show significant associations or consistent patterns, with the exception of consistent (nonsignificant) positive associations between data traffic duration and verbal memory.

Conclusions: Our findings for a cohort of Swiss adolescents require confirmation in other populations but suggest a potential adverse effect of RF-EMF brain dose on cognitive functions that involve brain regions mostly exposed during mobile phone use. https://doi.org/10.1289/EHP2427

Introduction

The rapid evolution of information and communication technologies (ICTs) during the past 20 y has caused an increase in man-made exposure to radiofrequency electromagnetic fields (RF-EMFs). However, the health effects of RF-EMFs are still unknown. Neurological functions are of special concern given that the brain is heavily exposed while calling with a mobile or cordless phone (Joseph et al. 2010). Present-day adolescents will likely have higher cumulative lifetime exposure to RF-EMF, and the developing brain might be particularly susceptible to RF-EMF–induced alterations up to 15 y of age (Kheifets et al. 2005; Luciana et al. 2005; Schüz 2005). In this age group, memory functions are particularly important because proper encoding, processing, and retrieval of information are required for learning. However, to date studies addressing this topic have produced inconsistent results.

Controlled-exposure studies in animals and humans have found limited evidence for both positive and negative effects of RF-EMF on memory performance and related neural processes (Bouji et al. 2012; Deshmukh et al. 2015; Hao et al. 2013; Jeong et al. 2015; Klose et al. 2014; Son et al. 2016). Among the few epidemio-logical studies, the Australian Mobile Radiofrequency Phone Exposed Users' Study (MoRPhEUS) cohort of 317 adolescents with a median age of 13 y observed faster but less accurate responses in working memory and associative learning tasks for frequent mobile phone users (Abramson et al. 2009). The same result was observed in relation to the number of text messages (SMS), which involve only marginal RF-EMF exposure. This may suggest that aspects other than RF-EMFs are the underlying cause of this association. A longitudinal analysis of the MoRPhEUS data indicated associations between mobile phone use and changes in response times for some cognitive tasks over a 1-y period, but the authors proposed regression to the mean as a potential explanation because associations were inconsistent and increase in exposure was mainly seen in those who had fewer calls and SMS at baseline (Thomas et al. 2010).

In the following Examination of Psychological Outcomes in Students using Radiofrequency dEvices (ExPOSURE) study by the same research group as MoRPhEUS, 617 primary school children were investigated and little evidence for cognitive effects due to RF-EMF was found (Redmayne et al. 2013). However, the number of calls was generally very low in these young children (8–11 y of age): a median of 2.5 and 2 calls per week for mobile phones and cordless phones, respectively, among those children using these devices.

In both studies, the RF-EMF exposure was assessed via self-reported number of calls, which usually yields an overestimation of the actual use by adolescents (Aydin et al. 2011). Further, personal exposure to RF-EMF is dependent on other factors such as the call duration, the distance of the device from the body (Joseph et al. 2010; Kühn and Kuster 2013), and the network used for calling. For instance, the global system for mobile communications standard (GSM) produces about 100–500 times higher exposure than the universal mobile telecommunication system (UMTS) (Gati et al. 2009; Persson et al. 2012). Furthermore, using mobile phone calls as a proxy for RF-EMF exposure ignores confounding by the media-related lifestyle impacting individuals' cognition, behavior, and emotion (Kuss et al. 2014; Kuss and Griffiths 2011, 2012; Roser et al. 2016). The present Health Effects Related to Mobile phone usE in adolescentS (HERMES) cohort was the first study in

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adolescents that used individually modeled RF-EMF doses and operator-recorded mobile phone use to investigate potential effects of RF-EMF exposure on cognitive functions (Roser et al. 2015). With this approach, cumulative RF-EMF brain dose was associated with a significant decrease in figural memory performance over a 1-y period (Schoeni et al. 2015), with a stronger decrease observed in right-side users.

The present study aims to follow-up our previous results using an approximate doubling of sample size. Further, we have updated the individual RF-EMF dose model using more recent information on adolescents' brain specific absorption rates (SARs) for different exposure scenarios and by calibrating self-reported call duration on objective operator-recorded call duration. In addition, the present study applies a new approach to control for confounding due to device usage in epidemiological RF-EMF studies.

Materials and Methods

Data of the prospective HERMES cohort study were collected in two independent sampling waves. The first wave of baseline investigations commenced in June 2012 among a cohort of seventh- through ninth-grade students from 24 secondary schools in Central Switzerland. A second wave commenced in April 2014 that included a new group of seventh- through ninth-grade students from 22 secondary schools. Of the 22 schools, 2 had already taken part in the first wave, 18 were newly recruited from Central Switzerland, and 2 were newly recruited from the Basel canton. Follow-up investigations were conducted approximately 1 y after each baseline until April 2016. Participating adolescents were recruited through an initial telephone contact by the head of the school and a subsequent informational visit in their respective classes by the study managers. Participation was voluntary and the informed consent of both adolescents and a parent was compulsory.

The data were collected during school lessons and consisted of completing a paper questionnaire to assess the adolescents' mobile phone and media usage as well as their psychological and somatic health and socioeconomic factors. Computerized cognitive testing was performed immediately afterward. Additionally, a subsample of 148 volunteers from both study waves was recruited to conduct personal RF-EMF measurements as described in detail for the first study wave ($n = 90$) by Roser et al. (2017). These participants were intentionally sampled depending on their place of residence and school in order to be representative of the entire far-field exposure range of the complete study sample. Participants were required to carry a portable measurement device (exposimeter) with an integrated Global Positioning System (GPS) for 3 consecutive days. Simultaneously, a time–activity app on a smartphone in flight mode had to be filled in to later link the RF-EMF records to a particular activity or place.

Ethical approval for conducting the study was received from the ethical committee of the canton of Lucerne, Switzerland, on 9 May 2012 (EKLU 12025 and EKBB 80/12).

Outcome Assessment: Memory Performance

Cognitive performance was measured using a standardized computerized testing system consisting of the figural and verbal memory subtest of the Intelligenz-Struktur-Test (IST) (Liepmann et al. 2007). For the verbal memory task, participants were given 1 min to memorize five sets of two to five words grouped by their common higher semantic category (e.g., city: Amsterdam, Rome, Hamburg, Madrid, York). The target words were presented by starting with a different letter each time. Immediately after the presenting phase, participants were given a letter and they had to recall the word starting with that letter and report the higher semantic category to which it belonged. This was repeated for 11 words, producing a maximum score of 11 points for the verbal memory task. For the figural memory task, participants were given 1 min to memorize 13 pairs of abstract figures, and immediately afterward one item per pair was shown and participants were asked to choose the correct counterpart out of five possible options. The matching task was repeated for 13 symbols, resulting in a maximum score of 13 points. For each of the two tests, 2 min were given to complete the matching task. Each student started with the verbal memory task.

For the statistical analyses, the difference between the continuous test score values at follow-up minus the baseline values were used as outcome. The coefficient of the outcome–exposure association corresponds directly to the change in score: A positive coefficient thus indicates an improvement in memory between baseline and follow-up in relation to the exposure of interest, whereas a negative association indicates a decrease in memory. In the age group of our study, without considering any exposure, one would generally expect an increase in verbal memory and an increase or little change in figural memory between baseline and follow-up. However, memory development during adolescence may vary largely interindividually (Luciana et al. 2005; Schneider and Pressley 2013).

Exposure: Mobile Phone and General Media Use

The detailed usage of mobile phones and other wireless communication devices was assessed via questionnaire. Questions focused on the average amount and type of mobile phone and media usage per day. Exposures of primary interest were those expected to produce relatively high RF-EMF exposure: specifically, the daily duration and number of calls on mobile and cordless phones. In addition, we asked whether students preferentially held mobile phones on the right or left side of their heads when making calls or whether they had no preference. Further, participants were asked about headset use while calling, which is an important factor for RF exposure because exposure to the body decreases rapidly with increasing distance from the device (Lauer et al. 2013). We also asked about activities that might be correlated with phone use but that would be expected to result in relatively low RF-EMF exposures, including the number of text messages sent per day, daily duration of data traffic on the student's mobile phone, daily duration of gaming on electronic devices, the frequency of social network use, and whether the student's mobile phone was left on or turned off at night. In addition, we used the brief MPPUS-10 scale to assess problematic mobile phone use in the students (Foerster et al. 2015).

For the self-reported usage measures included in the linear regression analysis (daily frequency of text messages, daily duration of mobile phone data traffic, daily duration of gaming, and daily duration of cordless phone use), we calculated the cumulative usage by taking the mean difference between baseline and follow-up, and interpreting this value as usage per day.

Detailed data records of daily quantitative mobile phone use from the 6 months preceding the baseline examination date until the follow-up investigations were obtained from the Swiss mobile phone network operators [Swisscom, Sunrise, and Salt (formerly known as Orange)] if adolescents and one of their parents had given additional written informed consent. These participants are subsequently referred to herein as the operator sample. The operator records included the number and duration of calls, number of text messages sent per day, and the daily volume of data traffic. In addition, the identity of the network (UMTS or GSM) used to start each phone call was obtained from the operators Swisscom and Salt, whereas the third operator, Sunrise, did not provide this information. The daily cumulative mobile phone call duration was calculated by summing up all recorded call durations between baseline and follow-up and dividing this sum by the recorded days between baseline and follow-up to obtain daily usage.

A comparison of self-reported mobile phone use with operator-recorded use indicated severe overestimation of self-reported mobile phone use. To avoid bias, we calibrated self-reported mobile phone call duration for participants without operator records. The calibration equation was derived from the operator sample using a multilevel linear regression model that was clustered by schools with average operator-recorded mobile phone call duration per day as dependent variable and the following predictors to be found relevant (likelihood ratio test for the nonclustered model including or excluding the predictor): age, gender, daily frequency of mobile phone calls at follow-up, daily frequency of text messages at follow-up, daily duration of mobile phone data traffic at follow-up, and daily duration of cordless phone calls at follow-up as well as the difference in daily duration of mobile phone calls between follow-up and baseline (see Table S1). Subsequently, the predicted values from the calibration model were used as estimated daily call duration for the participants without operator data. A similar model was constructed to predict the proportion of calls made on the UMTS network, with the following predictors to be found relevant: the place of residence (urban vs. rural—the UMTS proportion was usually lower in rural areas), UMTS exposure (as a proportion of total downlink) at place of residence obtained by geospatial propagation model (see below), and the number of smartphones at the home as well as the duration of mobile data traffic—all of which were indicators of a higher UMTS proportion. The proportion of GSM network was assumed to be $1-\text{proportion}(\text{UMTS})$. The distinction between both networks used was important in determining RF-EMF exposure because, compared with calls executed on the UMTS network, calls on the GSM network have been associated with irradiation levels heightened by a factor of 100–500 (Gati et al. 2009; Persson et al. 2012). For the participants for whom operator-recorded data was available, the objectively recorded data (cumulative call duration and, if applicable, network proportion) was used for all further analysis, including the RF-dose estimation.

Individual Cumulative RF-EMF Brain Dose

Individual RF-EMF brain dose was calculated using an updated dosimetric model described in detail by Roser et al. (2015) that considers RF-EMF exposure-relevant behaviors and circumstances from near- and far-field sources. Near field refers to the use of RF-EMF–emitting devices close to the body (e.g., mobile phones, wireless Internet), whereas far field refers to the surrounding environmental RF-EMF exposure (e.g., from fixed-site transmitters, W-LAN access points, people using mobile phones nearby).

The first step in dose modeling consists of simulating SARs of the brain gray matter for each exposure-relevant behavior and circumstance [for details see "1. Numeric simulations of brain gray matter specific absorption rates (SAR)" in the Supplemental Material]. SAR is a quantity that indicates the rate at which RF-EMF is absorbed in a certain mass or volume of tissue. SAR values are determined using numeric simulations based on two adolescent human body models from the phantom "virtual population," an 11-y-old girl (Billie) and a 14-y-old boy (Louis) (Gosselin et al. 2014). For near-field sources, SARs were simulated for three scenarios (positions of the emitting device with relation to the body): (*a*) device held close to the ear, (*b*) device kept in the pocket of trousers, and (*c*) device held at a distance of 20 cm to the ear (headset scenario).

SAR values were transformed to dose values by multiplying the SAR with relevant exposure durations (see Table S1). The following near-field exposures were considered in the model: daily duration of mobile phone use (separated by 2G/3G and headset use); daily duration of mobile phone data traffic (separated by transfer via WiFi and mobile phone network); daily duration of cordless phone calls (considering the phone's eco mode if applicable); daily duration of WiFi use on laptop, PC, and tablet; and daily duration of carrying the participant's own mobile phone close to body (e.g., in a pocket). The average output power of these devices was derived from the literature [for details see "1. Numeric simulations of brain gray matter specific absorption rates (SAR)" in the Supplemental Material].

The far-field dose modeling included exposure from mobile phone base stations (downlink) broadcasting (radio and TV), WiFi, DECT (Digital Enhanced Cordless Telecommunications base stations at the home), and far-field exposure from the mobile phones of other nearby people (uplink). Downlink and broadcasting exposure at home and at school was modeled for each participant by means of the geospatial NISMap software (Bürgi et al. 2010).The model is based on accurate operation parameters of all stationary mobile phone and broadcast transmitters and the three-dimensional building and topography model of the study area. Semi-empirical propagation algorithms such as COST-Walfisch-Ikegami (Cichon and Kürner 1999) were used to predict RF-EMF exposure at the receptor points, taking into account, for example, the shielding effects of buildings and topography. Duration of exposure at school was assumed to be 35 h per week in order to eventually obtain the average downlink and broadcasting exposure.

WiFi, uplink, and DECT cannot be modeled by NISMap. Thus, for WiFi and uplink factors, predicting exposure to these sources were identified by linear regression from personal measurement data available from 148 study participants (see Table S1). Relevant predictors for 24-h personal WiFi exposure were the mobile phone operator, presence of WiFi at school, the daily duration of mobile data traffic, and the study wave (2012–2014 vs. 2014–2016). Predictors of uplink were the mobile phone operator, mobile phone status at night (on vs. off), the number of smartphones at the home, the time spent in public transport (train and bus), and the study wave. Because no valuable predictors for DECT could be identified, it was assumed to be the mean DECT exposure as derived from personal measurements in 148 participants. These 24-h far-field exposure values were then transformed to SAR values of the brain gray matter using plane-wave-simulations in the Finite-Different Time-Domain-based simulation software SEMCAD-X, version 16 from SPEAG, Zürich, Switzerland (see Table S2). In a final step, the individual RF-EMF brain gray matter dose for each participant was calculated by summing up the contributions of all different near- and far-field exposure scenarios.

Statistical Analysis

All analyses were conducted for the complete sample as well as separately for the two subsamples investigated during 2012–2014 and 2014–2016, respectively. Following the protocol used in our previous analysis, three different types of exposure variable were considered: (*a*) cumulative RF-EMF brain dose, (*b*) cumulative wireless device use related to RF-EMF exposure (cordless phone calls and mobile phone calls), and (*c*) cumulative wireless device use not or only marginally related to RF-EMF exposure (duration of data traffic, duration of gaming, number of text messages sent). Outcome variables were changes in figural and verbal memory score (follow-up minus baseline) over 1 y.

Separate linear exposure–response models were used to estimate associations between each outcome (the change in verbal or figural memory scores from baseline to follow-up, respectively) and each primary exposure variable (modeled as a continuous variable). All models were adjusted for age, gender, nationality (Swiss, Swiss and other, other), school level [in ascending order according to the school system in Switzerland based on academic expectations: secondary school level C, secondary school level B, secondary school level A, college preparatory high school],

frequency of physical activity at follow-up (defined as working out for at least 40 min: ≤1 to 3 times per month, 1 time per week, 2–3 times per week, 4–6 times per week, daily), days of alcohol consumption per month at follow-up (none, ≤1 time per month, 2–4 times per month, 2–3 times per week), change in height between baseline and follow-up (as a proxy for developmental speed between both time points), duration between baseline and follow-up in months, and education of parents (training school, college preparatory high school, college or higher education, university).

In the second step, a laterality analysis of RF-EMF brain dose (head laterality was not considered in the RF-EMF dose model) was conducted given that the figural memory involves mainly the right hemisphere, whereas verbal memory processing is more left sided (Golby et al. 2001; Nagel et al. 2013). Because most of the study participants indicated they held their phone on the right side of their head, we dichotomized the participants into right-side users vs. left-side users and users with no preference (combined). Laterality analyses were performed using data for the entire sample and were repeated after restriction to the operator sample. To facilitate comparisons among the different exposure variables, all effect estimates are expressed as the difference in test scores associated with an interquartile range (IQR) increase in exposure.

Missing values in the confounder variables were either imputed via linear regression (17 missing values at follow-up for alcohol consumption were predicted by age, gender, school class, and school level; 14 missing values at baseline and 12 missing values at follow-up for information on height were predicted by weight, age, and gender) or by imputation, replacing the missing values with the most common category (i.e., 2 missing values at follow-up for frequency of physical activity were replaced by the most common category "2–3 times per week", and 167 missing values for educational level of the parents were replaced by the most common category "Training school"). Statistical analyses were carried out using STATA (version 14; StataCorp).

To evaluate residual confounding from unmeasured factors related to communication device use, we performed stratified analyses across five subgroups representing five different media usage profiles derived by means of latent class analysis of 11 media use variables from the baseline questionnaire data (Foerster and Röösli 2017). The following five classes were identified: Low Use, Medium Use, Call Preference, Gaming, and High Social Use (see Figure S1).

We performed separate linear regression models restricted to students in each of the five media usage groups and estimated differences in each outcome with an IQR increase (defined for the population as a whole) in cumulative RF-EMF brain dose. Next, we performed random effects meta-analyses to derive a summary estimate for each outcome in each subgroup and assessed heterogeneity using the I^2 statistic (Higgins et al. 2003). We assumed that physical effects of RF-EMF would have a similar impact across media use subgroups, independent of any psychological or cognitive effects of media use; therefore, evidence of heterogeneity among the five group-specific estimates would be consistent with uncontrolled psychobehavioral confounding.

Results

In total, 895 adolescents between 12 and 17 y of age were enrolled in the baseline investigation of the HERMES study. The first sampling wave included 439 [mean age ± standard deviation (SD): 14.0 ± 0.85)] students recruited from 57 classes in 24 schools. During the second wave, 456 students (14.1 ± 0.86 y of age) from 44 classes and 22 schools were recruited. A total of 843 participants (96.8% of wave-1 students, $n = 425$; and 91.7% of wave-2 students, $n = 418$) took part in the follow-up investigation 1 y later (Table 1). The average time between baseline and follow-up was 12.5 months. Of these students, 827 (98.1%) owned a mobile phone. The sample included more girls ($n = 457$, 56.4%) than boys ($n = 368$, 43.6%). Objectively recorded operator data for at least 6 months between baseline and follow-up were available for 322 participants (38.8%).

Outcome and Exposure Distributions

Due to technical problems with the computerized testing system, completed tests for both time points were available for only 676 (80.2%) of the participants for verbal memory and 670 (79.5%) for figural memory, respectively (Table 2). While the verbal memory score increased from baseline to follow-up (mean unit increase ± SD = 1.1 ± 3.0), figural memory score did not increase in general (mean increase of 0.2 ± 3.2). The intraclass correlation coefficient (ICC) within individuals was 0.76 for the verbal score, and 0.81 for the figural memory score.

The mean duration of self-reported mobile phone call time was 17.2 ± 27.6 min/d, in contrast with a mean operator-recorded time of 3.2 ± 13.3 min/d. After calibration based on multilevel regression of the subgroup with operator data, the estimated mean mobile phone call time for the sample as a whole was 10.6 ± 13.7 min/d. Mean self-reported cordless phone call duration was 6.2 ± 6.6 min/d (operator data were not available for calibration of cordless phone use). For media exposures associated with low RF-EMF, average daily durations were 56.7 ± 34.3 min/d for mobile phone data traffic and 43.0 ± 56.9 min/d for gaming, and the mean number of text messages sent per day was 35 ± 21.

The estimated mean cumulative RF-EMF brain dose for the population as a whole was 858 ± 1,027 mJ/kg per day when estimated using calibrated mobile phone call durations (mean 10.6 min/d) (Table 2). In the operator data sample ($n = 322$), the estimated mean cumulative RF-EMF brain dose based on recorded call durations (mean 3.2 min/d) was 469 ± 814 mJ/kg per day.

On average, the daily cumulative call duration accounted for 80.3% of the estimated cumulative RF-EMF brain dose in the population as a whole (see Table S3). The proportion for calls executed on the GSM network was much higher (79.8%) compared with the UMTS network (0. 5%). In comparison, when using only data from the operator data sample ($n = 322$), duration of mobile phone use accounted for 66% of estimated cumulative RF-EMF dose (data not shown).

Estimated cumulative RF-EMF brain doses varied among the five media use groups, primarily due to differences in mobile phone call duration (Table 2; see also Figure S1). For example, the Call Preference group ($n = 119$), which had calibrated daily mobile phone and cordless call duration estimates of 15.9 ± 11.9 and 10.8 ± 9.6 min/d, respectively, had a mean estimated daily RF-EMF brain dose of 1,214 ± 1,259 mJ/kg per day, compared with 551 ± 1,029 mJ/kg per day for the Low Use group ($n = 198$), mean calibrated mobile and cordless phone call duration estimates of 5.9 ± 7.7 and 6.0 ± 5.6 min/d, respectively.

Associations between Changes in Memory Performance and RF-EMF Dose and Media Usage

In the population as a whole, none of the exposure variables were significantly associated ($p < 0.05$) with changes in verbal memory scores (Table 3, Figure 1). However, there was a nonsignificant association with the cumulative duration of data traffic and the increase in verbal memory score [score change per IQR: 0.34; 95% confidence interval (CI): −0.05, 0.72; IQR: 55.4 min/d], which was consistent over both study waves (Figure 2).

Table 1. Distributions among different sociodemographic and lifestyle variables for all participants taking part in the follow-up investigations and the five media use groups separately.

Characteristic	Total [*n* (%)][a]	Gamer [*n* (%)][a]	Media use[b] [*n* (%)][a]	Low use [*n* (%)][a]	Call preference [*n* (%)][a]	High social use [*n* (%)][a]
n (total)	843 (100)	97 (12)	223 (26)	207 (25)	119 (14)	197 (23)
Age [y (min–max)]	14.0 (10.3–17.0)	14.1 (12.2–16.4)	13.9 (10.4–17.0)	13.8 (11.8–15.8)	14.3 (12.3–16.6)	14.1 (12.5–16.1)
Sex						
Female	475 (56.4)	96 (99.0)	102 (45.7)	90 (43.5)	32 (26.9)	48 (24.4)
Male	368 (43.6)	1 (1.0)	121 (54.3)	117 (56.5)	87 (73.1)	149 (75.6)
Sample						
Sample 1 (2012–2013)	425 (50.4)	40 (41.2)	51 (22.9)	191 (92.3)	118 (99.2)	25 (12.7)
Sample 2 (2014–2015)	418 (49.6)	57 (58.8)	172 (77.1)	16 (7.7)	1 (0.8)	172 (87.3)
Nationality						
Swiss	646 (76.6)	75 (77.3)	175 (78.5)	174 (84.1)	89 (74.8)	133 (67.5)
Swiss and foreign	120 (14.2)	11 (11.3)	31 (13.9)	25 (12.1)	19 (16)	34 (17.3)
Foreign	77 (9.2)	11 (11.3)	17 (7.6)	8 (3.9)	11 (9.2)	30 (15.2)
School level[c]						
Secondary school level C	151 (17.9)	23 (23.7)	30 (13.5)	22 (10.6)	34 (28.6)	42 (21.3)
Secondary school level B	242 (28.7)	36 (37.1)	69 (30.9)	43 (20.8)	30 (25.2)	64 (32.5)
Secondary school level A	272 (32.3)	20 (20.6)	68 (30.5)	80 (38.7)	41 (34.5)	63 (32)
High school level	178 (21.1)	18 (18.6 %)	56 (25.1)	62 (30)	14 (11.8)	28 (14.2)
Highest education of the parents[d]						
Training school	496 (58.8)	58 (59.8)	129 (57.9)	88 (42.5)	73 (61.3)	148 (75.1)
College preparatory high school	50 (5.9)	6 (6.2)	15 (6.7)	14 (6.8)	4 (3.4)	11 (5.6)
College of higher education	235 (27.9)	22 (22.7)	63 (28.3)	81 (39.1)	37 (31.1)	32 (16.2)
University	62 (7.4)	11 (11.3)	16 (7.2)	24 (11.6)	5 (4.2)	6 (3.1)
Physically active (FUP)[e]						
≤1 to 3 times per month	128 (15.2)	11 (11.3)	30 (13.5)	28 (13.5)	19 (16)	40 (20.4)
1 time per week	170 (20.2)	16 (16.5)	39 (17.5)	43 (20.8)	31 (26.1)	41 (20.9)
2–3 times per week	316 (37.4)	40 (41.2)	81 (36.3)	83 (40.1)	43 (36.1)	68 (34.7)
4–6 times per week	159 (18.9)	21 (21.7)	48 (21.5)	36 (17.4)	18 (15.1)	36 (18.4)
Daily	70 (8.3)	9 (9.3)	25 (11.2)	17 (8.2)	8 (6.7)	11 (5.6)
Number of days with alcohol consumption (FUP)[f]						
None	469 (55.6)	47 (48.5)	138 (61.9)	142 (68.6)	48 (40.3)	94 (47.7)
≤1 time per month	200 (23.7)	28 (28.9)	51 (22.9)	41 (19.8)	35 (29.4)	45 (22.8)
2–4 times per month	139 (16.5)	13 (13.4)	32 (14.4)	19 (9.2)	29 (24.4)	46 (23.4)
2–3 times per week	35 (4.2)	9 (9.3)	2 (0.9)	5 (2.4)	7 (5.9)	12 (6.1)
Change in height (cm ± SD) (follow-up–baseline)[g]	3.7 ± 6.7	5.8 ± 4.1	4.4 ± 4.4	4.4 ± 4.8	1.2 ± 13.7	2.5 ± 3.9

Note: FUP, follow-up; max, maximum value; min, minimum value; SD, standard deviation.
[a]Numbers are *n* (%) unless notes otherwise.
[b]Media use groups determined by latent class analysis on 11 qualitatively different media use variables as described in Foerster and Röösli (2017).
[c]According to the school system in Switzerland, school levels imply differing academic expectations (in ascending order: secondary school level C, secondary school level B, secondary school level A, college preparatory high school); 167 missing values for educational level of the parents replaced by the most common category "Training school."
[d]Highest level of education achieved by at least one of the parents.
[e]Physical activity defined as working out at least 40 min with perspiration; two values missing at follow-up for frequency of physical activity were replaced by the most common category "2–3 times per week."
[f]Seventeen values missing at follow-up for alcohol consumption were imputed via linear regression imputation predicted by age, gender, school class, and school level.
[g]Fourteen values missing at baseline and 12 values missing at follow-up for information on height were predicted by weight, age, and gender.

Changes in figural memory score were negatively correlated with cordless phone calls and, in tendency, with the duration of mobile phone calls and the cumulative RF-EMF brain dose (Figure 2). The association with RF-EMF brain dose was nonsignificant in the full sample (−0.22 (95% CI: −0.47, 0.03; IQR: 953 mJ/kg per day) and significant in the operator data sample (−0.26 (95% CI: −0.42, −0.10; IQR: 341 mJ/kg per day). When analyzing the two subsamples separately, for both study waves, nonsignificant negative effect estimates for the RF-EMF dose were seen, although the magnitude of this effect was greater for the second ($n = 288$) compared with the first wave ($n = 375$) but with a wider confidence interval for the second wave (first wave: −0.14 (95% CI: −0.42, 0.14); second wave: (−0.58 (95% CI: −1.17, 0.01); IQR: 953 mJ/kg per day). No association was observed with variables that were only marginally related to RF-EMF exposure (cumulative duration of data traffic, cumulative gaming duration, and cumulative number of text messages).

The association between figural memory score and cumulative brain dose became significant when analysis was restricted to users with right-side preference (full sample: $n = 532$; operator sample: $n = 217$) in the laterality analysis (full sample: −0.38; 95% CI: −0.67, −0.09; IQR: 953 mJ/kg per day; operator sample: −0.29 (95% CI: −0.46, −0.11; IQR: 341 mJ/kg per day) (Figure 3). When restricted to left-side/no-preference users, the effect estimates were, in general, imprecise due to the small sample size (full sample: $n = 137$; operator sample: $n = 57$). However, a significant negative association was found for verbal memory in the operator sample (−0.51; 95% CI: −0.89, −0.13; IQR: 341 mJ/kg per day).

Meta-Analysis over Media Use Groups

The pooled random effects estimate for the association between cumulative brain dose and figural memory score over the five media use groups (−0.39; 95% CI: −0.69, −0.09; IQR: 953 mJ/kg per day) was consistent with the main analysis, and did not support heterogeneity among the groups ($I^2 = 0.0\%$). The pooled effect for verbal memory score was 0.02 (−0.24, 0.31; IQR: 953 mJ/kg per day; $I^2 = 0.0\%$) (see Figure S2).

Discussion

In the present study, an IQR increase in estimated cumulative RF-EMF brain dose was associated with a nonsignificant decrease in figural memory score, but was not associated with verbal memory

Table 2. Descriptive statistics for all different exposure variables used in linear regression models for the whole sample and the five media use groups separately.

Variable	Total			Low use			Media use[a]			Gaming			Call preference			High social use		
	n	mean ± SD	IQR[b]	*n*	mean ± SD	IQR	*n*	mean ± SD	IQR	*n*	mean ± SD	IQR	*n*	mean ± SD	IQR	*n*	mean ± SD	IQR
Whole sample																		
Verbal memory score[c]																		
Baseline	751	4.9 ± 2.8	4.0	196	5.3 ± 2.7	3.5	191	4.8 ± 2.7	4.0	88	4.8 ± 2.8	3.5	110	4.8 ± 2.8	4.0	166	4.6 ± 3.0	5.0
Follow-up	738	5.9 ± 2.7	4.0	187	6.5 ± 2.6	5.0	193	5.9 ± 2.8	4.0	84	5.5 ± 2.7	4.0	110	5.8 ± 2.8	4.0	164	5.6 ± 2.8	4.0
Difference (follow-up–baseline)	676	1.1 ± 3.0	4.0	180	1.3 ± 2.9	4.0	168	1.0 ± 3.0	4.0	78	0.8 ± 2.7	3.0	106	1.2 ± 2.9	4.0	144	1.2 ± 3.3	4.5
Figural memory score[a]																		
Baseline	740	7.8 ± 2.8	4.0	195	8.5 ± 2.5	3.0	189	7.3 ± 2.8	4.0	86	6.9 ± 2.7	4.0	110	8.1 ± 2.7	4.0	160	7.6 ± 3.1	4.0
Follow-up	742	7.9 ± 3.3	6.0	189	8.5 ± 3.2	5.0	194	8.0 ± 3.2	5.0	85	6.8 ± 3.5	6.0	110	7.5 ± 3.3	5.0	164	7.7 ± 3.5	6.0
Difference (follow-up–baseline)	670	0.2 ± 3.2	4.0	180	0.1 ± 2.8	4.0	168	0.7 ± 3.0	4.0	77	−0.3 ± 3.6	6.0	106	−0.5 ± 3.2	5.0	139	0.5 ± 3.6	5.0
Usage related to EMF exposure to the head																		
Cordless phone calls [min/d]	843	6.2 ± 6.6	5.1	207	6.0 ± 5.6	5.1	223	4.7 ± 4.1	4.0	97	4.0 ± 3.6	2.3	119	10.8 ± 9.6	11.3	197	6.5 ± 7.6	5.1
Mobile phone calls [min/d][d]	843	10.6 ± 13.7	12.6	207	5.9 ± 7.7	7.4	223	9.0 ± 12.8	10.2	97	9.9 ± 12.3	15.7	119	15.9 ± 11.9	13.2	197	14.4 ± 18.4	15.3
Mobile phone calls, self-reported [min/d]	843	17.2 ± 27.6	16.3	207	7.3 ± 10.9	7.0	223	11.4 ± 19.1	9.9	97	13.8 ± 34.5	9.4	119	31.1 ± 35.8	27.5	197	26.7 ± 32.1	27.4
Usage marginally related to EMF exposure to the head																		
Data traffic [min/d]	843	56.7 ± 34.3	55.4	207	27.6 ± 25.2	35.5	223	51.3 ± 28.3	43.4	97	59.2 ± 30.5	44.7	119	66.7 ± 26.5	41.4	197	86.1 ± 27.3	44.8
Gaming [min/d]	843	43.0 ± 56.9	55.7	207	38.6 ± 48.6	51.3	223	20.9 ± 33.9	29.3	97	116.1 ± 63.2	63.6	119	49.6 ± 62.0	56.8	197	32.7 ± 50.2	40.0
Texts sent [number/d]	843	35 ± 21	40	207	15 ± 12	17	223	32 ± 18	30	97	36 ± 20	35	119	43 ± 17	24	197	54 ± 12	13
Cumulative brain dose [mJ/kg per day][e]	830	858 ± 1,027	953	198	551 ± 1,029	471	221	753 ± 824	800	97	806 ± 956	997	118	1,214 ± 1,259	1,391	196	1,098 ± 1,003	1,110
Sample with operator data																		
Duration mobile phone calls [min/d]	322	3.2 ± 13.3	1.8	116	1.1 ± 2.9	0.8	63	4.2 ± 4.1	1.7	30	1.7 ± 3.1	1.2	65	2.8 ± 3.8	2.7	48	8.8 ± 29.2	8.0
Cumulative brain dose [mJ/kg per day][e]	318	469 ± 814	341	115	357 ± 918	187	61	465 ± 638	324	30	344 ± 694	152	65	620 ± 793	517	47	607 ± 842	443

Note: EMF, electromagnetic field; IQR, interquartile range; SD, standard deviation.

[a]Media use groups were determined by latent class analysis on 11 qualitatively different media use variables as described in Foerster and Röösli (2017).

[b]User-group–specific IQRs are displayed for descriptive purposes. For reporting user-group–specific IQRs (see Figure S2), the whole population IQR was used.

[c]Due to technical problems with the computerized testing system, completed tests for both time points were only available for a reduced number of participants.

[d]Adjusted via multilevel linear regression estimates calibrated on the objectively recorded duration of calls obtained by mobile phone operators. Models were clustered over schools and the following predictors were selected from the self-reported questionnaire data: age, gender, daily frequency of mobile phone calls at follow-up, daily frequency of text messages at follow-up, daily duration of mobile phone data traffic at follow-up, daily duration of cordless phone calls at follow-up, difference in daily duration of mobile phone calls between follow-up and baseline.

[e]Cumulative brain dose derived based on the following cumulative exposure variables. Near-field bands (if not indicated otherwise, taken from the questionnaire): daily duration of mobile phone calls (for the whole sample: calibrated via operator data; for the operator sample: operator recorded), network proportions of UMTS and GSM (for the whole sample: calibrated via operator data and far-field UMTS proportion; for the operator sample: operator recorded), proportion of headset use, daily duration of cordless phone calls, daily duration of mobile phone data traffic on WiFi and 3G, daily duration of WiFi use via laptop, PC, and tablet, daily duration of mobile phone held close to body; far-field bands: Uplink from surrounding mobile phones and Wifi (modeled via linear regression estimation based on questionnaire and personal measurements), downlink GSM900, downlink GSM1800, downlink UMTS, radio/broadcast, TV [(determined by geospatial propagation modeling using the NISMap software (Bürgi et al. 2010)], DECT (mean of the measurements).

Table 3. Results of adjusted linear exposure models for the whole sample and the two subsamples (2012–2014 and 2014–2016).

Exposure	n	IQR	Whole sample [adjusted[a] (95% CI)]	n	Sample 2012–2014 [adjusted[a] (95% CI)]	n	Sample 2014–2016 [adjusted[a] (95% CI)]
Whole sample							
Usage related to EMF exposure to the head							
Verbal memory							
Cordless phone calls [min/d]	676	5.1	−0.02 (−0.20, 0.15)	375	−0.05 (−0.26, 0.15)	301	−0.10 (−0.46, 0.25)
Mobile phone calls [min/d][b]	676	12.6	−0.01 (−0.29, 0.27)	375	0.08 (−0.31, 0.46)	301	−0.15 (−0.57, 0.26)
Figural memory							
Cordless phone calls [min/d]	670	5.1	−0.23 (−0.42, −0.04)	381	−0.23 (−0.45, −0.02)	289	−0.21 (−0.64, 0.22)
Mobile phone calls [min/d][b]	670	12.6	−0.21 (−0.51, 0.09)	381	0.01 (−0.40, 0.41)	289	−0.44 (−0.90, 0.02)
Cumulative brain dose [mJ/kg per day][c]							
Verbal memory	675	953	0.02 (−0.22, 0.26)	372	0.01 (−0.26, 0.27)	293	0.03 (−0.52, 0.58)
Figural memory	669	953	−0.22 (−0.47, 0.03)	381	−0.14 (−0.42, 0.14)	288	−0.58 (−1.17, 0.01)
Usage marginally related to EMF exposure to the head							
Verbal memory							
Data traffic [min/d]	676	55.4	0.34 (−0.05, 0.72)	375	0.48 (−0.04, 1.00)	301	0.33 (−0.28, 0.94)
Gaming [min/d]	676	55.7	−0.03 (−0.30, 0.25)	375	0.04 (−0.33, 0.40)	301	−0.16 (−0.59, 0.27)
Texts sent (units/d)	676	40	0.16 (−0.31, 0.63)	375	0.40 (−0.21, 1.02)	301	0.00 (−0.75, 0.75)
Figural memory							
Data traffic [min/d]	670	55.4	−0.05 (−0.46, 0.37)	381	0.18 (−0.37, 0.73)	289	−0.47 (−1.14, 0.21)
Gaming [min/d]	670	55.7	−0.12 (−0.41, 0.17)	381	0.02 (−0.36, 0.41)	289	−0.36 (−0.83, 0.12)
Texts sent (units/d]	670	40	0.04 (−0.45, 0.54)	381	0.20 (−0.45, 0.84)	289	−0.22 (−1.05, 0.62)
Sample with operator data							
Verbal memory							
Mobile phone calls [min/d]	277	1.8	−0.01 (−0.10, 0.08)	210	0.15 (−0.06, 0.37)	67	−0.01 (−0.13, 0.11)
Cumulative brain dose [mJ/kg per day][c]	273	341	0.02 (−0.14, 0.18)	209	0.05 (−0.12, 0.21)	64	−0.30 (−1.04, 0.44)
Figural memory							
Mobile phone calls [min/d]	278	1.8	−0.03 (−0.12, 0.06)	212	−0.18 (−0.39, 0.04)	66	0.03 (−0.11, 0.16)
Cumulative brain dose [mJ/kg per day][c]	274	341	−0.26 (−0.42, −0.10)	211	−0.25 (−0.41, −0.09)	63	−0.35 (−1.20, 0.50)

Note: Coefficients relate to change score per IQR of exposure shown in the column "IQR." CI, confidence interval; EMF, electromagnetic field.
[a]All models adjusted for age, gender, school level, education of the parents, alcohol consumption at follow-up, physical activity at follow-up, change in height (follow-up–baseline) and time between baseline and follow-up.
[b]Self-reported use calibrated with the objectively recorded duration of calls as described in Table S1.
[c]Cumulative brain dose derived based on the following cumulative exposure variables. Near-field bands (if not indicated otherwise, taken from the questionnaire): daily duration of mobile phone calls (for the whole sample: calibrated via operator data; for the operator sample: operator recorded), network proportions of UMTS and GSM (for the whole sample: calibrated via operator data and far-field UMTS proportion; for the operator sample: operator recorded), proportion of headset use, daily duration of cordless phone calls, daily duration of mobile phone data traffic on WiFi and 3G, daily duration of WiFi use via laptop, PC, and tablet, daily duration of mobile phone held close to body; far-field bands [if not indicated otherwise, exposure was determined by geospatial propagation modeling using the NISMap software (Bürgi et al. 2010)]: Uplink from surrounding mobile phones (modeled via linear regression estimation based on questionnaire and personal measurements), downlink GSM900, downlink GSM1800, downlink UMTS, WiFi (modeled via linear regression estimation based on questionnaire and personal measurements), radio/broadcast, TV, DECT.

score. This inverse association of cumulative RF-EMF brain dose was consistently seen in the full sample analysis and the subgroup analysis of the two study waves (2012–2014 vs. 2014–2016), media usage groups, and the operator sample although the strength of the association differed somewhat. The association was stronger in the second than in the first wave (however, with a wider confidence interval) and statistically significant in the operator sample, but not in the whole sample with self-reported exposure (after calibration using operator data). A significant decrease in figural memory score with cumulative brain dose was further seen in laterality analysis for right-side users of both the full sample and the operator sample only. In left-side users, in contrast, we found a significant decrease in verbal memory score for the operator sample. However, there was no such association for the full sample and estimates for the left-side users were in general imprecise due to the small sample size and also less consistent. The more consistent association of right-side users with a decrease for figural memory and the decrease for verbal memory score seen in left-side users of the operator sample might be related to the lateralization of memory processes (Golby et al. 2001) and requires further study.

Regarding wireless media usage not related to high RF-EMF exposure, a nonsignificant positive association for cumulative duration of mobile phone data traffic and verbal memory score change was observed, whereas the coefficients for text messages and gaming were generally small. It is conceivable that a positive significant association of verbal memory and data traffic could cover a potential negative RF-EMF effect on verbal memory if data traffic and RF-EMF dose are highly correlated. To control for this, we post hoc calculated the Spearman's correlation and fitted a regression model on verbal memory including both variables and adjusted for the same confounding variables as before. Spearman's correlation was weak ($\rho = 0.25$), and the linear regression estimates for neither RF-EMF dose nor duration of data traffic changed majorly in the mutually adjusted model (data not shown).

Strengths and Limitations

The present study is unique in its approach to overcoming the main challenges in epidemiological research on RF-EMF. We estimated individual RF-EMF brain doses for the population as a whole using objectively recorded operator data from a subset of participants to calibrate self-reported call duration and thus reduce misclassification. The operator-recorded data allowed us to estimate the very exposure-relevant proportion of calls on the GSM and UMTS networks (Erdreich et al. 2007; Gati et al. 2009). In our sample, the respective brain dose contributions were 79.8% (GSM) and 0.5% (UMTS) (see Table S2).

The modeling allowed addressing the associations with mobile phone use and RF-EMF brain dose separately to evaluate potential residual confounding of lifestyle and media use related to wireless device use itself. These factors might act on human health, cognition, and behavior independently from a potential biological radiation effect (Kuss et al. 2014; Kuss and Griffiths 2011, 2012; Roser et al. 2016). To control for such confounding, we adjusted our analysis for age, gender, school level, parents' education, alcohol consumption, and physical activity at follow-up, and the time and change in height between baseline and

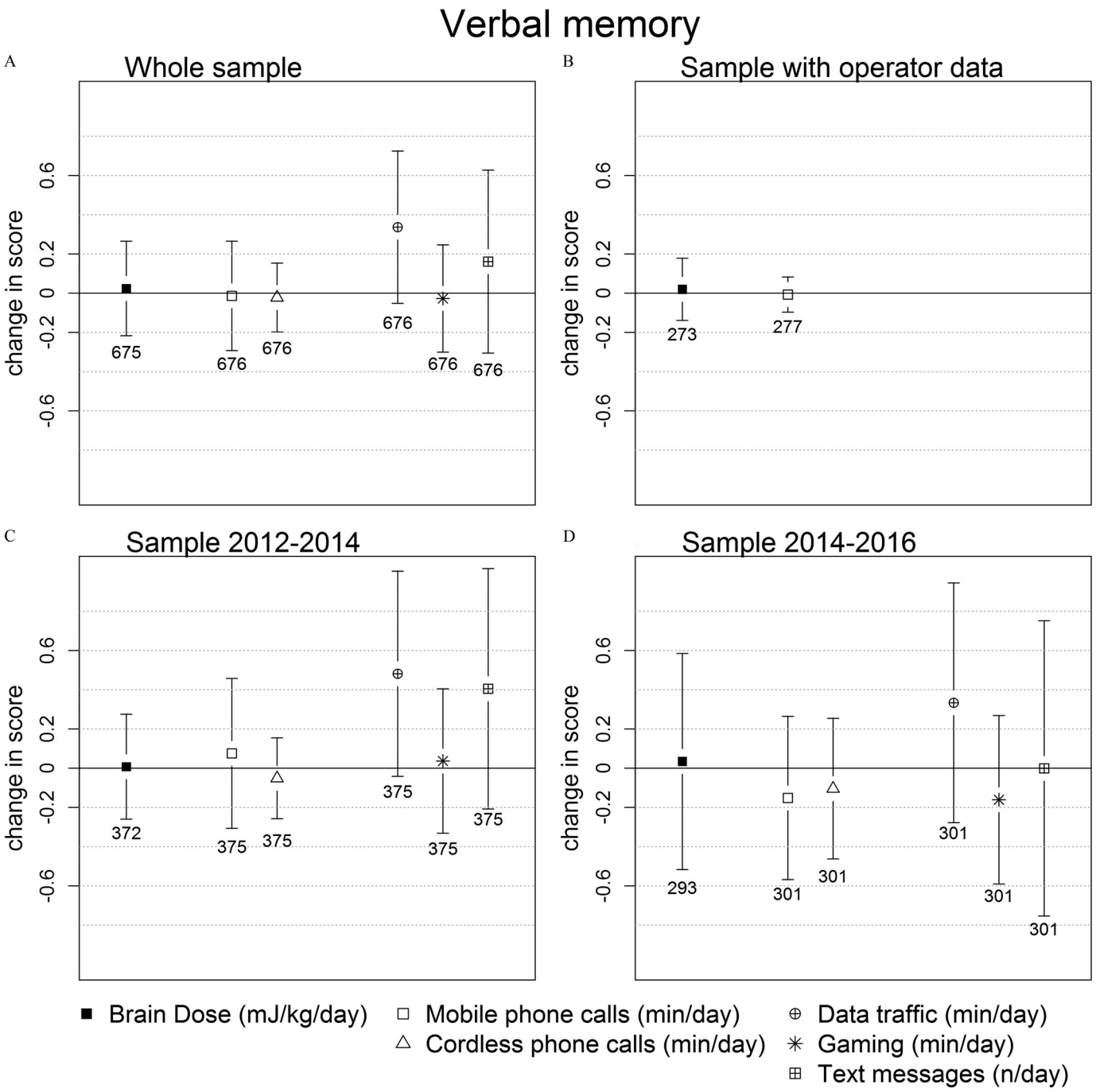

Figure 1. Results of linear exposure–response models for change in verbal memory scores (follow-up–baseline): estimates relate to change in memory score for (*A*) the whole sample per interquartile range (IQR) of exposure of the whole sample; (*B*) the operator sample per IQR of operator sample; (*C*) the sample 2012–2013 per IQR of exposure of the whole sample; and (*D*) the sample 2014–2015 per IQR of exposure of the whole sample. IQRs of the whole sample: brain dose, 953 mJ/kg per day; mobile phone calls, 12.6 min/d; cordless phone calls, 5.1 min/d; data traffic, 55.4 min/d; gaming, 55.7 min/d; and text messages, 40 per day. IQRs of the operator data, brain dose: 341 mJ/kg per day; and mobile phone calls, 1.8 min/d. All models were adjusted for age, gender, baseline score, nationality, school level, physical activity, alcohol, and education of parents and change in height and time between baseline and follow-up investigation. Number of observations for each calculation is indicated below each estimate.

follow-up. In addition, we estimated associations with media exposures associated with low RF-EMF exposures (minutes of gaming, minutes of mobile phone data traffic, and numbers of texts sent each day) to assess the potential impact of media use unrelated to RF-EMF.

In addition, we applied a new approach to control for residual confounding by stratifying the analysis for the RF-EMF brain dose over independent patterns of media use. Separate estimates for students classified according to the five media use patterns were similar among the groups for both verbal and figural memory, with I^2 statistics indicating little or no heterogeneity, and pooled estimates were consistent with estimates based on the main analysis. This pattern does not support major bias from uncontrolled confounding and is compatible with associations due to biophysical effects of RF-EMF, rather than effects of media use unrelated to RF-EMF. However, sample sizes within the five media use groups were small, and residual confounding cannot be ruled out based on this analysis.

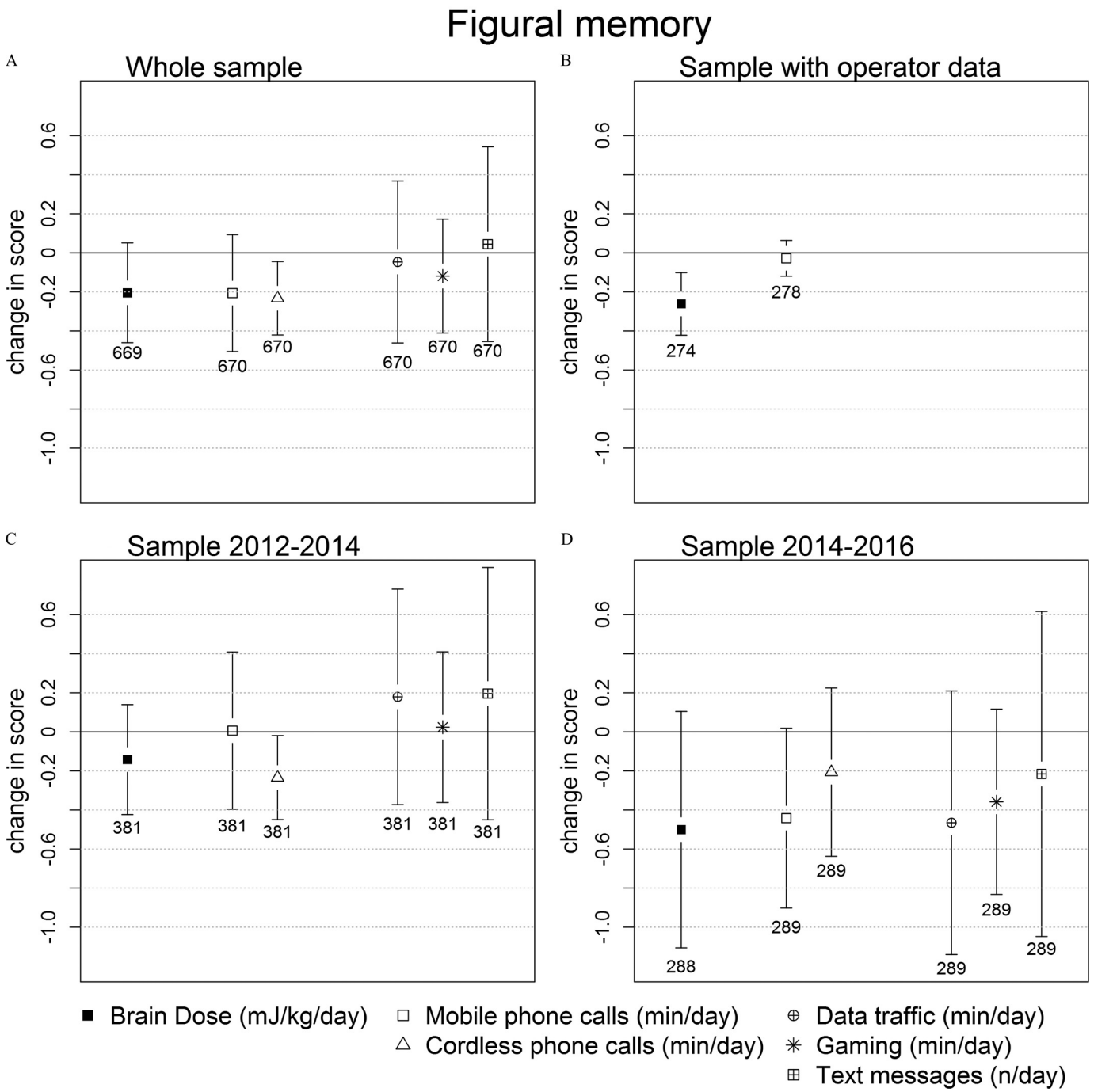

Figure 2. Results of linear exposure–response models for change in figural memory scores: (follow-up–baseline estimates relate to change in memory score for (*A*) the whole sample per interquartile range (IQR) of exposure of the whole sample; (*B*) the operator sample per IQR of operator sample; (*C*) the sample 2012–2013 per IQR of exposure of the whole sample; and (*D*) the sample 2014–2015 per IQR of exposure of the whole sample. IQRs of the whole sample: brain dose, 953 mJ/kg per day; mobile phone calls, 12.6 min/d; cordless phone calls, 5.1 min/d; data traffic, 55.4 min/d; gaming, 55.7 min/d; and text messages, 40 per day. IQRs of the operator data: brain dose, 341 mJ/kg per day; and mobile phone calls, 1.8 min/d. All models were adjusted for age, gender, baseline score, nationality, school level, physical activity, alcohol, and education of parents and change in height and time between baseline and follow-up investigation. Number of observations for each calculation is indicated below each estimate.

This study put a lot of emphasis on the exposure assessment and dose calculation. Information for the far-field exposure was retrieved from propagation models (Bürgi et al. 2010) and from personal measurements in 148 children (Roser et al. 2017). Operator-recorded mobile phone data is an asset, and, to our knowledge, it has not been available for other epidemiological studies of children and adolescents. Although operator data are objectively recorded, they have a disadvantage in that calls on other people's phones are not recorded. Furthermore, information on short message services does not represent texting behavior of adolescents using mostly Internet-based applications such as WhatsApp, and besides, the duration of data traffic and cordless phone use was not available from the operator. Thus, for these variables, the corresponding self-reported data had to be used for dose estimation as in the operator sample.

Uncertainty in the exposure assessment and in the RF-EMF dose calculations cannot be avoided. Estimation of SAR assumes a typical distance between emitting devices and body and average

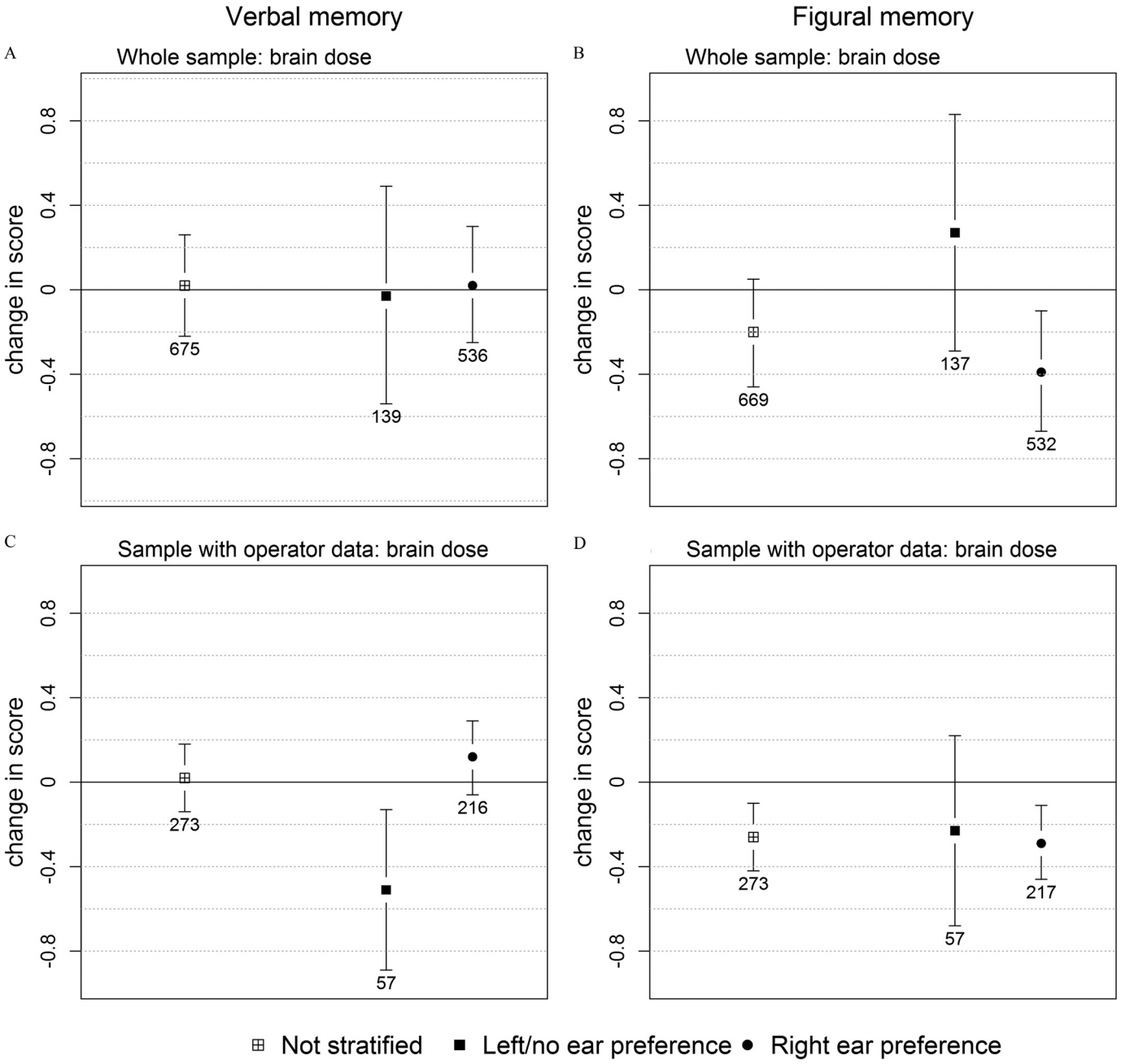

Figure 3. Results of the laterality analysis for the adjusted linear exposure response for the brain dose on changes in verbal and figural memory scores of the Intelligenz-Struktur-Test (IST). Estimates relate to (*A*) change in verbal memory score per interquartile range (IQR) of exposure for the whole sample; (*B*) change in figural memory score per IQR of exposure for the whole sample; (*C*) change in verbal memory score for the operator sample per IQR of the operator sample; and (*D*) change in figural memory score for the operator sample per IQR of the operator sample. Brain dose was derived via individual exposure modeling of relevant near- and far-field exposure sources. The most relevant predictors—duration of mobile phone calls and network proportion—were derived directly by network operators for the operator data sample. For the whole sample, these parameters were calibrated via multilevel linear regression models, predicting these parameters by self-reported questionnaire data, fitted for the operator sample. Change in memory score per IQR range of exposure. IQR for the whole sample, 953 mJ/kg per day; and IQR for the operator sample, 341 mJ/kg per day.

absorption characteristics of the body. But all of these aspects are variable in reality. A validation study could not be confirmed given than dose is not directly measurable and can only be computed.

Our study participants were recruited from the four common public school levels in urban and rural areas of Switzerland. Neither private nor religious schools were included because they play a minor role in Switzerland. All schools were located in Swiss German-speaking cantons, although Switzerland also has large French-, Italian-, and Rhaeto- Romanic-speaking areas. Generalizability might thus be restricted to public schools in German-speaking Switzerland. However, because RF-EMF brain dose is a biological measure, the exposure route should not differ among adolescents in general. Loss to follow-up was low (5.8%), but selection bias cannot be ruled out given that participation rates at baseline were only 37% for the first-wave (2012–2014) but 56% for the second-wave (2014–2016) study samples.

Comparison with Previous Analysis

The association between memory and RF-EMF exposure in the 2012–2014 sample has been analyzed previously (Schoeni et al. 2015). In the present work, we applied an improved RF-EMF dose estimation to the whole HERMES sample. The Spearman's correlation between the resulting new RF-EMF brain dose and the former dose estimate in the 2012–2014 sample was $\rho = 0.58$, demonstrating inherent uncertainties in dose estimation. The main difference compared with the previous dose modeling (Roser et al. 2015) was the use of operator calibrated self-reported call duration and different SAR values. Our new estimate of the first sample wave was of similar magnitude but less significant [−0.14 (−0.42, 0.14) per IQR of 953 mJ/kg per day] than in the previous analysis reported by Schoeni et al. (2015) [−0.26 (95% CI: −0.42, −0.10) per IQR of 1,579 mJ/kg per day].

Compared with the previous analyses, we have improved the dose calculations by various aspects. First, in the previous study, self-reported mobile phone use data was used for the dose calculation. It is well known that adolescents tend to overestimate duration of use and that the extent of overestimation is related to various sociodemographic factors (Aydin et al. 2011). This time, we used operator-recorded mobile phone data to adjust self-reported mobile phone use in order to reduce the overestimation of self-reported use. Consecutively, this led to a lower average RF-EMF dose estimation that might be closer to reality. The calibration was based on the assumption, that the factor and pattern by which participants overestimate their use could be extrapolated from the operator data sample. However, it must be noted that a large majority (approximately 75%) of the operator sample were participants from the first study wave. This might affect the generalizability of the operator sample–based estimates to the sample as a whole, in particular if relationships among self-reported variables considered for calibration and the operator-recorded data would be different for the first and second study wave due to increasing dissemination of smartphones in the study sample and the expansion of the UMTS network in the study region. However, differences in media usage behavior between the study waves might be more related to smartphone-specific applications rather than mobile phone calls (Foerster and Röösli 2017). Second, in the framework of the EU project GERoNiMO (Generalized EMF Research using Novel MethOds), new SAR estimates have been computed for various near- and far-field exposure conditions. Most relevant, these SAR estimates are based on the adolescent models Billie and Louis from the virtual population [for details see "1. Numeric simulations of brain gray matter specific absorption rates (SAR)" in the Supplemental Material], whereas in the past only SAR calculations from adult phantoms were available.

Brain Exposure and Differential Memory-Related Neuronal Circuits

Our findings require confirmation in other populations but suggest that RF-EMF brain exposure may have an adverse effect on figural memory functions in adolescents. The decrease in figural memory score with an IQR increase in exposure was 0.22 (95% CI: −0.47, 0.03; IQR: 953 mJ/kg per day) in the full sample ($n = 669$) and 0.26 (95% CI: −0.42, −0.10; 341 mJ/kg per day) in the operator sample ($n = 274$). To put this difference into context, in our main model adjusting for various factors, we observed a mean difference in figural memory score of 0.41 (95% CI: 0.13, 0.69) between adolescents from a lower school level (e.g., secondary school level C) to the next higher one (i.e., secondary school level B). Memory functions continue to develop in adolescents, and the ability to maintain and manipulate multiple spatial units (which is tested by the figural memory task) continues to develops until 15 y of age (Luciana et al. 2005).

Different brain areas and activation patterns are involved in neural memory processing, which is measured by different cognitive tests. Due to the differing specificity of cognitive tests, results often cannot be compared directly. Although we found decreases in figural memory, some experimental and epidemiological studies on RF-EMF found improvements in working memory performance. Working memory is usually assessed via reaction time tasks such as the *n*-back paradigm, where participants need to react in an accurate manner on a stimulus after a short time interval as fast as possible. This type of memory is also known as working attention and is related to very early stages of memory where stimuli are held actively in mind before being stored (Baddeley and Hitch 1974). For working memory, main brain activity is seen in executive structures involved in decision-making, predominantly the anterior cingulate and dorsolateral and inferior prefrontal cortices (Jansma et al. 2000). In addition to voluntary encoding, the memory processes evaluated in our study require consolidation (storage) of a stimulus and its subsequent recognition (retrieval) after a short period of time. In these later stages of memory, the activation shifts toward the temporal (verbal and object information processing) or parietal (spatial information processing) areas and later to the hippocampal and parahippocampal areas (memory storage and retrieval) (Brewer et al. 1998; Schacter and Wagner 1999; Schon et al. 2004). The memory tasks used in the present study might be more reliable for detecting alterations in adolescents' memory functions given that its execution involves more areas prone to high RF-EMF exposure from a mobile phone at the ear. This may partly contribute to the ambiguous results between our study and studies testing the working memory. However differences among populations with regard to specific exposures (or exposure patterns), differences in susceptibility, and other noncausal factors related to uncontrolled confounding or other sources of bias cannot be completely excluded.

Visual memory tasks similar to those applied in our study were also used in the Australian MoRPhEUS and ExPOSURE cohort studies in adolescents and primary school children. In line with our results, these studies found less accurate answers in the most frequent mobile phone and cordless phone callers (Abramson et al. 2009; Redmayne et al. 2013).

Although preliminary, findings from the laterality analysis might reflect separate lateralized neural pathways for verbal and figural memory. Figural and spatial memory processing are associated more with the right hemisphere of the brain, and verbal and auditory processing with the left hemisphere (Golby et al. 2001; Nagel et al. 2013). A more detailed description of the neural paths involved in the generation of new memory gives the influential model of working memory of Baddeley and Hitch (1974). The model differentiates between the visuospatial sketchpad for visual and the phonological loop for verbal information, running through the right and left temporal lobe, respectively. Evidence of a possible laterality effect in our study population might be consistent with impairment of this component step in object information memory processing.

How RF-EMF interacts with the brain is still unclear and no biophysical model exists for SAR values that do not noticeably increase the body temperature (International Commission on Non-Ionizing Radiation Protection 2010; Redmayne 2016). It may be speculated that our results are related to relatively consistently observed alterations in the electroencephalogram (EEG) during sleep in randomized crossover studies of participants exposed to mobile phone radiation prior to sleep (Loughran et al. 2012; Lustenberger et al. 2013; Regel et al. 2007; Schmid et al. 2012). Disturbed sleep negatively affects memory consolidation, in particular, in relation to

abstract and complex tasks involving higher brain functions (Kopasz et al. 2010). Lustenberger et al. (2013) observed reduced overnight performance improvement in a motor sequence task after a night with RF-EMF exposure compared with the sham condition. Thus, future studies should clarify whether RF-EMF has an impact on sleep-facilitated learning processes via altered sleep brain activity.

Conclusion

We found preliminary evidence suggesting that RF-EMF may affect brain functions such as figural memory in regions that are most exposed during mobile phone use. Our findings do not provide conclusive evidence of causal effects and should be interpreted with caution until confirmed in other populations. Associations with media use parameters with low RF-EMF exposures did not provide clear or consistent support of effects of media use unrelated to RF-EMF (with the possible exception of consistent positive associations between verbal memory and data traffic duration). It is not yet clear which brain processes could be potentially affected and what biophysical mechanism may play a role. Potential long-term risk can be minimized by avoiding high brain-exposure situations as occurs when using a mobile phone with maximum power close to the ear because of, for example, bad network quality.

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Supplemental Material

A Prospective Cohort Study of Adolescents' Memory Performance and Individual Brain Dose of Microwave Radiation from Wireless Communication

Milena Foerster, Arno Thielens, Wout Joseph, Marloes Eeftens, and Martin Röösli

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Figure S2. Forest plots of the meta-analysis over the linear exposure estimates for the brain dose calculated separately for the right side users of the five use groups. Coefficients relate to the change in score per interquartile range of the whole sample RF-EMF dose (953 mJ/kg/day).

References

Derivation of the Cumulative RF-EMF brain gray matter dose

1. Numeric simulations of brain gray matter specific absorption rates (SAR)

This section outlines the methodology used to estimate the specific absorption rate (SAR) in adolescents' brains' grey matter. The SAR quantifies the rate at which radio-frequency power is absorbed in (biological) tissue. This quantity cannot be measured in living subjects and therefore needs to be simulated. These simulations rely on human body models or phantoms obtained using imaging techniques such as magnetic resonance imaging.
In this study, the heterogeneous phantoms Billie and Louis from the 'virtual population' are used to obtain SAR values for female and male adolescents, respectively (Gosselin et al. 2014). Billie is an eleven-years-old girl with a height of 1.49 m and a mass of 34 kg. Louis is a male of fourteen years old with a height of 1.68 m and a mass of 49.7 kg. The human body consists out of different tissues that have different properties seen by electromagnetic waves, so called dielectric properties. These properties depend on the frequency of the electromagnetic waves. The phantoms were assigned dielectric parameters from the Gabriel database (Gabriel et al. 1996) corresponding to the frequencies listed in Table S3.

Near field source modeling

In addition, the source of the RF exposure needs to be modeled for the simulation. In this study, the near field source of exposure, the mobile device, was modeled as a dipole antenna. In each frequency band listed in Table S3 a dipole antennas, was tuned to operate next to the body. These dipole antennas represent the mobile phone in the simulation and their dimensions of the dipole antennas can be found in (Aminzadeh et al. 2016).In total, six dipoles are modeled that resonate and emit at the center frequencies of the frequency bands listed in Table S3.

The following three different exposure situations were modelled for near field sources:

- **Close to the body:** During these simulations, the wireless device is assumed to be in the pocket of trousers. A distance between body and dipole of 1 cm was chosen, with the dipoles aligned to the phantom's sagittal and coronal planes.
- **Close to the ear:** In this exposure scenario, the dipoles are placed at 1 cm from the ear of one of the two phantoms and are rotated over 45° towards the phantom's back in the sagittal plane, which contains the dipoles.
- **Hands free kit:** In this exposure scenario, the dipoles in the 'close to the ear' scenario are translated 20 cm further away from the ear orthogonal to the sagittal plane which contains the dipole in the 'close to ear' scenario.

Numerical simulations using the finite-difference time-domain (FDTD) technique (Taflove and Hagness 2005) with Sim4Life (ZMT, Zürich, Switzerland) were executed to obtain SAR values under the RF exposure conditions listed above.

During each of the simulations, a dipole was fed a harmonic signal of 1 W at its resonance frequency and emitted RF-EMFs which are partially absorbed in the human body models. The simulations are executed until a steady state was reached. The induced electric fields in

each location of the grey matter of the phantoms were then extracted and used to calculate the SAR in the phantoms in each exposure scenario. These SAR values were then averaged over the mass of the grey matter of the phantoms. This resulted in a set of 5 (frequencies, Table S2) x 1 (averaging volume, the grey matter) x 2 (phantoms, Billie and Louis) x 3 (exposure conditions) = 30 SAR values, which were used for dose calculations.

The obtained near field SAR-values are normalized to 1 W output power of the dipoles used in the simulations. However, a real source might have another output power. Therefore, the SAR values were multiplied with the output power for respective sources in order to properly rescale them. These output powers were derived from literature (Persson et al. 2012). To obtain the GSM output power we assumed a difference in power control of approximately 23dB to an average UMTS output power of 0.45 mW (Kühn and Kuster 2013; Persson et al. 2012). For WiFi we assumed an average output power of 100 mW with an average duty cycle of 3.5 % assuming 10 % of time watching youtube and 90 % surfing (Joseph et al. 2013; Plets et al. 2015). These values were then averaged over the two phantoms and in the case of GSM also averaged over the two GSM frequencies. The resulting SAR grey matter values are listed in column four of Table S2.

Far field source modeling

The simulations described above are valid for exposure from devices relatively close to the human body. However, subjects are also exposed by sources, which may be devices or a mobile network, further away from the human body. In order to model this exposure, a common technique is to use plane waves incident on a human body model. In this study, we have modelled the far-field exposure and corresponding SAR values using plane-wave-simulations in the FDTD-based simulation software SEMCAD X. These plane waves will have a frequency, an angle of arrival (a direction), an amplitude, and a polarization. Our evaluation covered the frequency range from 50 MHz to 5.2 GHz as we simulated at the following frequencies: 50 MHz, 100 MHz, 450 MHz, 835 MHz, 1450 MHz, 2140 MHz, 2450 MHz, 3500 MHz, and 5200 MHz. The field was incident from 6 sides of the body: top, bottom, front, back, left, and right in two mutually orthogonal polarizations. The simulated human body models under this exposure are Billie and Thelonius from the same virtual population. Thelonius is a six-year-old boy with a mass of 18.6 kg and a height of 1.16 m. The Louis model was not available in this configuration.

The simulations result in specific absorption rate values (SAR) in the grey matter of these two phantoms. These SAR values are averaged over the grey matter of the phantoms. For each phantom and each frequency, 12 SAR values are extracted corresponding to the six directions of incidence and two orthogonal polarizations. These SAR values correspond to an incident electric field strength of 2.45 V/m, which is chosen in the simulation. They are renormalized to mean incident field strengths, see Table S2, obtained using geospatial propagation models (Bürgi et al, 2010).The SAR values are then averaged over these 12 values, the two phantoms, and interpolated to the centre frequencies of the respective telecommunication frequency band. The resulting values are listed in Table S2 for far-field exposure.

2. Usage variable overview

Table S1: Derivation of the individual durations of near field exposure situations and mean incidence fields of environmental far field sources

RF-EMF near field source	Source	Derivation for estimated variables
Mobile phone calls		
Daily duration (min/day)	- HERMES questionnaire - Operator recorded data	Estimated via multilevel linear regression modeling with the school as cluster variable calibrated on the objectively recorded cumulative operator data call duration per day. Variables from the HERMES questionnaires were stepwise included in order to determine the best fitting model. The predicted values from the model were used for further data analysis as estimated cumulative daily call duration for all participants without operator data records. The following predictors were used in the final model - Age - Gender - Difference in daily duration of mobile phone calls (follow-up-baseline) - Daily frequency of mobile phone calls at follow-up - Daily frequency of messages per day at follow-up - Daily duration of mobile phone data traffic at follow-up - Daily duration of DECT phone calls at follow-up
Network proportion (%)	- HERMES questionnaire - Operator recorded data - Propagation model	RF-EMF exposure is strongly related to the network used for calling. During the HERMES study the GSM and the UMTS network were used in Switzerland. The proportion of UMTS was estimated via multilevel linear regression modeling with the school as cluster variable calibrated on the operator recorded UMTS proportion. Variables from the HERMES questionnaires were stepwise included in order to determine the best fitting model. The predicted values from the model were used for further data analysis as estimated proportion of UMTS for all participants without operator data records. The proportion of GSM was subsequently assumed to be 1-proportion(UMTS). The following predictors were used in the final model - Place of residence (urban vs. rural) - Far field UMTS-proportion of modeled mobile phone downlink - Number of smartphones at home - Daily duration of mobile phone data traffic
Headset use (%)	- HERMES questionnaire	The answer categories “never”, “seldom”, “often” and “most of the time/always” were translated to the numerical values 0, 0.25, 0.50 and 1, respectively, and furthermore averaged over baseline and follow-up.
Mobile phone data traffic		
Daily duration (min/day)		
Proportion 3G /WiFi (%)	-HERMES questionnaire	
Mobile phone close to body; (min/day)		Exposure to RF-EMF only while the mobile phone is actively transmitting or sending data (receiving a message, connecting to a mobile phone antenna) or receiving a call. This actual exposure time to be assumed 1 % of total time on body
Landline phone calls (DECT)		
Daily duration (min/day)	- HERMES questionnaire	
Eco mode (yes/no)		
Computer, laptop and tablet use with WiFi		
Daily duration use (min/day)	- HERMES questionnaire	
Proportion of WiFi connection (%)		

Table S1 continued

RF-EMF far field source [a]	Source	Derivation of estimated variables
Uplink (from other people)	-Personal RF-EMF measurements - HERMES questionnaire	Estimated via multivariable linear regression modeling calibrated on the mobile phone uplink obtained via personal RF-EMF measurements of 148 participants. Variables from the self-reported baseline questionnaire were stepwise included in order to determine the best fitting model. Subsequently the predicted values from the model were used as uplink estimates for dose calculation for all participants without personal measurement data. The following predictors were used in the final model - Mobile phone operator - Mobile phone on/off during night - Number of Smartphones at home - Daily duration using public transport: train - Daily duration using public transport: bus - Investigation phase (2012-3014 vs. 2014-2016)
Downlink GSM900 Downlink GSM1800 Downlink UMTS	- Propagation model	Described in Bürgi et al, 2010
WiFi	-Personal RF-EMF measurements - HERMES questionnaire	Estimated via multivariable linear regression modeling calibrated on the WiFi band obtained via personal RF-EMF measurements of 148 participants. Variables from the self-reported baseline questionnaire were stepwise included in in order to determine the best fitting model. Subsequently the predicted values from the model were used as WiFi estimates for dose calculation for all participants without personal measurement data. The following predictors were used in the final model - Mobile phone operator - WiFi at school - Daily duration of mobile data traffic - Investigation phase (2012-3014 vs. 2014-2016)
DECT	-Personal RF-EMF measurements	Mean far field exposure for the DECT frequency derived from the personal measurements conducted with 148 participants
TV Radio/Broadcast	- Propagation model	Described in Bürgi et al, 2010

[a] Adolescents far-field exposure in school might differed from far-field exposure at home. Adolescents' time in school was assumed to be one fifth of 24 hours on weekdays and modelled values from the place of school were used for this proportion of time. Further far-field exposure might be substantially higher in public transports than elsewhere due to the many people actively engaged with their mobile phones. Average times spent in public transports were derived from personal measurements or the questionnaire. The remaining time neither spent in school nor in public transports was assumed residential time at home.

3. Overview of the parameters considered for RF-EMF brain gray matter dose

Table S2: Parameters used for the derivation of the cumulative near field dose. Individual exposure to a source is calculated via multiplying the individual time per exposure scenario with its respective SAR value. The brain and whole body dose is consecutively calculated as the sum of the individual exposure of the near-field sources. The table below summarizes the mean values used for the individual RF-EMF dose calculation for all HERMES participants who took part in baseline and follow-up investigations. Note that the duration refers to the average daily device use between baseline and follow-up

RF-EMF near field source	N	Mean duration sec / day (SD)	Brain SAR (mW/kg)	Average dose contribution (%)
Mobile phone calls				
GSM mobile phone calls without headset [a]	844	107 ± 153	6.24	79.79
GSM mobile phone calls with headset [a]	844	22 ± 57	0.75	
UMTS mobile phone calls without headset	844	140 ± 383	0.03	0.45
UMTS mobile phone calls with headset	844	33 ± 112	$4*10^{-3}$	
Mobile phone data traffic				
Via mobile internet connection	843	743 ± 980	$7*10^{-5}$	1.82
Via WiFi	843	2590 ± 1846	$2*10^{-5}$	3.44
Mobile phone close to body (passive mobile phone data traffic)	843	192 ± 166	$2*10^{-5}$	0.25
Cordless phone calls (DECT)				
With eco mode	766	373 ± 398	0.61	
Without eco mode	77		0.06	8.29
Computer, laptop and tablet use with WiFi	843	2602 ± 3329	$2*10^{-5}$	0.01

RF-EMF far field source	Mean electric field [V/m]	Brain SAR (mW/kg per V/m)	Average dose contribution (%)
Uplink (mobile phone connections from surrounding people)	0.11	$6.5*10^{-3}$	2.02
Downlink GSM900	0.08	$8.2*10^{-3}$	1.45
Downlink GSM1800	0.07	$6.5*10^{-3}$	0.92
Downlink UMTS	0.08	$5.6*10^{-3}$	0.99
WiFi	0.04	$4.6*10^{-3}$	0.24
Radio/Broadcast	0.02	$2.9*10^{-3}$	0.02
TV	0.03	$8.0*10^{-3}$	0.21
DECT	0.01	$6.3*10^{-3}$	0.01

[a] For calls with the mobile phone on the GSM network the mean of the SARs for the GSM900 and the GSM1800 network was used because there was no differentiation between GSM900 and GSM1800 network in the mobile phone operator data. A headset is assumed to be wired to the phone.

Table S3: Simulated RF frequency bands with frequency range and center frequency

RF signal	**Frequency range (MHz)**	**Center frequency (MHz)**
GSM 900-UL	880-915	897
GSM 1800-UL	1710-1785	1748
DECT	1880-1900	1890
UMTS-UL	1920-1980	1950
Wi-Fi 2 GHz	2400-2483.5	2450

Meta-analysis over five latent classes of media use

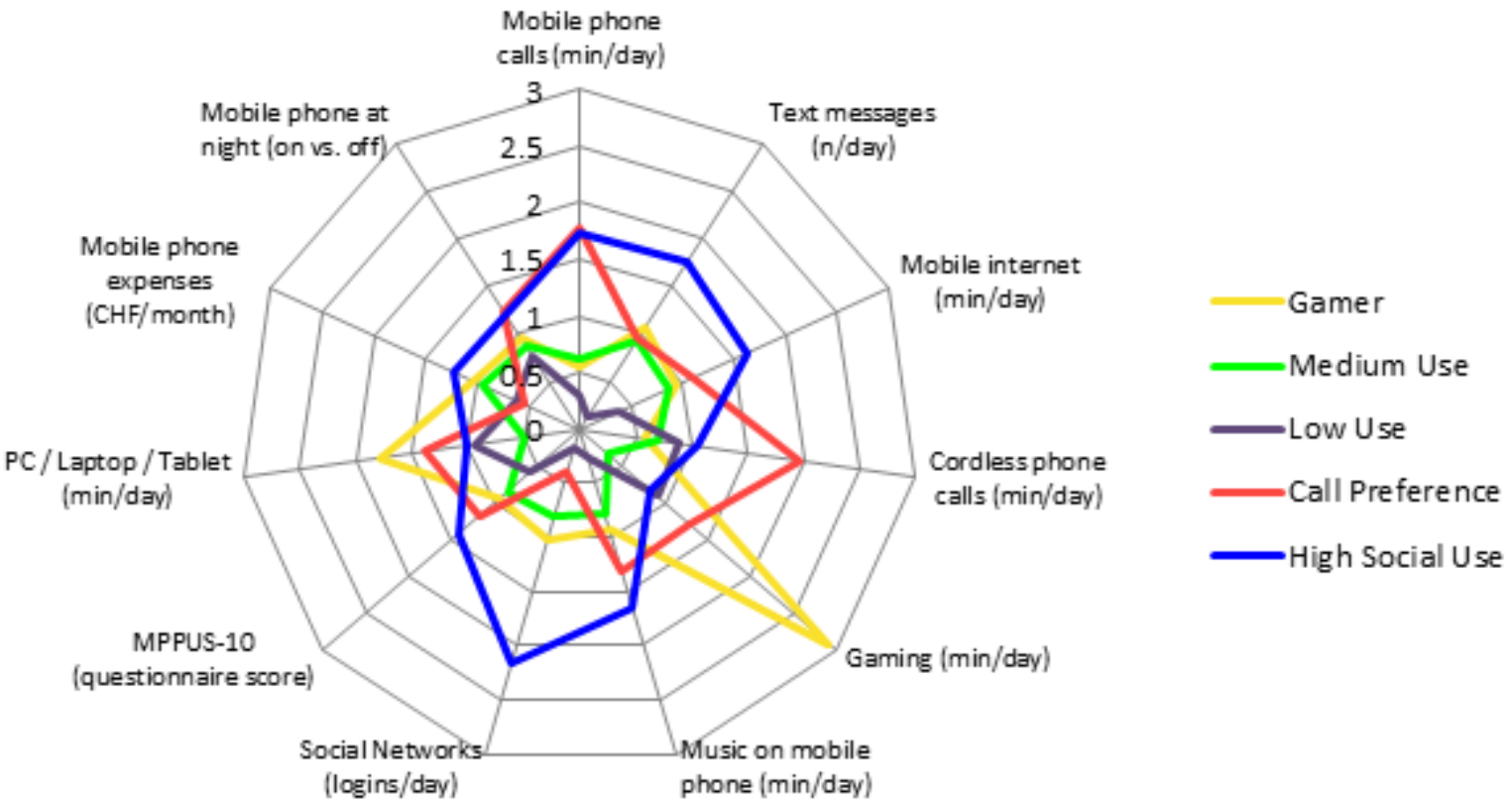

Figure S1: Spider plot displaying the profile of the five different media use patterns (Foerster and Röösli 2017) on 11 different media use variables. Values are relative and relate to the ratio between the group mean and the overall mean of the whole sample on the raw questionnaire scores (e.g. a peak of the "Gaming" group at 3 relates to a three times (300 %) higher daily gaming duration compared to the whole sample whereas a value of 0.5 relates to a 50 % lower value on the respective variable.

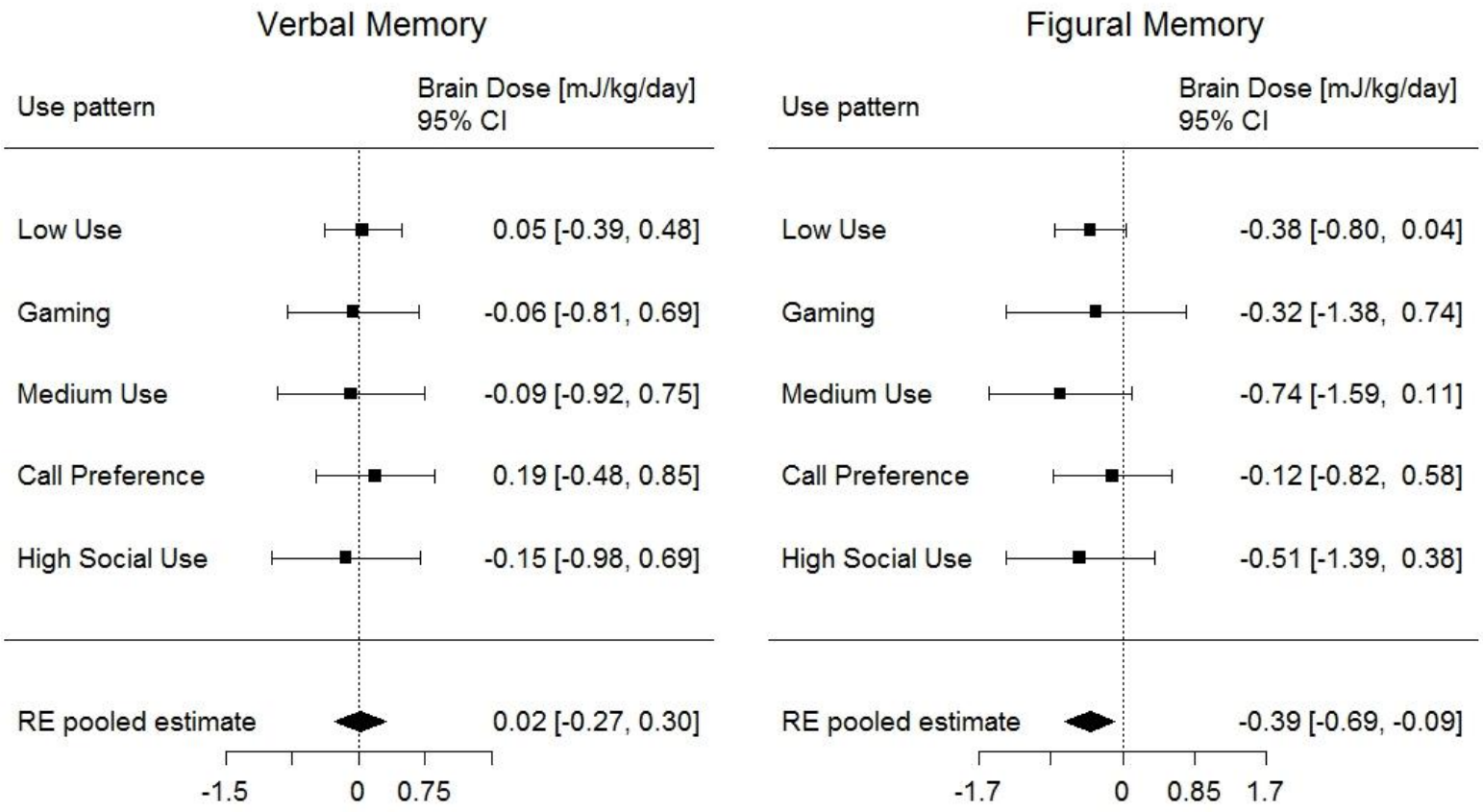

Figure S2: Forest plots of the meta-analysis over the linear exposure estimates for the brain dose calculated separately for the right side users of the five use groups. Coefficients relate to the change in score per interquartile range of the whole sample RF-EMF dose (953 mJ/kg/day).

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6. Summary of the main findings

Objective 1: To investigate problematic mobile phone use and potential health effects in Swiss adolescents.

Article 1: Using data of the HERMES1 subsample a short screening tool for assessment of problematic mobile phone use (MPPUS-10) in adolescents was developed. Principal component analysis on the original MPPUS (Bianchi and Phillips 2005) was applied revealing four factors associated with behavioral addiction and one factor (Peer Dependence) suggesting an additional social dimension of problematic mobile phone use.

Article 2: Higher values on the MPPUS-10 went along with being female, more behavioral problems, less psychological well-being and worse relationships with parents and teachers.

Objective 2: An in depth investigation of general media use in Swiss adolescents.

Article 3: Media use in adolescents is not restricted to a single type of use which should be taken into account if assessing its health effects. In order to account for combined use of different media devices in adolescents a latent class analysis on the whole HERMES sample was performed. We found five distinct media use groups: Low Use, Medium Use, Gaming, Gaming and Call Preference.

We found differences amongst the groups regarding their health related quality of life. Hereby the High Social Use group reported generally worst and the Low Use group generally most well-being on scales measuring affective well-being and relations with parents or teachers. In contrast the picture was reversed for relationships with peers..

Objective 3: To update the RF-EMF dose measure used in the previous HERMES1 study for use in the whole sample.

Article 4: Two major changes were applied on the RF-EMF dose model developed in HERMES1 in order to better fit our data:

- New SAR-values based on simulations based on adolescents instead of adults physical properties were included.
- The self-reported mobile phone call duration was adjusted using the operator data recorded call duration in order to reduce recall bias.

The new estimates correlated only moderately with the ones obtained by the old model ($_{rs}$= 0.58).

Objective 4: To apply the RF-EMF dose measure in order to investigate a potential effect of RF-EMF dose on changes in adolescents' memory performance over one year.

Article 4: Using the new RF-EMF brain dose measure in the whole sample we could replicate the findings of an HERMES 1 analysis which found decreases in figural memory performance with higher cumulative RF-EMF brain dose over one year assuming a linear exposure-response relationship.

A significant decrease for the subsample with operator data and a strong trend in the whole sample towards decreases in figural memory changes over one year was found.

- The result was consistent when analyzing the HERMES1 and the HERMES2 sample separately.
- The figural memory processing is lateralized with more activation on the right side of the head. In a laterality analysis for right side of the head vs. left side of the head/no preference phone callers the decrease in figural memory with higher cumulative brain dose was significant only for the right side callers whereas for the left side/no preference group no association was seen.

No association was seen with figural memory and negative exposure control variables only marginally associated with RF-EMF (text messages, gaming)

Objective 5: To try a new approach to control for life-style confounding in epidemiological research on RF-EMF.

The laterality analysis was stratified over the right side callers of the five media use groups derived by the latent class analysis (article 3). A meta-analysis over the five single estimates was conducted in order to evaluate potential residual confounding due to media usage per se.

The meta-analysis revealed only a small amount of heterogeneity amongst the different estimates rejecting a major impact of confounding by differences in use.

7. General discussion

A detailed discussion of the results is given in the respective articles. The following section a few thoughts going beyond the scope of the articles will be discussed.

7.1. Article 1-3 Technology addictions and general media use

In the first and second article the MPPUS-10 a screening tool to assess problematic mobile phone use was developed. Higher scores in the questionnaire applied in the first HERMES1 sample were associated with more behavioral problems or and lower health related quality of life. In the third article defining general media use groups in adolescents we found that not necessarily media addiction but maybe certain patterns of media use are associated with adolescents health related quality of life. Hereby particularly the High Social Use group stood out indicating higher negative affectivity and worse relationships with parents and teachers but better relations with peers compared to the other groups.

In the following section the association of technology addictions and depressive symptoms will be discussed questioning a potential public health impact in the light of entering the digital age.

7.1.2. The public health perspective

The public health relevance of a risk factor depends on its prevalence in the general population and the impact of this risk factor on health.

In the case of the risk factor wireless media use is distribution is enormous: The penetration of digital media devices and associated use preferences of Swiss adolescents is assessed each two years by the descriptive representative JAMES (Jugend | Aktivität | Medien – Erhebung Schweiz) survey (Waller et al. 2016). The last survey was conducted in 2016 in 1086 adolescents in between 12 and 16 and revealed a high prevalence of owning different media devices. Amongst them the most common were:

- Mobile phones (99 %)
- PC or Laptop (76 %)
- MP3 Player (53 %)
- Portable Gaming Console (54 %)
- Digital camera (44 %)

According to the high numbers of media use the public health relevance of the exposure can be judged very high: even a very small risk increase for whichever detrimental health effects would lead to a considerable impact on a population level. While the case is less clear with RF-EMF a high

number of studies in psychological research emphasize associations of different types of technology addictions with health effects

7.1.3 Problematic mobile phone use and depression

As in our articles 1 and 2 the majority of psychological research has set different types of media technology use in the framework of behavioral addictions. Like other mental diseases behavioral addiction should be considered as a mental state which prevents the individual from the normal functioning via induced distress and increased suffering (American Psychiatric Association (APA) (2013)) and indeed, various health impairments have been found to go along with different kinds of technology addictions (Elhai et al. 2017; Kuss and Griffiths 2011; Daria Joanna Kuss and Mark D Griffiths 2012). Furthermore, prevalence rates are high. A recent meta-analysis on internet addiction in 31 nations worldwide yielded a prevalence of 6 % (Cheng and Li 2014) and in studies on problematic mobile phone use numbers go even up to almost 40 % (for a review see Billieux (2015)).

A very constant association with technology addictions in adolescents is found with more depressive symptoms or decreased mood (Banyai et al. 2017; Elhai et al. 2017; Kim et al. 2006; Ko et al. 2014; Ostovar et al. 2016; Stetina et al. 2011; Young and Rogers 1998). Given the high prevalence rates of technology addictions worldwide (Billieux et al. 2015; Cheng and Li 2014) it might be assumed that a major impact on health should be seen in raised prevalence rates of the respective health effects during the last 20 years. The worldwide prevalence rate of depression indeed has risen 18.5 % in between 2005 and 2015 (Vos et al. 2016) and in the global burden of disease study 2015 depression was the first time the single largest contributor to non-fatal health loss accounting for 7.5 % of years lived with disability (YLD) in total (WHO 2017). Although in the report it is argued that this development is largely attributable to an ageing society a recent review on children and adolescents mental health also revealed an increase in internalizing problems (amongst them is depression) in the 21st century (Bor et al. 2014). Moreover this development was particularly seen for adolescent girls, a population particularly prone to problematic mobile phone use and generally high media use as also emphasized by our results of articles 2 and 3.

However, we should regard the numbers with caution, this holds true for the high prevalence rates of technology addiction as well as the raising number of depression cases. Both also bear the threat of pathologizing our own society. To prevent from this it may be worth it to approach the topic in the light of two generations entering the digital age.

7.1.4. Entering the digital age as a mediating factor?

In the early 90s presumably only very few people (if any) had an idea of the far-reach societal changes the world's population will undergo through the public availability of the internet or mobile

phones and the device connecting both, the Smartphone. in some ways the situation might be considered similar to the first half of the 15th century when Johannes Gutenberg invented the printing press (Bawden and Robinson 2000; Dittmar 2011). In both situations the world got more connected and "faster". But while in the 15th century only a very limited number of persons had permanent access to the enormous new amount of information the internet was soon permeable to all social strata and reshaped our social communication patterns. It is no wonder that such a drastic event in the first moment raises fears, doubts and uncertain feelings in the general population (Baym 2015). And it is also not bewildering that some people adopt quicker such a situation while others may get overburdened.

In this light the concept of technology addictions may be also questioned. When Young first brought up the term Internet Addiction in 1998 the world stood on the edge of digitalization(Young 1998). Now, almost 20 years later technology use has become ubiquitous and it is hard to doubt a population wide dependency on technologies. The high prevalence rates of technology addictions might also contradict a legacy of such behaviors at abnormal.

Maybe the concept of technology addictions should be (at least partly) suspended to prevent from pathologizing. It might be more appropriate to think of the technological revolution and induced changes in communication as a new language. It is common knowledge that learning a language is always harder later in life than in early ages. It is well thinkable that nowadays adolescents, the first generation of digital natives, will learn to use technologies in a more "natural" way which we as digital immigrants are not able to judge. In this way what looks like technology addiction might be a behavior congruent with a new life style (Toda et al. 2006).

7.2. Article 4: critical in depth discussion of the analysis design

In article 4 we assessed the relationship of cumulative RF-EMF brain dose and changes in memory functions over one year.

Congruent models were fitted for cumulative media usage either related or unrelated to RF-EMF whereby the RF-EMF unrelated exposure variables served as negative exposure controls. Further we tried a new approach to control for residual confounding due to different media use patterns.

Two critical issues of our analysis design are discussed in the following section exemplary on two different variables, the biological variable RF-EMF brain dose and the behavioral variable number of text messages.

The latent media use patterns derived in article 3 will be used as proxy for individual differences to highlight the interplay of behavioral and environmental factors.

7.1.2. The case of cumulative exposure

Choosing an appropriate longitudinal analysis design is challenging. In case of the environmental agent RF-EMF we do not know in which way RF-EMF exposure might act on the human body; this makes it particular difficult to decide on how to include the RF-EMF exposure in the analysis. The most common longitudinal approaches appropriate for data like ours where only two measurement points are available are

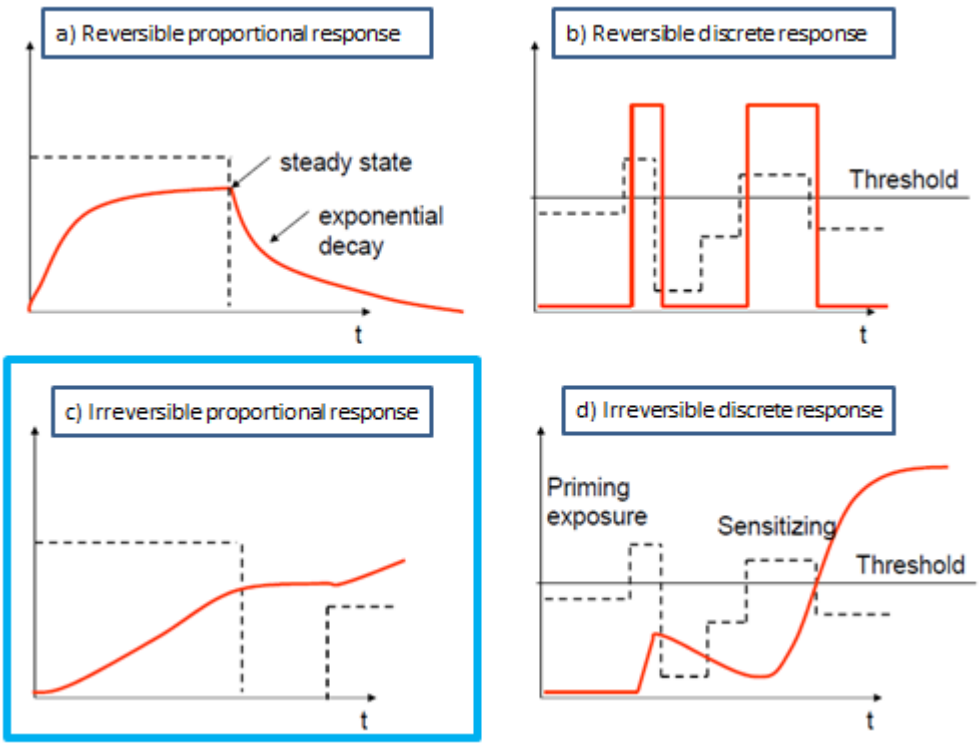
a) a change analysis which questions if change in exposure are related to changes in the outcome

b) a cohort approach in which only "healthy" cases at baseline are targeted whether their baseline exposure sets them at higher risk to get "ill" at follow-up.

In our longitudinal analysis we assessed whether changes in memory function are related to cumulative exposure variable which is a very common approach for environmental epidemiology. Hereby the exposure is expressed by an average per unit time, in our case an average RF-EMF brain dose per day.

Cumulative exposure and biological response

For biological responses to an exposure we differentiate in general between reversible vs. irreversible responses which can occur either proportional vs. discrete in relation to the time course of the exposure. The different time courses of the four most typical exposure-response patterns are displayed in Figure 7-1.



Adapted from Röösli and Vienneau (2014)

Figure 7-1: The four typical exposure-response time courses for biological processes. The response may either occur proportional (a and c) or discrete (B and d) after exceeding a certain threshold. The dashed line shows the time course of exposure and the solid red line the respective biological response. The exposure-response pattern c) in the blue box refers to a cumulative exposure.

A cumulative exposure response usually relates to the *irreversible proportional response* (c) which implies:

- The response is proportional to the amount of exposure (not dependent from a threshold).
- An induced biological response does not decline in times then where is little or no exposure.

However, there are other situations feasible for a cumulative exposure assumption there the response is not necessarily proportional to the exposure. Examples are stochastic processes where an event is more likely to occur with higher cumulative exposure or a continuous change in physiological markers which gradually affects the outcome by exceeding one or more thresholds.

The cumulative exposure is in principle just correlated with any unknown adverse threshold for biological response. Hence, the more exposure the more likely it is to exceed such an acute threshold. If we consider the individual differences in exposure responses for the general population an exposure response somewhat proportional to the cumulative exposure may be assumed. That is why in particular for environmental exposures the cumulative exposure often works quite well.

Very simplified, our cumulative approach assumes that the daily RF-EMF exposure is “collected” inside our body and that a potential health effect will get more probable with more RF-EMF absorbed by our body throughout time.

Behavior and biological response

In our analysis we contrasted the dose measures by negative exposure control variables (gaming and texting) which are not or only marginally related to the environmental agent RF-EMF. Instead, the negative control variables relate to media use behaviors which per se might have an impact on health; in this case the assumption of an accumulated exposure impacting on health might be too far-fetched. While for cumulative environmental exposure fluctuations in exposure might be negligible increases or decrease of certain behaviors might impact directly on the outcome and thus should be taken into consideration. The issue here is that mathematically the cumulative exposure does not account for differences in change over time. In particular if just two measurement points are available this might get problematic.

To discuss this problem we might first consider a simple mathematical implication of the cumulative exposure calculation variables in our data: high exposure phases might get substituted by low exposure phases. A person X who is always exposed at a level of 50% over a certain time would have the same cumulative exposure than a person who is half of the time 100% exposed and half of the time not exposed at all. Or very simplified, in a longitudinal design with two measurement points (baseline and follow-up) there are three possible differing scenarios which all lead to the similar (medium) cumulative exposure.

- Low exposed at baseline, high exposed at follow–up
- High exposed at follow–up, low exposed at baseline
- Medium exposed at baseline, medium exposed at follow-up

Figure 7-2 displays the baseline and follow-up mean values for the environmental agent RF-EMF and the behavioral media use application of sending text messages for the whole sample and the five media use patterns. The pointed lines relate to the mean cumulative exposure entering the longitudinal analysis.

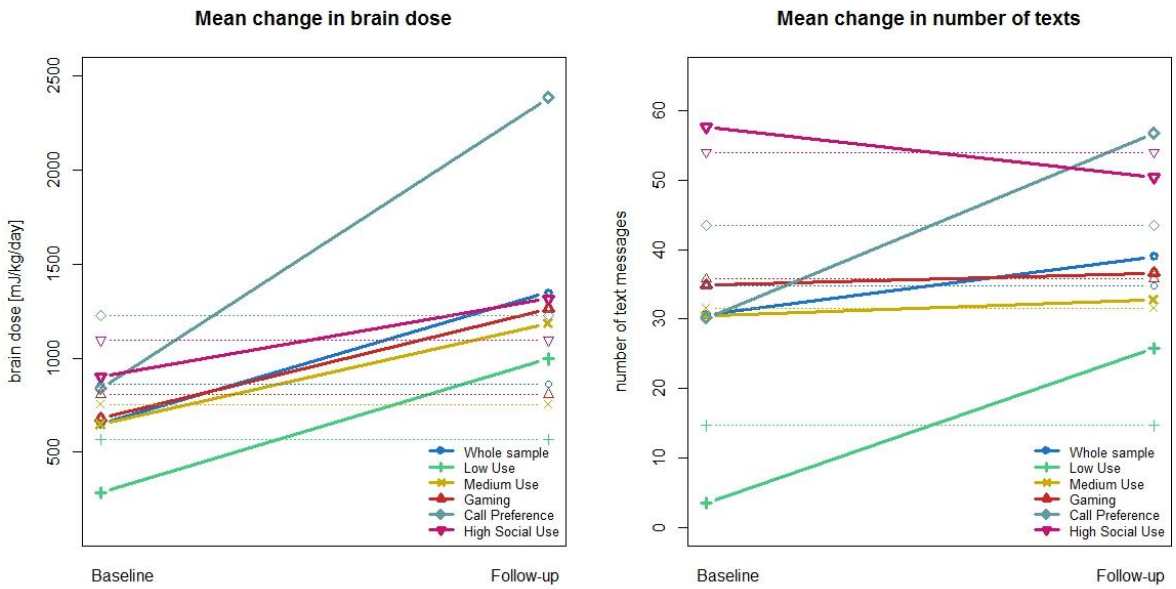


Figure 7-2: Mean changes in two exposure variables. The pointed lines relate to the mean cumulative score which entered the longitudinal analysis as exposure variable.

As we can see, the patterns of lines for the different media use behaviors look different for these two exposure variables: one relates to biological exposure, the other to a behavior. In the text graph the pattern over the classes is less synchronous compared to the dose graph.

For the brain dose we might assume that the cumulative exposure is mainly driven by a low baseline and a high follow up value even if we consider the individual differences in media use. The number of text messages is also increasing in the whole sample. However, there seems to be more variety within the classes. All three baseline - follow-up combinations which might lead to similar cumulative exposure are prevalent. A lower baseline and higher follow- up number of text messages within the class is seen in the Call Preference and the Low Use class. The picture is reversed for the High Social Use class (high at baseline, lower at follow-up) and within the Gaming and Medium Use class no change in the number of text messages is seen (medium at baseline, medium at follow up).

Thus from the graph we may assume that the correlations for the change in score and the cumulative score might be higher for the dose than for the text variable. Indeed, the Pearson correlation is r=0.36 for the dose and r=0.04 for the texts.

Implications for analysis design

As emphasized the cumulative approach does not account for the differences in change. This would require an analysis where the change in exposure is included instead of a cumulative measure. In

contrast, the choosing the change in exposure would not account for the general exposure level which is better depicted via the cumulative approach.

In case of our data this situation is tricky since it might be assumed that for an environmental exposure entering a longitudinal analysis the cumulative exposure (means the general level of exposure) might be more important to determine its potential effect on health. For the behavioral variable instead changes in the variable might be particularly important considering changes in health outcomes. Since the main focus of our analysis was the environmental exposure RF-EMF we choose the cumulative exposure approach. In our results on changes in figural memory the brain dose coefficient was considerably more negative compared to the negative exposure control variables. However, maybe the results do not account for the individual changes from baseline to follow-up which might be more important in the case of behavioral variables. This development can be seen with the two variables number of texts and brain dose. The estimates for figural memory change for the cumulative and the change (follow-up – baseline) are displayed in Table 7-1.

Cumulative texts	Difference in texts	Cumulative brain dose	Difference in brain dose
0.04	-0.07	-0.22	0.08

Table 7-1: Estimates for cumulative value and change (follow-up minus baseline) of a behavioral and a biological exposure variable on figural memory change. Change in score per interquartile range.

In both cases the algebraic signs change. Further the coefficient for the difference in texts is higher than for cumulative texts and in the opposite way in the dose. This means that a higher cumulative dose has a negative impact on the figural memory, whereas the positive sign of dose change would suggest that an increase in dose is rather associated with figural memory increase. For the texts it is the opposite way. A higher cumulative number of texts but less texting at follow-up compared to baseline would suggest a better memory at follow-up. And although the

It might be worth for future analysis to consider different exposure-response determinants for differing exposure situations. Although it is unusual practice a possible approach for comparison of RF-EMF related and unrelated variables would be to include the former as cumulative and the latter as change variable. Otherwise the coefficients of the negative exposure controls might be biased since their true effect due to behavioral changes may not be detected.

7.2.3. Baseline adjustment

A similar question a longitudinal analysis is which outcome to choose. We decided to conduct a change analysis where we calibrated linear regression model on the change in memory scores

between follow-up and baseline. We controlled the models for various individual factors (confounders) in order to reduce between subject variability. However, we did not control for the baseline figural memory score which is often proposed to reduce within subject variability.

As briefly introduced in the beginning of this chapter alternatively the follow-up score could have been used in a cohort approach. In that approach usually the baseline score is included in the model. This decision is more ambiguous with a change score. In some cases adjusted models and in other cases unadjusted models might heavily bias the results (Glymour et al. 2005).

As displayed in table 7-2 the coefficients for the baseline unadjusted and adjusted model, again exemplary for cumulative dose and cumulative text messages, considerably differed.

	Verbal memory coefficients		**Figural memory coefficients**	
	not adjusted for baseline	adjusted for baseline	not adjusted for baseline	adjusted for baseline
Cumulative Brain Dose	0.02	-0.06	-0.20	-0.34
Cumulative texts	0.16	0.01	0.04	-0.20

Table 7-3: coefficients of the baseline unadjusted and adjusted linear regression models for the cumulative brain dose and the cumulative texts. Change in score per interquartile range.

In all cases the baseline adjustment led to changes in the estimates. While in the case of the verbal memory the adjustment mainly lowered the text coefficient close to zero for the figural memory the adjustment in both coefficients led to a more (or “inflated”) negative association. The height of change in coefficients in both cases was higher in the negative exposure variables.
We decided not to adjust for the baseline score since we assumed that the large changes in estimates particular for the cumulative texts might be due to two sources of bias:

a) Regression to the mean
b) A horse racing effect

In the following chapter this decision will be discussed also raising arguments which would have spoken in favor of baseline adjustment in our case.

Why might adjustment for baseline score bias the results?

To understand the problem two things should be considered in advance.

a) In observational studies the outcome is usually measured with error. In our case we would distinguish between the real memory **function** and the memory **score** measured by the IST. Their relationship hereby is given as follows:

Score = Function + Error

b) Thus in a change score calculated as the difference in between the score at follow-up and the score at baseline the measurement error of follow-up and baseline are inversely related:

Change in ScoreFUP-BL =FunctionFUP + ErrorFUP – (FunctionBL + ErrorBL)

Change in ScoreFUP-BL = (FunctionBL + ChangeFUP-BL + ErrorFUP) – (FunctionBL + ErrorBL)

Change in ScoreFUP-BL = ChangeFUP-BL + ErrorFUP - ErrorBL

Causal relationships between variables may be depicted by directed acyclic graphs (DAGs). DAGs follow strict mathematical rules. An introduction in DAGs for drawing relations and causal inferences can be found in Shrier (2008). A DAG of a causal relationships in an analysis on change in which baseline adjustment would bias the result through the baseline measurement error is depicted in Figure 7-3.

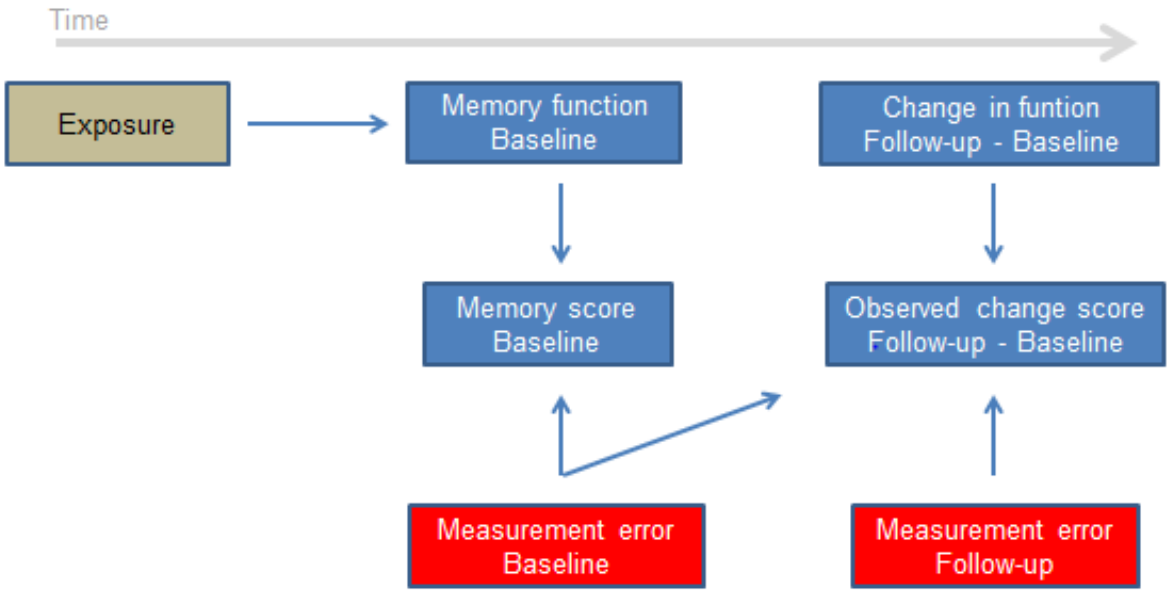


Figure 7-3: DAG of causal relationships in an analysis for change where adjustment for baseline score might lead to biased estimates.

In this DAG we can see the following causal relationships relevant for our problem:

- The exposure is not directly associated with the change in function (no arrow pointing from the exposure to the change in function).
- The exposure is preceding the baseline function assessment and directly associated with baseline function.
- The only path from exposure to the observed change score is blocked by the baseline score which is a collider (two arrows pointing towards the baseline score: baseline score is the common effect of measurement error and baseline function).
- The measurement error of the baseline function is associated with both: the baseline score and the change in score.

Through conditioning on the baseline score the path between the exposure and the change in score would get unblocked and create a spurious association between both variables if the baseline function is measured with a large baseline measurement error. Large baseline measurement errors often lead to a regression to the mean: Unreliable measured lower and higher values at baseline will lead to a higher increase and decrease in change score, respectively. This development is clearly seen for our data for the verbal but less for the figural memory score (Figure 7-4).

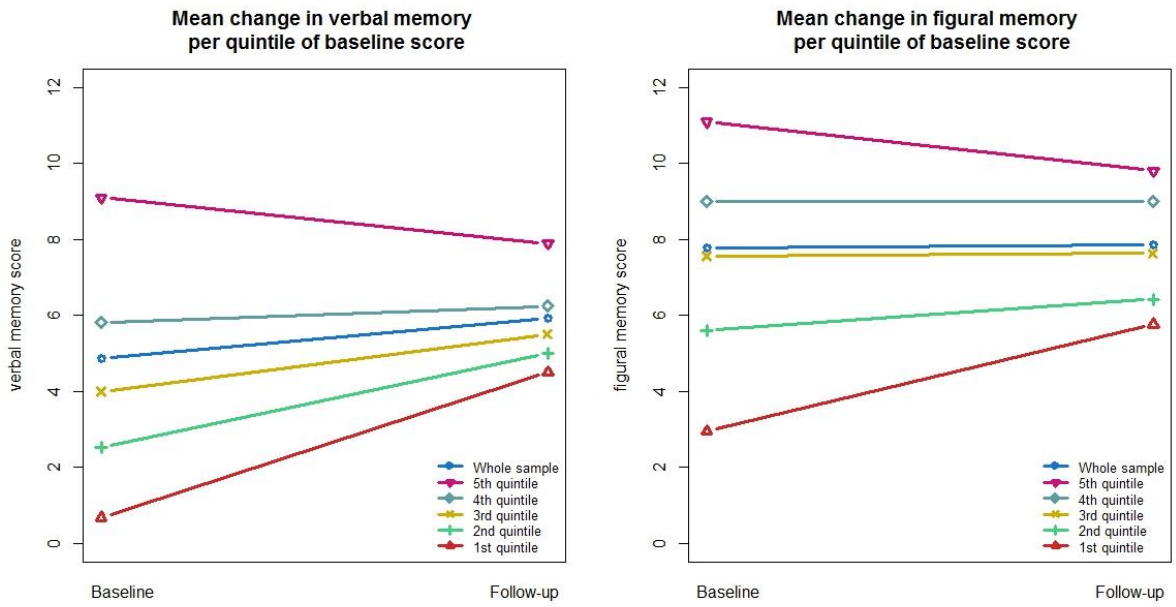


Figure 7-4: Change in score for the whole sample and per quintiles of baseline score. The baseline and follow-up values relate to the mean memory score of each baseline quintile.

The baseline distributions of the memory scores are very wide which might indicate large baseline measurement errors in both cases. This leads to a regression to the mean: the baseline measurement error is inversely associated with the change in score. In a regression model adjusted for an unreliable measured baseline score the regression to the mean would attenuate its coefficients towards zero (a fact we cannot prove of course). This would consecutively lead to inflated coefficients of variables in the regression model associated with the baseline function, in our case the exposure. From this viewpoint baseline adjustment would bias our results.

The horse-racing effect, another issue that might come with baseline adjustment might also contribute to the higher baseline adjusted coefficients (Figure 7-5).

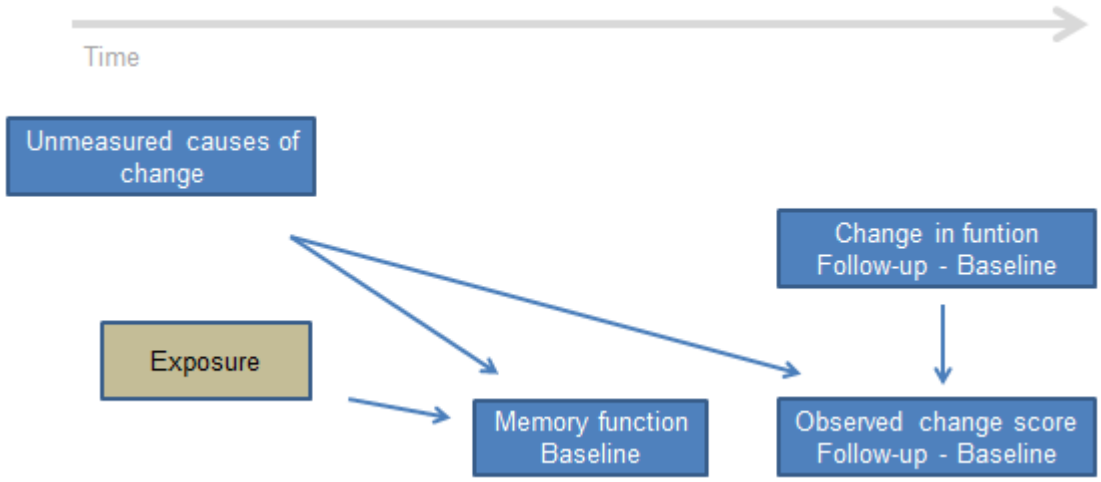


Figure 7-5: The horse-racing effect. Unmeasured causes of memory change precede the baseline function assessment.

The horse- racing effect might appear if change in memory function already started before the baseline function assessment. In this case the baseline score in the model might reflect the preceding change in memory function and an associated exposure might consecutively be biased. In this scenario inflated regression coefficients might even appear without regression to the mean. This situation is likely in our sample since memory development should have been already ongoing and individual developmental differences (Friedman et al. 2008) might account for different states of memory development at baseline function assessment.

Both of these situations favor our decision not to adjust for the baseline and seemingly reduced the bias. However, the (hopefully smaller) bias through not adjusting for the baseline will be briefly discussed in the following section..

When might adjusting for the baseline score justified?

I. If baseline function causally affects the change in function
II. If the exposure is assessed in between baseline and follow-up outcome score measurements
III. If floor or ceiling effects might influence the outcome assessment

(I.) If baseline function causally affects the change in function

Not adjusting for the baseline score implies the assumption that there is no direct causal effect of the baseline function on change in function: the change in score does not give information about the general cognitive ability. If the change in function causally depends on the baseline function models unadjusted for baseline score will bias the result because other factors associated with

baseline function will substitute the baseline score in the model. In this case the baseline score is a confounder since it if affects both, change in memory and exposure (Figure 7-6).

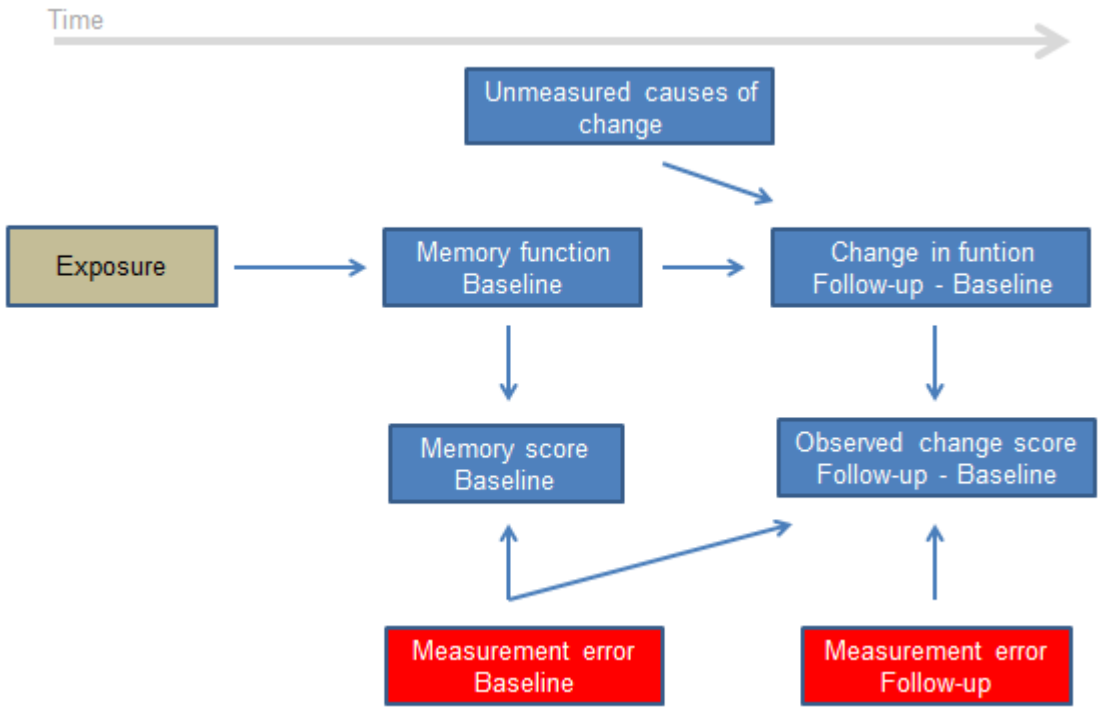


Figure 7-6: DAG of baseline memory function causally affects change in function.

Unfortunately, for a dataset with only two measurement points we cannot model the change in cognitive function and its dependency on the baseline cognitive function. We still should take into consideration that our unadjusted results might be affected by this particularly in a sample of adolescents where cognitive changes occur individually (and genetically) different and not necessarily linear (Dosenbach et al. 2010; Friedman et al. 2008; Luciana et al. 2005). For future studies on this problem more measurement points might be an opportunity to model growth curves of memory function dependent from RF-EMF dose.

(II.) If the exposure is assessed after baseline function

In the DAGs justifying our decision (figure 4 and figure 6) the exposure is preceding the outcome. In our situation this is not the case. The cumulative exposure variables we calculated refer to approximately the time in between baseline and follow–up. This is particularly true for the cumulative dose and call duration (main source: the operator data in between the two time points) and less for the other cumulative variables (calculated as the mean of baseline and follow-up questionnaire information; baseline questionnaire refers to the time before the baseline). The baseline function in our data is associated with our later assessed cumulative exposure which means that baseline score is a confounder. However, controlling for the baseline score via adjustment in

our model cannot prevent regression to the mean (as we can see in table 3). But again we may assume that where is some bias in our estimates due to not controlling for baseline. In such cases structural equation models with latent variables for the measurement errors might lead to unbiased results.

(III.) If floor or ceiling effects might influence the outcome assessment

If an outcome measure is censored to certain values as it is the case with our assessment of memory function via questionnaire (range 0 – 12) floor and ceiling effects may lead to unreliable outcome assessment. In this case the baseline function has a direct effect on the baseline measurement error as depicted in the DAG in Figure 7-7.

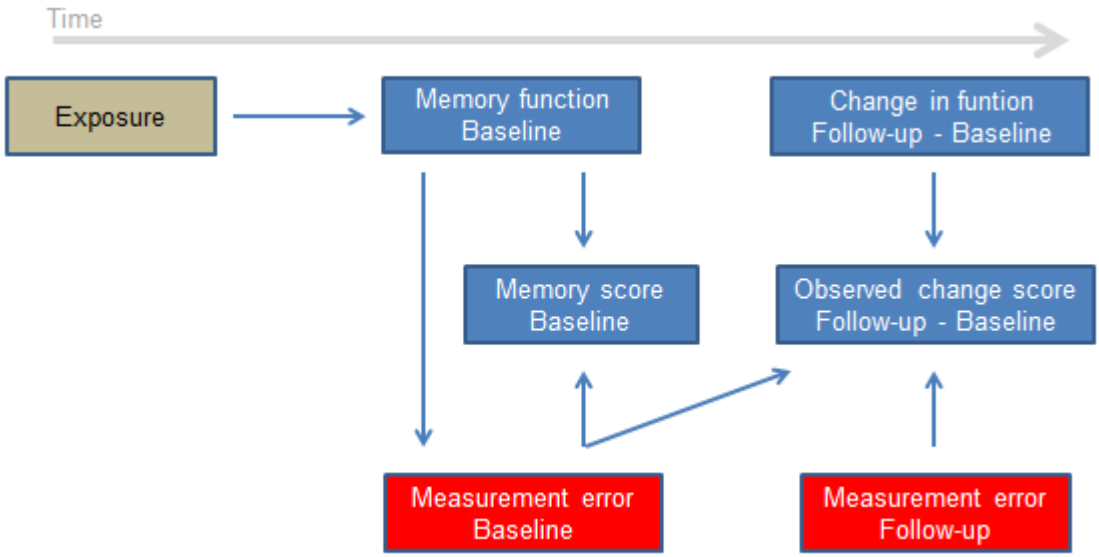


Figure 7-7: DAG of baseline memory function directly influencing baseline measurement error.

If we look at the highest baseline score quintile in figure 3 we can see that the average of this quintile is close to the upper censoring. 43 participants at baseline and 51 at follow-up scored at this maximum 12 points which relates to 6.4 % and 7.6 % of participants entering our analysis, respectively. Although only 7 of these scored at 12 points in both scores we cannot suspend the possibility of a direct effect of cognitive function on the measurement errors.

8. Outlook and Conclusion

Epidemiological research on wireless media use in adolescents will keep challenging researchers in the upcoming years. In this field it is hard to keep track with the rapid development of new technological devices. New devices lead to different RF-EMF exposure situations hence they require the utilization of higher frequencies to master a faster transmission of larger volumes of data. Additionally, new use behaviors are fostered by new applications (e.g. Snapchat) which are quickly adopted in particular by digital natives.

If we only think about the HERMES cohort, the first investigation phase took part in between 2012 and 2014. At this point for example the Smartphone penetration has not yet reached close to 100 % and mobile internet flatrates were less frequently included in mobile phone subscriptions. In the follow-up investigation of the second sample all adolescents using a mobile phone owned a Smartphone and as we could see in the media use groups of article 3 the group affiliation was strongly dependent from belonging to either HERMES or HERMES2.

In our data not even the 4th generation of networks LTE (long term evolution) was considered and it will not take long anymore until even the 5G network enters the market and quite certainly joined with new devices and applications waiting for a higher rate of data transmission.

The present work emphasized both, potential impact of RF-EMF and psychological life-style effects. In the analysis on RF-EMF brain dose and memory functions the residual confounding by media use related life-style was rather low and the effect seem to be due to RF-EMF dose. From this result it might be speculated that neural processes which are located close to high exposed brain areas like figural memory functions might be susceptible to RF-EMF induced changes. Interestingly, several outcomes of the RF-EMF unrelated analysis of this thesis are located in adjacent brain areas. Neural correlates for social emotion processing important for maintaining healthy social relationships or the behavioral inhibitory control circuit which plays a role in behavioral addictions are located close to the right ear (Aron et al. 2004; Dong et al. 2012; Garavan et al. 1999). Most studies on this topic focus on the behavioral aspect of technology use. A similar analysis design than conducted for the memory changes might be a feasible approach to control whether or not RF-EMF impacts as well.

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Curriculum Vitae

Personal Data

Name	Milena Foerster, Dipl. Psych.
Date of birth	16.12.1985
Place of birth	Konstanz, Germany
Nationality	German
Private	Jägerstrasse 17 4058 Basel, Switzerland milena.foerster@unibas.ch +41 (0) 61 284 286 04

Academic Studies

	PhD Student at the Department of Epidemiology and Public Health, Swiss Tropical and Public Health Institute (Swiss TPH), Basel, Switzerland.
2014 – to date	Title of PhD project: The Interplay of mobile phone radiation and psychological effects somatic and psychological health, cognitive functions and behavior.
	Diploma Studies of psychology, Julius-Maximilians Universität Würzburg, Germany.
2007–2013	Diploma thesis on the impact of violent video games on psychophysiological emotional responses as measured by the startle reflex.
2007	**Literature studies, Julius-Maximilians Universität Würzburg, Germany**
2006	**Theater-, movie- and media-studies, University of Vienna, Austria**

Internships and work experience

2012	**Internship and temporary assistant at the institute for blind persons, Würzburg, Germany.** Supply teacher at the school class for children with multiple disabilities
2010	**Research Internship at the competence center for behavioral addictions (*Kompetenzzentrum Verhaltenssucht*), University Hospital Mainz, Germany.** Working group on internet and online gaming addiction supervised by Dr. Klaus Wölfling.
2007-2010	**Nursing assistant at the psychiatric center Reichenau (*ZfP Reichenau*).** Emergency admission ward for acute psychiatric patients.

Stays abroad

2009-2010	Bologna, Italy: Semester abroad with the Sokrates- Lifelong Learning Programme (*ERASMUS*)
2005	Bologna, Italy: Language school attendance (*Cultura Italiana*)

Additional Skills

EDV	MS Word/Excel: advanced knowledge Statistics: STATA: advanced knowledge R: advanced knowledge SPSS: basic knowledge
Languages	German: mother tongue English: fluent Italian: fluent Spanish: basic

Interests	Theater/film: Experience in acting, directing, costumes and scenography
	Literature: Member of literature club for sociology and gender
	Experimental arts and performance: Activist of the weekly group *Körper und Bild*, design school, Basel
	Sports: Climbing, yoga, aerial silk, mountaineering

Publications

Foerster, M., & Röösli, M (2017). A latent class analysis on adolescents' media use and associations with health related quality of life. Computers and Human Behaviour, 71, 266-274.

Foerster, M., Roser, K., Schoeni, A., & Röösli, M. (2015). Problematic mobile phone use in adolescents: derivation of a short scale MPPUS-10. International journal of public health, 60(2), 277-286.

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Röösli, M., Foerster, M., Roser, K., Schöni, A., Urbinello, D., & Struchen, B. (2015) Strichprobenkonzept für Messungen der nicht-ionisierenden Strahlung mit Exposimetern. Basel: Schweizerisches Tropen- und Public Health-Institut, im Auftrag des Bundesamtes für Umwelt (BAFU).

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Other activities related to the PhD project

2016

Co-supervision	Andrea Henneke, Public Health Master student at the Charité Berlin, Germany. Co-Supervision of Master thesis.
	Der Zusammenhang von Mobiltelefongebrauch, Schlafqualität und Allgemeinbefinden bei Jugendlichen (Associations of mobilephone use, sleep quality and general health in adolescents).

Conference poster	Annual meeting of the International Society of Environmental Epidemiology (ISEE), Rome, Italy. *Abstract: Foerster, M., Schindler, C., & Röösli, M. (2016). A new approach to control for confounding and reverse causality in radiofrequency electromagnetic field research on health related quality of life.*
Lecture	Practical on electromagnetic fields, ETH Zurich, Master of environmental sciences. Lecture on psychological effects of media use.
Talk	PPHS PhD Day, University of Basel. Presentation of own PhD project as representative of doctorate in epidemiology.
Seminary	EPH Student Seminary, Swiss TPH. *Gamer, Socializer, Low user… Who is who in adolescents' smartphone-society?* *A latent class analysis on adolescents' media use and associations with psychological and somatic well-being*

2015

Talk	Design School Basel (Schule für Gestaltung), non scientific presentation (lay audience) on mobile phone radiation. *Sendungsbewusstsein / strahlende Aussichten.*
Workshop	Development of an electromagnetic field workshop for children on electromagnetic fields and pilot workshop at the "Zukunftstag ".
Workshop	Development of an electromagnetic field module for the SwissTPH visitors program and pilot workshop with young adults.

Conference Talk	Annual meeting of the International Association of Media and Communication Research (IAMCR), Montreal, Canada. *Abstract: Foerster, M., Roser, K., Schoeni, A., & Röösli, M (2015). Problematic mobile phone use: Derivation of a short scale and associations with health, behavioural and social factors in adolescents.*
Speed talk	EPH Monday Plenary, Swiss TPH. *XMobiSurvey - Assessing mobile device usage in Europe.*

2014

Seminary	EPH Student Seminary, Swiss TPH. *My mobilephone just burnt my skin! Myths and facts about mobilephone radiation.*
Conference talk	Swiss Public Health Conference, Olten. *Abstract: Foerster, M., Roser, K., Schoeni, A., & Röösli, M. (2014). Mobile Phone Addiction in Swiss adolescents. Development of a ten item screening scale.*
Conference poster	Annual meeting of the Bioelectromagnetic Society (BioEM), Capetown, South Africa. *Abstract: Foerster, M., Urbinello, D., Struchen, B., & Röösli, M. (2014).Exposure to extremely low frequency magnetic fields in various Swiss and Belgium microenvironments.*
Lecture and Workshop	Tagung Umwelt und Gesundheit *(Environment and health congress),* Schützen Kliniken, Rheinfelden . *Elektromagnetische Hypersensibilität.*