Dissertation

Prevalence and Correlates of Internet-related Addictive Behaviour among Styrian Pupils

submitted by

Mag.rer.nat

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I. Statutory Declaration

I hereby declare that this thesis is my own original work and that I have fully acknowledged by name all of those individuals and organisations that have contributed to the research for this thesis. Due acknowledgement has been made in the text to all other material used. Throughout this thesis and in all related publications I followed the "Guidelines of the Medical University of Graz on Good Scientific Practice".

Graz, 11.11.2024	Thomas Lederer-Hutsteiner

II. Disclosures

The dataset of this thesis is used with kind permission by Gesundheitsfonds Steiermark, who is the owner of the data (see ☛Appendix A). The data was collected in course of a commissioned work to the social research company x-sample. The author of the current dissertation thesis is also affiliated to x-sample and was therefore involved in all phases of the data collection.

A positive vote of the Ethics Committee of the Medical University of Graz for data collection was received on March, 3rd 2022 (see ☛Appendix B).

Some parts of this thesis have already been presented at or published in:

- Publication A: Lederer-Hutsteiner T, Müller KW, Penker M, Stolz E, Greimel ER, Freidl W. The mediating effect of after-midnight use of digital media devices on the association of internet-related addictive behavior and insomnia in adolescents. Frontiers in Public Health. 2024;12. doi:10.3389/fpubh.2024.1422157 (Lederer-Hutsteiner et al., 2024).
- Publication B: Lederer-Hutsteiner T, Freidl W. Prevalence and correlates of internet-related addictive behaviour among Styrian pupils. Poster presentation at the annual Doctoral Day Conference at the Medical University of Graz. 2023; Graz, Austria (Lederer-Hutsteiner and Freidl, 2024).

All listed publications and the thesis were carried out with contributions from the following persons:

- **Univ.-Prof. Dr.phil Wolfgang Freidl** (Institute of Social Medicine and Epidemiology, Medical University of Graz, Graz, Austria)
  - Contribution to thesis: main supervision at all stages
  - Contribution to publication A: conceptualization, review and editing of the original draft
  - Contribution to publication B: conceptualization, review and editing of the original draft
- **Univ.-Ass. Priv.-Doz. Dr.phil. MA Erwin Stolz** (Institute of Social Medicine and Epidemiology, Medical University of Graz, Graz, Austria)
  - Contribution to thesis: co-supervision at all stages

- Contribution to publication A: methodological and statistical input, review and editing of the original draft

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  - Contribution to publication A: conceptualization, review and editing of the original draft
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  - Contribution to thesis: conceiving, conception and methodological design of the thesis, definition of research questions, statistical analyses, interpretation of findings and writing of the thesis
  - Contribution to publication A: conceiving, conception and methodological design, statistical analyses, visualization, drafting and revising the original manuscript
  - Contribution to publication B: conceiving, conception and methodological design, statistical analyses, visualization, drafting and revising the original manuscript

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Graz, 11.11.2024	Thomas Lederer-Hutsteiner

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VII. Abbreviations

95%-CI	95%-confidence interval
b	Unstandardized estimate
β	Standardized estimate
ARAB	Application-related addictive behaviour
DMD	Digital media device
DRAB	Digital media device-related addictive behaviour
DSM (-IV; -5)	Diagnostic and Statistical Manual (4^{th}; 5^{th} edition)
GD	Gaming disorder
IA	Internet Addiction
ICD (-10; -11)	International Classification of Diseases (10^{th}; 11^{th} edition)
IGD	Internet gaming disorder
IUD	Internet use disorder
IRAB	Internet-related addictive behaviour
SD	Standard deviation
SE	Standard error
SES	Socioeconomic status
WHO	World Health Organization

VIII. Zusammenfassung

Rund 20 Jahre nach den ersten wissenschaftlichen Publikationen zum Suchtverhalten im Internet hat die Weltgesundheitsorganisation im Jahr 2018 auf Basis der bis dahin gesammelten klinischen, neurophysiologischen und epidemiologischen Evidenz entschieden, zwei konkrete Manifestationen dieses Phänomens als Suchterkrankungen in der aktuellen elften Auflage der Internationalen Klassifikation der Krankheiten (ICD-11) zu listen. Suchtverhalten im Internet wurde bislang in zahlreichen epidemiologischen Untersuchungen entweder generell oder bezogen auf einzelne Anwendungsbereiche des Internets, wie etwa Soziale Medien oder Spiele, betrachtet. Umfassende Vergleiche einzelner Anwendungen wurden in diesem Kontext bisher allerdings kaum durchgeführt. Zudem existieren für Österreich keine aktuellen und belastbaren Daten für Jugendliche, die in diesem Kontext als besonders vulnerable Risikogruppe gelten. Diese Lücke erschwert die Planung entsprechender und vielerorts eingeforderter Präventions- und Interventionsmaßnahmen. Demnach ist das Ziel der vorliegenden Dissertation, diese Lücke durch Prävalenzschätzungen mehrerer Suchtverhaltensmuster zu schließen und durch eine anwendungsspezifische Analyse damit assoziierter Korrelate eine Grundlage für eine evidenzbasierte Maßnahmenplanung zu legen.

Die Ergebnisse der vorliegenden Dissertation basieren auf einer Sekundäranalyse von Querschnittsdaten einer repräsentativen Erhebung unter 2.812 Schüler:innen vom Frühling 2022 unter Anwendung anerkannter Screeninginstrumente. Nach umfangreichen Maßnahmen zur Sicherung der Datenqualität, wurden im Zuge der Auswertungen logistische und lineare Mehrebenen-Regressionsanalysen angewandt.

Die Ergebnisse decken sich weitgehend mit früheren Untersuchungen und zeigen, dass digitale Medien und die damit zugänglichen Internetanwendungen zentrale Aspekte und ständige Begleiter im Leben von Jugendlichen darstellen. Die untersuchten Jugendlichen weisen eine bemerkenswert hohe Prävalenz von internetbezogenem Suchtverhalten auf, insbesondere in Bezug auf Smartphones und Soziale Medien. Weibliche Jugendliche zeigen diesbezüglich jeweils deutlich mehr Suchtverhalten als männliche. Darüber hinaus ist ein erheblicher Teil der Schüler:innen von weiteren psychischen Problemen sowie Insomnie betroffen, die im Zusammenhang mit internetbezogenem Suchtverhalten stehen. Ein höherer Symptomschweregrad dieses Suchtverhaltens zeigt sich mit mehreren Nutzungsmustern, mit psychischen Begleitproblematiken, mit soziodemografischen und psychosozialen Merkmalen sowie mit familiären Rahmenbedingungen.

Die Ergebnisse liefern Hinweise darauf, dass Maßnahmen an verschiedene Zielgruppen gerichtet und auf unterschiedlichen Ebenen angesetzt werden sollten, wie beispielsweise Maßnahmen zur Bewusstseinsbildung bei Eltern, Maßnahmen zur Sensibilisierung von Fachkräften im Gesundheits- und Bildungsbereich, Maßnahmen zur Förderung nicht-digitaler Belohnungsmechanismen sowie Maßnahmen zur allgemeinen Stärkung der psychischen Gesundheit von Jugendlichen, mit besonderem Fokus auf die Rolle Sozialer Medien.

IX. Abstract

Approximately 20 years after the first scientific publications on internet-related addictive behaviour (IRAB), the World Health Organization decided in 2018 to classify two concrete manifestations of this phenomenon as addiction-related mental health disorders in the latest edition of the International Classification of Diseases (ICD-11), based on clinical, neurophysiological and epidemiological evidence collected up to that point. IRAB has been heavily issued in numerous epidemiological studies, either generally or in relation to single specific areas of internet use, such as social media or gaming. However, extensive comparisons across several applications are scarce. Moreover, there is a lack of current and robust data for adolescents in Austria, who are considered a particularly vulnerable risk group in this context. This gap severely limits the planning of widely requested prevention and intervention measures. The present dissertation aims to address this gap by providing prevalence estimates of various specific IRABs and establishing a foundation for evidence-based planning of policies through application-specific analyses of associated correlates.

The results of this thesis are based on secondary cross-sectional data of a population-representative sample of 2,812 school students that were surveyed in spring 2022 using recognized screening instruments. Data analysis involved multilevel logistic and linear regression and was preceded by extensive measures to maximize data quality.

The findings largely converge with prior research and indicate that digital media devices (DMD) and internet applications represent pivotal aspects and constant companions of adolescents' lives. The screened adolescents exhibit remarkably high prevalences of IRAB, especially related to smartphones and social media. In this regard, female adolescents demonstrate significantly higher prevalences than males. Moreover, other mental health problems and insomnia, both significantly linked to IRAB, affect a substantial proportion of students. A higher symptom severity of IRAB is associated with several use patterns, comorbid mental problems, sociodemographic and psychosocial characteristics as well as with family environmental aspects.

The findings provide evidence for measures to be addressed at different target groups and levels such as measures to strengthen parental awareness, measures to strengthen awareness among health and school professionals, measures to foster non-digital reward mechanisms as well as measures to generally strengthen mental health among adolescents with a special focus on the role of social media.

1 Introduction

1.1 Why is it an issue of public interest?

As already described in a previous publication of this thesis' author (Lederer-Hutsteiner et al., 2024), there has been a continuous increase in the frequency and duration of digital media device (DMD) use as well as online application usage at least since the introduction of smartphones, which provide nearly unrestricted access to internet-based applications without spatial and temporal limits. The Austrian Internet Monitor reported that in 1996, only 2% of Austrians aged 14 and above used the internet daily (Integral, 2023). However, with the launch of the iPhone in 2007 (the precursor of today's smartphones), this percentage rose to 43% and reached 82% in 2022. For young people aged 14 to 19 years, the percentage is even higher in 2022 at 91%. The JIM study, conducted in Germany since 1998 among 12 to 19-year-olds shows similar trends and also provides data on the development of daily usage time since 2010. While the average daily usage time in 2010 was 138 minutes, 10 years later in 2020 it was 258 minutes, which corresponds to an increase of 87% (Medienpädagogischer Forschungsverbund, 2023a).

At its core, there is nothing wrong with this global development as digital media devices and internet-based applications support daily matters and provide numerous advantages for adolescents in many respects. They potentially enhance productivity, provide information and social interaction and as such offer an opportunity to establish and maintain contact to peers, clearly promote entertainment (van Deursen et al., 2015), and even potentially reduce disparities in access to counselling for mental health issues (Odgers and Jensen, 2020), to pick just a few. Moreover, increasing use of digital media devices doesn't come as surprising considering the ongoing governmental and business-related digitization efforts and initiatives yielding numerous innovations in the field of information and communication technologies such as broadband internet that expands speed and availability, laptop classrooms, the Internet of Things as well as more recently artificial intelligence massively expanding the contexts and areas where digital media devices and internet-based services are used.

Apart from interesting questions related to the (hardly predictable) anthropological impact of increasing involvement of artificial intelligence applications, there is also evidence for concrete adverse individual and societal effects due to the intensive use of digital media devices, especially among adolescents and children. There is convincing longitudinal evidence of negative effects on young children's cognitive development (Tomopoulos et al., 2010), whereas age and media content act as important moderators (Anderson et al., 2017a), prosocial behaviour that is moderated by the content of video games, whereby violent content increased aggressive and prosocial content increased prosocial behaviour (Greitemeyer and Mügge, 2014), school performance (van den Eijnden et al., 2018), dangerous driving (Steelman et al., 2012), depression (Yi and Li, 2021), sleep (Pagano et al., 2023), myopia (Dolgin, 2015) and obesity (Wen et al., 2014) to tease just a few (an in-depth discussion will be carried out in ☛section 1.8). With this in mind, the constant increase in DMD and internet use is associated with increasing concern not only among healthcare institutions, but also across sectors, as the rising use of DMD and internet applications and its diverse potentially negative effects not only affects healthcare, but also impacts other sectors such as education, the labour market and consequently the economy as well (Shetty et al., 2022).

These concerns are also evidenced by significantly increasing prevalence rates of internet-related addictive behaviour (IRAB) over time as shown in a recent meta-analysis of respective epidemiological research (Pan et al., 2020) and have led to governmental public health strategies to address this issue. Pioneering work on that issue has been carried out by South Korea establishing the first national policy plan worldwide as a reaction of its radical development in Information and Communication Technology (ICT), which has channelled the emergence of excessive internet use especially among children and adolescents (Koh, 2015). Other countries followed, e.g. China's *"The program of comprehensive prevention and intervention for online games addiction among juveniles"* or Switzerland's *"National Addiction Strategy 2017 – 2024"* and its associated policy plan 2021 – 2024, which also includes internet-related issues on behavioural addictions (cf. (Saunders et al., 2017)).

Clinics have also responded to this issue and established treatment services, many in Asia, but also in Europe, North America and Australasia (cf. (Saunders et al., 2017)). In Germany, for example, *"… the number of specialized services for Internet-related disorders including Gaming Disorder increased fourfold from 2008 to 2015 …"* (Rumpf et al., 2018b, p. 558).

As indicated above, the use of DMD and internet applications has been issued in the context of addiction research for about 30 years which will be discussed in the coming chapters.

1.2 The very beginnings 30 years ago

The first recorded comment on this phenomenon is attributed to the psychiatrist Dr. Ivan Goldberg, who posted a note on internet addiction disorder, which was fictitious and satirical in nature, but received an unexpected flood of responses and requests from affected people due to the note's serious presentation (Dalal and Basu, 2016).

In scientific context internet addiction was first addressed in 1996 by Kimberly S. Young as a case report of a 43 year old female homeworker (Young, 1996) and by Mark Griffiths (Griffiths, 1996) after introducing the concept of technological addictions in 1995 (Griffiths, 1995). Another publication followed by Young in 1998 reporting the first empirical results based on conceptual and diagnostic claims regarding pathological gambling (Young, 1998b). In fact, this publication can be considered a trend-setter, as evidenced by a total of 10,257 scientific citations by April, 3rd 2024 (based on Google Scholar).

Research articles related to problematic smartphone use first appeared in 2008 (Turel et al., 2008), one year after the launch of the iPhone, and since then the issue has seen an exponential increase in respective publications and a steady increase in research interest (Busch and McCarthy, 2021).

1.3 Terminology reflects conceptual ambiguity

The issue of interest has been referred to in a broad variety of designations such as *internet addiction* (Griffiths, 1996, Young, 1996), *problematic internet use* (Beard and Wolf, 2001, Caplan, 2002), *pathological internet use* (Davis, 2001, Morahan-Martin and Schumacher, 2000), *compulsive internet use* (Greenfield, 1999, Meerkerk et al., 2006), *internet related problems* (Widyanto et al., 2008) or the more neutral and cautious *excessive internet use* (Weinstein and Lejoyeux, 2010) and finally *internet use disorder* (IUD) (Rumpf et al., 2021) as an umbrella term in accordance with the established definitions for *internet gaming disorder* in DSM-5 (American Psychiatric Association, 2022) as well as *gambling disorder* and *gaming disorder* in ICD-11 (World Health Organization, 2022).

This is just a small excerpt from the entire terminological repertoire related to overexposed internet use. As mentioned above in 2008 a closely related research line was initiated focussing on excessive use of DMD as gadgets that provide access to the internet. Researchers concentrating on that issue contributed an additional variety of designations such as *smartphone addiction* (Kwon et al., 2013), *problematic smartphone use* (Elhai et al.,

2017) or *nomophobia* (no mobile phone phobia) (King et al., 2010), suggesting a conceptually different issue.

To a certain extent, this multitude of terms also reflects the ongoing controversy about the proper conceptualization of this phenomenon which is also reflected in the fact, that for a long time, it was conceptualised as an impulse control disorder, but simultaneously in most published articles it was (and still is) referred to as Internet Addiction.

1.4 Phenomenological approaches

The different terms listed in ☛section 1.3 include specific characteristics that imply varying conceptual classifications. While the term *excessive internet use* is somewhat vague, given that there is no indication of any kind of associated burden, *problematic internet use* may be considered as too unspecific since it simply implies that the internet use is associated with "problems" but gives no indication about their severity. *Pathological internet use* is unspecific too, since there is no indication of the pathology's conception. *Compulsive internet use* and also *obsessive internet use* introduce a conceptual idea included both in the Diagnostic and Statistical Manual (DSM) of the American Psychiatric Association and in the International Classification of Diseases (ICD) of the World Health Organization, but are both misleading since addictive usage patterns aim to achieve pleasure (at least in the early stages of addictive processes), whereas compulsive and obsessive behavioural patterns aim to reduce anxiety (Miele et al., 1990).

According to Dalal and Basu, 2016 (Dalal and Basu, 2016) the conceptualisation of the behaviour of interest may be guided by three phenomenological core questions:

- Should this behaviour be conceptualized as a mental and behavioural disorder?
- If yes, should it be conceptualized as an addictive disorder?
- If yes, what are affected people addicted to?

With regard to the first two questions, several validation criteria have been established that need to be fulfilled to justify a behavioural phenomenon to be classified as a psychiatric disorder (mainly extracted from Lam (Lam, 2014)). According to Robins and Guze (Robins and Guze, 1970) these are a clear clinical description, evidence from laboratory, follow-up and family studies and exclusion of other disorders. Other authors contributed similar criteria, such as genetic linkage, well-established aetiology and pathology as well as consistency of course, prognosis, stability, and response to treatment across different populations (Pies, 2009) as well as well-known risk and protective factors and related comorbidities (Gentile et al., 2011). The World Health Organization, having strong influence in defining what constitutes a mental and behavioural disorder, provides the following definition in the ICD-11: *'Mental, behavioural and neurodevelopmental disorders are syndromes characterised by clinically significant disturbance in an individual's cognition, emotional regulation, or behaviour that reflects a dysfunction in the psychological, biological, or developmental processes that underlie mental and behavioural functioning. These disturbances are usually associated with distress or impairment in personal, family, social, educational, occupational, or other important areas of functioning.'* (World Health Organization, 2022, introduction of chapter 6 "Mental, behavioural or neurodevelopmental disorders", online edition of ICD-11).

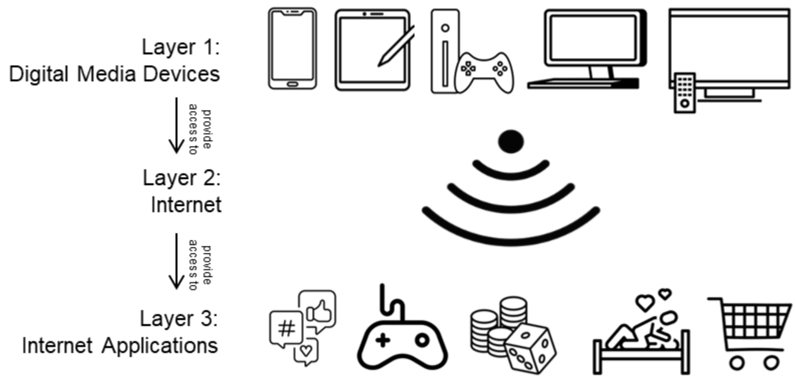
To anticipate and keep it short, already in 2013, the American Psychiatric Association decided to include *Internet gaming disorder* as a condition for further study, i.e. as a research diagnosis to the 5th edition of the DSM (American Psychiatric Association, 2022). A few years later, a consensus decision of an international and multidisciplinary group of 66 experts was made (Rumpf et al., 2018b, Saunders et al., 2017) to include *Gaming disorder* (online and/or offline coded as 6C51.0 and 6C51.1, respectively) in the 11th revision of the ICD in the chapter *Disorders due to addictive behaviours* (World Health Organization, 2022) based on extended reviews of clinical, epidemiological and neurophysiological evidence (World Health Organization, 2015). Arguments regarding the clinical relevance are based on clinical pictures of help seeking gamers *"… whose lives are dominated by online gaming to the extent that they spend 10 or more hours per day gaming and experience disorders due to consequent sleep deprivation, day‑night reversal, dehydration, malnutrition, seizures, and pressure sores, as well as irritability, physical aggression, depression, and a range of social, academic, and vocational problems."*, as summarized in Saunders et al. (Saunders et al., 2017, p. 3). Furthermore, at least one death case causally linked to excessive gaming is documented (Lee, 2004): a 24-year-old South Korean male with no documented prior clinical impairments suddenly died during near continuous internet gaming for about 80 hours at an internet café due to venous thromboembolism as a direct cause of sitting immobile at a computer screen. Embedding excessive internet-related behaviours in the addiction framework has also been justified by the argument that the observed symptoms of people (those affected by disordered gaming, for example) are similar to those found in disorders which arise due to substance-related and gambling disorders as recognized addictive behaviours (Saunders et al., 2017). Regarding neurophysiological evidence, Weinstein et al. reviewed findings of brain imaging studies such as the role of ventral striatum in reward and craving conditions or dysfunctional prefrontal brain areas reflecting problems in inhibitory control typical for progressed stages of addictive processes. They conclude that *"… the* *neural mechanisms underlying Internet Gaming Disorder (IGD) resemble those of drug addiction"* (Weinstein et al., 2017, p. 314) (for a more in-depth discussion of the neurobiological mechanisms see ☛section 1.5).

Also, *gambling disorder* (online and/or offline coded as 6C50.1 and 6C50.0, respectively), which has previously been referred to as *pathological gambling*, is now included in the addiction chapter and was shifted from the chapter *Habit and impulse disorders* (ICD-10). These allocations are considered a milestone in the phenomenological classification of these disorders. The ICD-11-chapter *Other specified disorders due to addictive behaviours* also opens a window for coding other addictive behaviours related to the internet or DMD, such as a disordered social network or pornography use or disordered buying-shopping as proposed by Brand et al. (Brand et al., 2020). They also suggest the following criteria as a guide through the diagnostic process, to justify the inclusion in this ICD-11-chapter: included behaviours have to be clinically relevant, theoretically embedded in the addiction framework and involve empirically evident psychological and neurobiological mechanisms underlying addictions.

While there is a broad consensus regarding the potential detrimental effects of excessive use of DMD or of the internet, agreement of its inclusion in the aforementioned manuals is a different story. A summary of scientific divergence has been provided in a review article by Fumero et al. (Fumero et al., 2018), who highlight the lack of consensus on the question whether excessive use of DMD or the internet is rather a consequence of other mental disorders or maladaptive coping and on whether traditional concepts of addiction also apply to this field. Another area of disagreement refers to whether non-substance related patterns of excessive and rewarding behaviour should be labelled as stable addictive patterns since a 5-year longitudinal study showed transient patterns of several excessive behaviours likely to remit (Konkolÿ Thege et al., 2015). Conversely, untreated substance-related addictive phenomena tend to end up becoming chronic and progressive (Starcevic, 2017). Several authors criticized the inclusion of *Gaming disorder* in the ICD-11 (Aarseth et al., 2017, Dullur and Starcevic, 2018, van Rooij et al., 2018), arguing that the conceptual and empirical foundation for diagnosing *Gaming disorder* is still too weak and expressing concern that young people may be stigmatized and wrongly pathologically labelled as a consequence of *"Moral panics around the harm of video gaming …"* (Aarseth et al., 2017, p. 3). Billieux et al. (Billieux et al., 2015) critically question the widespread scientific approaches in the research field of addictive behaviours at large, which are atheoretical and merely criteria-based and confirmatory and at risk of over-pathologizing everyday behaviour. Such a risk is further exacerbated by the low positive predictive value of many tests, yielding a substantial amount of misclassifications (Maraz et al., 2015) (more detailed in ☛sections 1.6 and 1.7). Although some of their arguments (for example, the ongoing debate on validity issues or the potential of pathologizing recreational gaming) have been acknowledged by other authors (King et al., 2018), some articles involving authors predominantly covering clinical and public health backgrounds have been published as a direct response to the yielded criticism. They argue that *“The harm related to including a specific diagnosis, i.e., a health condition that can be shown to be associated with burden of disease, is less than the harm generated from its exclusion …”* (Rumpf et al., 2018b, p. 558), that the critics’ argument related to potential stigmatization *“… is equivalent to suggesting that because millions of people consume alcohol without problems that we should ignore the manifest harms (and mortality) that arise from its consumption for fear of stigmatizing those who are not harmed.”* (Saunders et al., 2017, p. 2), and also that *“Critics of IGD often draw attention to non-empirical and non-clinical observations and critiques, while overlooking the larger body of robust work that supports the validity of the disorder.”* (King et al., 2018, p. 1). In their response to the criticism, Rumpf et al. (Rumpf et al., 2018b) also highlighted the precautionary principle that states *“… that in the case of serious or irreversible threats to the health of humans or the ecosystem, acknowledged scientific uncertainty should not be used as a reason to postpone preventive measures.”* (Martuzzi et al., 2004, p. 1).

When considering the third question, there are several sublevels that have to be considered. The question is: What is the object to which an affected person is hooked while addictively using social media, online video games, online gambling offers, pornography or shopping facilities? ☛Figure 1 illustrates the potential objects coming into play. DMD, such as smartphones, tablets, gaming consoles, laptops/computers or smart TVs, as layer 1 provide access to the internet as layer 2, which provides access to using internet-based applications mentioned above as layer 3.

Figure 1: Objects of potential IRAB



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To illustrate the conceptual problem, Griffiths (Griffiths, 2000) considered addicted gamblers or gamers who use the internet simply as the place to engage in their addictive gambling or gaming behaviour. According to ☛Figure 1, they use a certain DMD, let us assume a smartphone, to get access to the internet to finally engage for example in gambling as a specific internet-based application. To continue Griffiths' consideration, one might ask: what would happen to this gambler if gambling is withdrawn from smartphones or from the internet (Griffiths and Szabo, 2014), for example, due to legislative regulations? Most probably, the gambler may initially switch to other DMD or seek offline gambling options rather than completely abstaining from gambling and exploring other areas of his smartphone or the internet. Therefore, the addictive pattern of this individual is clearly related to gambling and he or she might be considered as addicted to gambling, rather than addicted to his smartphone or to the internet in a generalized form. According to this conception, DMD or the internet are just vehicles or media which provide access to specific contents that are used addictively. This is in line with an empirical examination by Griffiths and Szabo (Griffiths and Szabo, 2014), according to which participants' internet use time would decrease by 65% if their favourite applications were no longer available online. 16% would not even go online anymore. Despite inherent bias in the study's results (e.g. hypothesized questioning or no differentiation of responses between addictive and non-addictive users) the authors concluded that internet addiction as a term is too non-specific since individuals do not seem to be addicted *to the internet* per se, but rather *on the internet* to certain associated behaviours as proposed by Griffiths (Griffiths, 2000) and further differentiated by Davis

(Davis, 2001) into both generalized pathological internet use for internet-related addictive behaviour with no specific activity and specific pathological internet use for addictive online behaviour with a clear focus regarding specific applications. Montag et al. (Montag et al., 2015a) conducted a cross-cultural study in China, Taiwan, Germany and Sweden and compared specific measures for online social network addiction, shopping addiction, pornography addiction and video game addiction, respectively with two generalized measures of internet addiction. Although nearly all specific measures did not highly correlate with generalized ones, the specific measure of online social network addiction showed high correlations with generalized measures in all countries ($r = 0.49 – 0.68$) indicating that addictive social network use is strongly associated with generalized internet addiction. They suggest that addictive social network use may be better characterized as generalized IA since social media do not exist beyond the online world. Related to DMD as potential addictive objects a similar discussion is on-going and consensus of which is still pending. While some authors argue that an addiction which is related to a mobile phone is just a manifestation of an underlying application-based addictive behaviour (e.g. gaming, social network use) (Billieux, 2012), others yielded empirical results justifying a respective distinction (Davazdahemami et al., 2016).

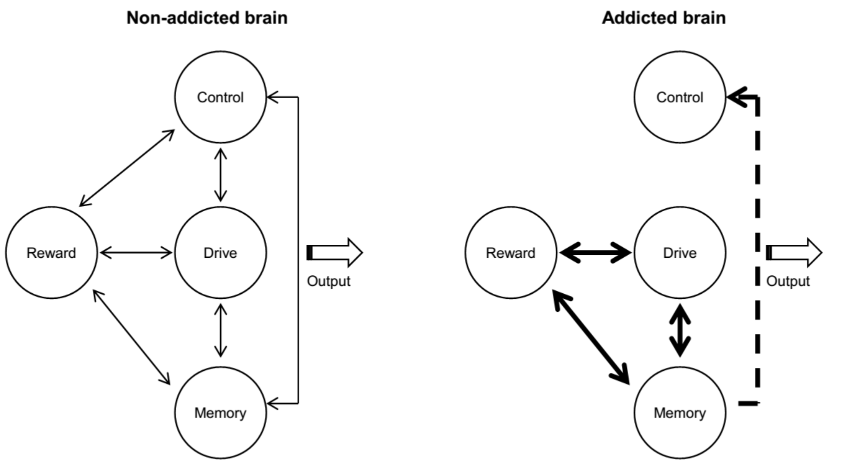
In accordance with the ICD-11 definitions, Rumpf et al. (Rumpf et al., 2021) suggested using *internet use disorder* as an umbrella term and *gambling disorder*, *gaming disorder*, *social network use disorder*, *pornography use disorder* and *shopping disorder* as corresponding specifications of respective behaviours shown predominantly online. Unfortunately, the suggested term *internet use disorder* is lacking the specificity within the scope of addiction that it is intended to capture and is running the risk of summarizing a very heterogeneous group of affected people. Besides, this designation is at risk of being misinterpreted as disorders that are not associated with addictive processes and are by no means covered by the available screening instruments. For example, severe depressive and anxiety symptoms caused by cyberbullying due to non-addictive chatting or social media use may also represent disorders caused by using the Internet, but are in no association with an addictive usage.

1.5 Neurobiological foundations of Internet Addiction

An important approach in justifying behavioural addictions such as IGD or generally IRAB to be classified as clinically relevant disorders involves the examination of neurobiological similarities to the well-researched and established substance-related disorders such as alcohol, nicotine or opioids.

According to the highly recognized review by Volkow et al. (Volkow et al., 2003) addictive patterns are generally associated with an impaired neurobiological interplay of four circuits (see ☛Figure 2): (1) the reward circuit linked to salience, (2) the motivation/drive circuit linked to internal states, (3) the memory circuit linked to learned associations and (4) the control circuit associated with conflict resolution.

Figure 2: Four-circuit network of addiction by Volkow et al., 2003



Note: Modified illustration adapted from Volkow et al. (Volkow et al., 2003, p. 1,447) used with kind permission of the Copyright Clearance Center on behalf of the American Society for Clinical Investigation (see ☛Appendix C).

According to the model by Volkow et al. (Volkow et al., 2003) all circuits are grouped as a network that affects the individual's addiction-related behaviour (referred to as output) which is influenced by genetic, neuronal and environmental aspects. The addictive process is characterized by the fact that reward, motivation and memory circuits dominate the control circuit, which in turn does not adequately provide feedback to reward, motivation and memory. The reward and the control circuits, which involve key and well-researched brain regions in the context of addiction and show very consistent findings, are presented as follows.

The reward circuit involves mechanisms related to the mesolimbic dopaminergic pathway. According to this pathway, the neurotransmitter dopamine primarily originates in the ventral tegmental area and mainly terminates in the ventral striatum, especially the nucleus accumbens (Adinoff, 2004). The release of dopamine involves upstreaming interactions with serotonin, which stimulates endorphins, which in turn regulate gamma-aminobutyric acid (GABA), which finally regulates the dopamine release in the nucleus accumbens (Blum et al., 2020). This brain area and this mechanism, referred to as the *brain reward cascade* (Blum et al., 2020), is highly recognized as the major neuronal correlate of reward, well-being, pleasure and reduced feelings of stress and mediates physiologically driven reward such as satisfaction of hunger, but also mediates more unnatural reward of learned and positively reinforcing activities such as substance use, as well as gambling or gaming (Blum et al., 2020). Already previously Blum et al. (Blum et al., 1996) postulated the *reward deficiency syndrome* that manifests itself in addictive behaviour (whether substance-related or not) and suggested that exaggerated seeking for unnatural reward might be the result of a dopamine- and reward-deprived brain, impaired to obtain reward from natural activities. As such, they consider addiction primarily as a neurochemically disordered brain and the typical craving symptom of addicted individuals as an expression of the *want* for dopamine release and the accompanied positive feelings. Volkow et al. compiled strong evidence of dopaminergic bursts during drug consumption, but also already in the expectation mode of drugs craving (Volkow et al., 2003). Studies have also shown that the dopaminergic pathway is not only triggered by actually engaging in certain addictive behaviours, but also already in case of the presentation of related cues. This phenomenon, referred to as *cue reactivity*, has been examined in many studies indicating a stronger activity in the striatal brain in addictive individuals compared to healthy controls while being confronted with addictive cues (e.g. stimuli from World of Warcraft in case of gamers or cues related to smoking in case of smokers) for a broad spectrum of addictive behaviours (e.g. addictive gaming, alcohol, nicotine and heroin use) (Montag et al., 2017).

Dopamine mediated reward deficiency has been linked to genetics resulting in a lower density of the dopamine D2 receptor, which is highly evidenced to be associated with a predisposition for addictive behaviour (no matter if substance-related or not) generally (Blum et al., 1996) and was also found in studies among people addictively using the internet (Kim et al., 2011). It is assumed that the lack of dopamine D2 receptors requires higher thresholds for drug stimulation (Montag et al., 2017). Among the genetic mechanisms negatively affecting the dopamine D2 receptor density in the striatum, the Taq1A1 allele of the dopamine D2 receptor gene is well-recognized and was found to be associated with reward dependence which was also confirmed in a study among adolescent excessive internet gamers, who were more likely to show Taq1A1 compared to a healthy control group (Han et al., 2007). Noble (Noble, 2000) reviewed studies that examined polymorphisms of the dopamine D2 receptor gene and conclude that Taq1A1 is associated with a 30 to 40% reduction of striatal dopamine D2 receptor density. Additionally, findings by Thompson et al.

(Thompson et al., 1997) suggest Taq1A1 to impair the capacity of dopamine binding at the D2 receptor.

The second well-established and crucial neuronal mechanism in addiction research is related to Volkow et al.'s control circuit which is linked to control monitoring and resolution. Impaired inhibitory control is a major diagnostic criterion of addiction generally referred to as loss of control (see ☛section 1.6). Impairments of the prefrontal cortex and the anterior cingulate cortex as two highly evidenced brain areas in this regard (Kerns et al., 2004, Royall et al., 2002) have been shown in imaging studies among addictive individuals generally (see the reviews by Goldstein and Volkow (Goldstein and Volkow, 2002) and Lubman et al. (Lubman et al., 2004)) and also among adolescents and young adults showing IRAB (Dong et al., 2010, Zhou et al., 2011). Especially at progressed stages of an addiction process the consumption of a drug or an addictive behaviour is increasingly linked to declining reward and pleasure. According to Robinson and Berridge's *incentive sensitization theory of addiction*, suggesting that brain changes affect psychological processes such as hypersensitivity and biased attention towards drug-associated incentives, individuals may no longer *like* but still *want* the drug (Robinson and Berridge, 1993). Addicted individuals have long known that their behaviour provides serious harm to them and maybe others in many ways; nevertheless they continue although adverse consequences related to health, relationships, education or jobs have long since occurred.

1.6 Approaches to assessing Internet Addiction

An essential part in epidemiological and clinical research and practice is determining whether or not people are affected by whatever the object of investigation is. The accuracy of assessment tools is a crucial aspect in that course since it is a major part of the foundations warranting internal validity and excluding systematic errors. Internal validity affects both prevalence estimates (☛section 1.7) as a descriptive epidemiological approach to support decisions related to public health implications as well as the study of risk and protective factors (☛section 1.8) as analytical approaches providing evidence for theoretical models, prevention and treatment (Rumpf et al., 2019).

Based on that claim, numerous assessment tools have been developed. Reviews of epidemiological research on IA concluded that the research field of behavioural addictions in general (Rumpf et al., 2019) and IA in particular suffers from an excess of screening tools using inappropriate conceptions, lacking validation and cut-off scores, diagnostic specificity and sensitivity and thus clinical and epidemiological utility (Kuss et al., 2014, Laconi et al., 2014, King et al., 2020) as well as lacking positive predictive value (Maraz et al., 2015 illustrate for compulsive shopping that just 24% of people scoring positive on the Compulsive Buying Scale are likely to be actually diseased, although the test shows a high sensitivity of around 90% (Maraz et al., 2015)). Another critical aspect, which does not concern the survey instruments per se, but the survey method, relates to the fact that the instruments used in epidemiological research are predominantly administered in a self-reporting mode. Anderson et al. (Anderson et al., 2017b) indicate evidence for inaccurate answering due to the lack of judgement capabilities, self-insight and willingness to respond honestly. This may result in severe under- and over-reporting, which has been shown in a meta-analysis examining discrepancies of self-reported versus logged digital media use (Parry et al., 2021).

With regard to the excess of assessment instruments, a systematic review of the psychometric properties of scales assessing IA found a total of 45 tools in 2014 (Laconi et al., 2014). More recent reviews on IA-associated scales identified an additional total of 78 scales assessing problematic smartphone use (Harris et al., 2020) and an additional total of 32 scales assessing GD (King et al., 2020). Regarding lacking validations, Laconi et al. found that validations among clinically diagnosed individuals are scarce (Laconi et al., 2014). The mentioned reviews also state that the comparability of epidemiological findings (such as prevalence rates) are likely to be severely biased due to the application of different assessment tools. This assumption has been confirmed in a meta-analytic review of 113 studies from 31 nations. The meta-analysis also showed that studies using assessments based on IGD-criteria of DSM-5 yielded lower prevalence rates compared to those adopting measures based on pathological gambling of DSM-IV (Pan et al., 2020). In summary, authors demanded to stop the development of new assessment tools and rather to put efforts in harmonizing the most promising existing ones with respect to conceptualization and cut-off scores to finally aim for an international gold standard (Harris et al., 2020, King et al., 2020, Kuss et al., 2014, Laconi et al., 2014). However, concern was also expressed that the current inclusion of GD in the ICD-11 would instead fuel further new developments (Harris et al., 2020).

When it comes to the question of the most promising existing scales, a brief outline of the history of scale development is worthwhile. The very first scales assessing IA were the *Internet Addiction Diagnostic Questionnaire* (IADQ) (Young, 1998b) and the *Internet Addiction Test* (IAT) (Young, 1998a). Both were based on DSM-IV criteria for pathological gambling (which in turn are based on criteria for substance dependence). The recent diagnostic criteria for gambling disorder (formerly referred to as pathological gambling) are depicted in ☛Table 1 now included in the disorder class *Substance-Related and Addictive*

Disorders and specified as *“Persistent and recurrent problematic gambling behavior leading to clinically significant impairment or distress, as indicated by the individual exhibiting four (or more) of the following in a 12-month period”* (American Psychiatric Association, 2022, retrieved online):

Table 1: DSM-5 criteria for gambling disorder

Criteria	Definition
Preoccupation	*“Is often preoccupied with gambling (e.g. having persistent thoughts of reliving past gambling experiences, handicapping or planning the next venture, thinking of ways to get money with which to gamble).”*
Tolerance	*“Needs to gamble with increasing amounts of money in order to achieve the desired excitement.”*
Unsuccessful attempts	*“Has repeated unsuccessful efforts to control, cut back, or stop gambling.”*
Withdrawal	*“Is restless or irritable when attempting to cut down or stop gambling.”*
Escapism	*“Often gambles when feeling distressed (e.g., helpless, guilty, anxious, depressed).”*
Loss chasing	*“After losing money gambling, often returns another day to get even (“chasing” one’s losses).”*
Deception	*“Lies to family members, therapist, or others to conceal the extent of involvement with gambling.”*
Jeopardized life	*“Has jeopardized or lost a significant relationship, job, or educational or career opportunity because of gambling.”*
Bailout	*“Relies on others to provide money to relieve a desperate financial situation caused by gambling.”*

Note: Definitions are quoted from DSM-5 (American Psychiatric Association, 2022, retrieved online).

Based on the theoretical basis of pathological gambling[1] of DSM-IV (American Psychiatric Association, 1994) and substance dependence a lot of generalized IA-related assessment tools have been developed. Although the majority show shortcomings mentioned above the following have been validated multiple times and show promising psychometric properties according to the systematic review by Laconi et al. (Laconi et al., 2014): *Internet Addiction Test* (IAT) (Young, 1998a), *Compulsive Internet Use Scale* (CIUS) (Meerkerk et al., 2009), which is used within this thesis (see ☛sect. 2.7.1), *Chen Internet Addiction Scale* (CIAS) (Chen et al., 2003), *Online Cognition Scale* (OCS) (Davis et al., 2002), *Generalized Problematic Internet Use Scale 2* (GPIUS-2) (Caplan, 2010), *Problematic Internet Use*

[1] Pathological gambling was the designation used when most of the assessment tools on IA were being developed. The definitions depicted in ☛Table 1 remained the same with minor changes to the criteria preoccupation and escapism. One criterion (*illegal acts)* of the DSM-IV version was dropped.

Questionnaire (PIUQ) (Demetrovics et al., 2008) and *Internet Related Problem Scale* (IRPS) (Armstrong et al., 2000). As already mentioned, all are grounded on DSM-criteria for gambling disorder[2], substance dependence or both, except GPIUS-2 and OCS which are based on cognitive-behavioural theory. According to a systematic review of longitudinal research on problematic internet use, the IAT, CIUS and CIAS are most commonly used (Anderson et al., 2017b).

The inclusion of internet gaming disorder as a condition for further research in the DSM-5 (American Psychiatric Association, 2022) has fuelled the development of specific assessment tools related to gaming. While King et al. (King et al., 2013) identified 18 instruments in their review aimed at assessing GD as a specific IA-related condition, a subsequent review in 2020 found 32 such tools (King et al., 2020). Harris et al. identified an additional total of 78 validated scales on the issue of excessive smartphone use (Harris et al., 2020).

While there is still disagreement related to a desired gold standard, including IGD in the DSM-5 in 2013 is considered a milestone (Király and Demetrovics, 2021) regarding the assessment of excessive internet use, since it promoted conceptual consistency of the tools that have been developed since then (King et al., 2020, Király and Demetrovics, 2021). The convergence of most newly developed tools on functional impairment and disrupted control, which are regarded as central criteria in that context (Billieux et al., 2015, Saunders et al., 2017, Rumpf et al., 2018a, Billieux et al., 2017), was highlighted in the review by King et al. (King et al., 2020). They identified five assessment instruments that show more evidence regarding sound psychometrics with no one being superior: *Game Addiction Scale* (GAS-7) (Lemmens et al., 2009), nine-item short-form of the *Internet Gaming Disorder Scale* (IGDS-SF9) (Pontes and Griffiths, 2015), *Internet Gaming Disorder Test* (IGDT-10) (Király et al., 2017), *Lemmens' Internet Gaming Disorder Scale*, short form (IGD-9) (Lemmens et al., 2015) and *Assessment of Internet and Computer Game Addiction* (AICA-S) (Wölfling et al., 2012).

DSM-5 and ICD-11 have set the following criteria for diagnosing IGD and GD, respectively, which largely correspond to the ones for gambling disorder as symptomatology and neurobiological mechanisms, show great overlaps (Brand et al., 2016, Dong and Potenza, 2014) (see ☛sect. 1.5).

[2] As above.

Table 2: DSM-5 criteria for internet gaming disorder and ICD-11 criteria for gaming disorder

DSM-5-criteria	Definition
Preoccupation	*“Preoccupation with gaming.”*
Withdrawal	*“Withdrawal symptoms when gaming is taken away or not possible (sadness, anxiety, irritability).”*
Tolerance	*“Tolerance, the need to spend more time gaming to satisfy the urge.”*
Unsuccessful attempts	*“Inability to reduce playing, unsuccessful attempts to quit gaming.”*
Loss of interests	*“Giving up other activities, loss of interest in previously enjoyed activities due to gaming.”*
Continued use	*“Continuing to game despite problems.”*
Deception	*“Deceiving family members or others about the amount of time spent on gaming.”*
Escape	*“The use of gaming to relieve negative moods, such as guilt or hopelessness.”*
Jeopardized life	*“Risk, having jeopardized or lost a job or relationship due to gaming.”*
ICD-11-criteria	**Definition**
Impaired control	*“Impaired control over gaming (e.g., onset, frequency, intensity, duration, termination, context).”*
Increasing priority	*“Increasing priority given to gaming to the extent that gaming takes precedence over other life interests and daily activities.”*
Continuation	*“Continuation or escalation of gaming despite the occurrence of negative consequences.”*
Impaired functioning	*“The pattern of gaming behaviour results in marked distress or significant impairment in personal, family, social, educational, occupational, or other important areas of functioning.”*

Note: Definitions are quoted from DSM-5 (American Psychiatric Association, 2022, retrieved online) and ICD-11 (World Health Organization, 2022, retrieved online).

In addition to the aforementioned critics regarding shortcomings of psychometric and diagnostic properties of many developed instruments, conceptional and operational issues have also been addressed. Petry et al. (Petry et al., 2014) for example suggested operationalisations for each of the DSM-5 criteria für IGD, which was subjected to a thorough examination by 28 experts in the field of GD (Griffiths et al., 2016). The authors widely confirmed GD-applicability of criteria such as jeopardized life (impaired functioning in ICD-11), continued use despite gaming-related problems and unsuccessful attempts to reduce or stop gaming despite a given desire to do so (impaired control in ICD-11, sometimes also referred to as loss of control). However, concerns were raised related to criteria such as preoccupation, withdrawal, tolerance, loss of interests, deception and escape. Billieux et al. argued that tolerance as a criterion may be hard to conceptualize as well as operationalize and is at risk of neglecting that increased usage of games as a putative addictive behaviour might result from motives that are unrelated to tolerance (Billieux et al., 2015).

Considering disordered gambling as another condition embedded in DSM5 and ICD-11 as well as other specific IRAB such as disordered social media use, online pornography use or online shopping, pretty much the same applies as to disordered gaming assessment. Despite sufficient availability of assessment tools (with some of them showing promising psychometric properties), according to respective reviews, a gold standard has not yet been met largely due to lacking validations with diagnostic interviews (for gambling see (Otto et al., 2020), for social media use see (Kuss and Griffiths, 2017), for online pornography use see (de Alarcon et al., 2019), for online shopping see (Müller et al., 2017)).

Aiming for a gold standard of psychometrically sound fully-structured diagnostic interviews and screening tools for gaming and gambling disorders, the WHO established the *WHO Collaborative Project on the Development of New International Screening and Diagnostic Instruments for Gaming Disorder and Gambling Disorder* in 2017 to provide an international framework for health professionals and epidemiologists in order to strengthen consensus, significance and comparability across studies (Carragher et al., 2022).

1.7 Prevalence estimates of Internet Addiction and their pitfalls

Prevalence estimations may support the evaluation of prevention and treatment demand and are therefore an important foundation for policy planning. Considering the increasing concern expressed about the extent of DMD and internet use among young people, solid prevalence estimates are particularly important in order to provide an evidence-based indication of the problem's extent.

Numerous epidemiological studies on IA and its associated specific forms including those of multiple countries from Asia, Europe, America and Oceania have been published (summarised in two recent reviews and meta-analyses (Lozano-Blasco et al., 2022b, Pan et al., 2020)). The meta-analysis by Pan et al., 2020 (Pan et al., 2020) included 113 epidemiological studies (75% of the studies were representative samples) with almost 700,000 subjects from 31 countries. The study found a pooled prevalence of generalized internet addiction to be 7%, with individual studies reporting estimates ranging between 1 and 40%. The pooled prevalence of IGD was 2.5%. The meta-analysis by Lozano-Blasco (Lozano-Blasco et al., 2022b) indicates significant differences of IA by age with younger people showing more addictive patterns in their internet use. Adolescents and young adults are consistently reported as the target group with the highest prevalences (Nakayama et al., 2017, Mihara and Higuchi, 2017, Lozano-Blasco et al., 2022b). It should be noted that the single studies included in the meta-analysis by Pan et al. (Pan et al., 2020) did not reflect the burdens due to the COVID-19 pandemic in many countries, which contributed to high and increasing rates of IRAB among adolescents as shown in three studies in Germany. Paulus et al. (Paulus et al., 2022) indicate a prevalence rate of 43.7% for problematic internet use among students in secondary schools. Results by Werner et al. (Werner et al., 2021) among university students as well as Neumann and Lindenberg (Neumann and Lindenberg, 2022) among students in secondary schools are based on two cross-sectional waves each (before and during the COVID-19 pandemic) and they showed a doubling of the IRAB prevalence each (from 3.9 to 7.8% according to Werner et al. and from 7.1% to 14.8% according to Neumann and Lindenberg). Increased prevalence rates have also been reported in Asia. Fung et al. (Fung et al., 2021) showed increasing rates of problematic smartphone use within a three-wave longitudinal study among students in primary schools in China. Another cross-sectional study based on stratified cluster-sampling in Taiwan indicated a prevalence of IRAB of around 25% among junior high school students (Lin, 2020). To the best of the authors' knowledge, no recent population-representative data regarding IRAB are available in Austria.

A number of the published studies have focused on prevalence estimates while also identifying risk and protective factors associated with this phenomenon. The majority of these studies are cross-sectional and a considerable amount of them suffer from methodological limitations, such as impaired validity as indicated in a recent review and meta-analysis on IA in young adults: *"The criteria of methodological rigor and measurement instruments led to the exclusion of most of the studies. The main error detected was either the absence of standardized instruments or the incorrect measurement of the study parameters according to the pre-established psychometric test."* (Lozano-Blasco et al., 2022b, p. 2-3). Another systematic review (Moreno et al., 2011) examined the quality of research on problematic internet use among US-adolescents till 2010. Quality assessment was based on the *Strengthening the Reporting of Observational Studies in Epidemiology (STROBE)*-statement (von Elm et al., 2007). On average the included studies scored low on the STROBE-based quality review tool (on average 23 out of 42 possible points) which is why the authors recommended a very cautious interpretation of the yielded prevalence rates.

The shown limitations increase random and systematic error, bias estimates and thus negatively impact epidemiological research of addictive behaviours in general and thus also IRAB (Rumpf et al., 2019, Király and Demetrovics, 2021). Of course, the observed shortcomings do not only negatively affect the validity and reliability of single studies, but also of reviews and meta-analyses which are based on them. Common shortcomings, negatively impacting the studies' validity, are partially summarized by Rumpf et al. (Rumpf et al., 2019) as well as Király and Demetrovics (Király and Demetrovics, 2021) and include:

- Inappropriate non-probability sampling models (cf. (Lozano-Blasco et al., 2022b)) that heavily negatively affect representativeness and thus generalizability. However, it should be noted that the meta-analysis by Pan et al. (Pan et al., 2020) showed that prevalence rates were not moderated by sample representativeness, neither for generalized internet addiction (β = -0.027; p = 0.119) nor for IGD (β = 0.006; p = 0.807).
- Small sample sizes that do not account for low disease rates and negatively affect effect sizes
- Screening instruments lacking robust and agreed-upon conceptual foundations and diagnostic criteria, as well as inadequate cut-off scores that are not validated based on structured diagnostic interviews as a gold standard (Maraz et al., 2015). Even in case of meta-analyses including studies that used well-established measures, the huge variety of applied instruments, conceptions and cut-off scores poses a problem related to comparability and pooling.
- Lacking positive predictive value of many screening tools causing misclassification of positively screened individuals (Maraz et al., 2015).
- Over- and under-reporting in self-reporting instruments as already mentioned in ☛section 1.6 is a serious issue. Jeong et al. (Jeong et al., 2018) compared diagnostic results from self-reports based on the Internet Gaming Disorder Questionnaire (IGDQ), which is a self-report form of the Structured Clinical Interview for DSM-5 IGD (Koo et al., 2017), and blinded clinical diagnostic interviews for IGD as a widely agreed-upon gold standard and yielded a high false-negative rate of the IGDQ-measure of 44% and a false-positive rate of 9.6% in an adolescent sample (Jeong et al., 2018).
- Another problem that may yield overestimated prevalence rates is mischievous responding discussed in Przybylski's article (Przybylski, 2016), who identified a rate of 2.3% of mischievous responders in a young adult sample by including a sham item in his questionnaire. Mischievous responding was higher among male participants who reported more indicators for IGD which would lead to overestimated prevalences without appropriate corrections. For example, self-reported gender identity was shown to be biased based on mischievous responding among adolescents: Robinson-Cimpian (Robinson-Cimpian, 2014) detected 40% of individuals assigning themselves a self-reported transgender identity as suspicious for mischievous

responding, whereas this rate was only 1.5% among individuals assigning themselves a cisgender identity.

- With these issues in mind, it is heavily criticized (Király and Demetrovics, 2021) that lots of studies solely based on screenings report prevalence rates as a true estimate of the proportion of clinically relevant individuals and also label them according to DSM- or ICD-terminology. Prevalence estimates based on structured diagnostic interviews are scarce.

In order to strengthen the quality of epidemiological research on the issue of behavioural addictions, some collaborations have been established to set harmonizing standards related to methodological issues (Rumpf et al., 2019). In this regard, Fineberg et al. for example, mention the *European Network for Problematic Usage of the Internet* as part of an action of the *European Cooperation in Science and Technology* (COST) (Fineberg et al., 2018). Another measure to improve the quality of studies may be the mandatory implementation of criteria of the STROBE-statement (von Elm et al., 2007) in scientific journals.

1.8 Conceptual frameworks and risk factors of Internet Addiction

In epidemiology, the term risk *"… refers to the likelihood, or in statistical language probability, of an individual in a defined population developing a disease or other adverse health problem."* (Bhopal, 2016, p. 220). Accordingly, a risk factor is a certain condition that increases the likelihood of developing a specific impairment or disease. The study of risk factors therefore implies knowledge about causality and directionality (if a certain risk factor x is present, then a certain impairing health condition y results and not vice versa, assuming that all other variables other than x or y are held constant). Claims about causality and directionality require evidence generated from studies that are suitable to address covariation, temporal order and non-spuriousness as recognized criteria to establish causality (Hayes, 2022) with experimental studies such as randomized controlled trials as a gold standard.

The literature of the current research topic is largely dominated by cross-sectional studies. For example, a recent review of peer-reviewed publications on IA between 2010 and 2019 yielded a rate of 86% of all included studies being cross-sectional, 6% were cohort or case-control studies and 8% longitudinal studies (Duong et al., 2020). A similar massive overrepresentation of cross-sectional studies was observed in a meta-analysis covering publications on IA among adolescents between 2002 and 2017 (Fumero et al., 2018). The dominance of cross-sectional study designs are mirrored in a dominance of correlational findings that are not able to contribute to causal and directional claims. However, such claims are crucial for a better understanding of the mechanisms involved in the development and maintenance of IRAB and for designing effective preventive and (early) interventive treatment measures. Billieux (Billieux, 2012, p. 5) put it in a nutshell when he stated *“For example, an alternative explanation to the established link between self-esteem and dysfunctional mobile phone use could be that negative outcomes resulting from exaggerated use of the mobile phone (e.g., financial problems) have a negative impact on self-esteem*.” To carry on this idea, preventive measures focussing on the promotion of self-esteem of adolescents are indeed essentially a worthwhile endeavour, but might be ineffective in that particular issue of reducing dysfunctional mobile phone use since it might fail to address its real cause. Without unravelling directional questions, bidirectional paths have to be assumed, which are indeed theoretically justified as depicted in Brand et al.’s I-PACE model (Brand et al., 2016) discussed in ☛section 1.8.1. Addictive behaviours are basically characterized as co-morbid phenomena with massive interaction and moderation of the involved intra- and inter-personal as well as environmental factors. Therefore, we have to assume that the linkage between two variables x and y causally go from x to y for a specific subgroup of adolescents, while the causal path goes vice-versa for another subgroup. However, not moving beyond bidirectionality also results from cross-sectionalism in this research-field. As a result, many authors have repeatedly emphasized the significant need for promoting research based on suitable study designs to gain solid knowledge about the causes and consequences of this phenomenon (Lam, 2014, Odgers and Jensen, 2020, Rumpf et al., 2019, Anderson et al., 2017b, Mihara and Higuchi, 2017, Zhuang et al., 2023).

Since the data the current thesis is based on is also cross-sectional, the following summary of research findings on risk and protective factors of IRAB and IA is, whenever possible, primarily driven by longitudinal studies as well as reviews and meta-analyses of longitudinal studies. Since the data per se do not justify causal claims, conceptual frameworks may support directional interpretations of the yielded associations.

1.8.1 Conceptual frameworks

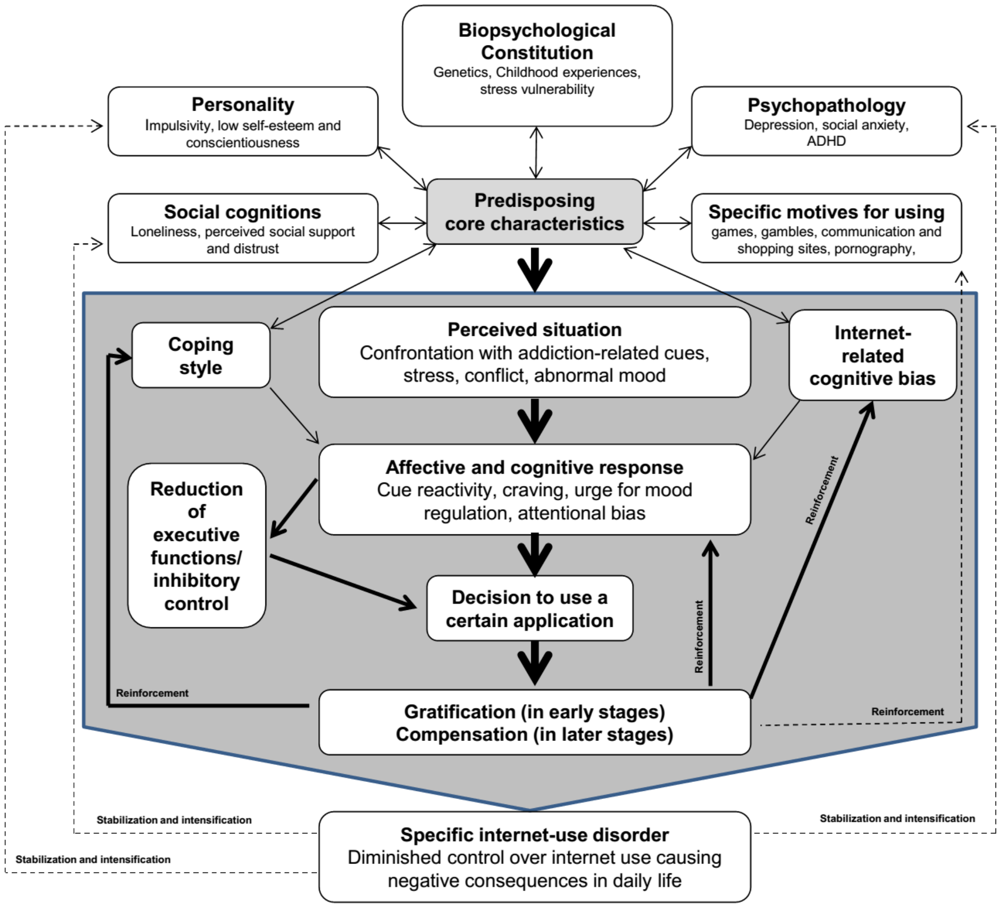
Several models and frameworks have been established to explain the development and maintenance of IRAB over the past 30 years. An early and generally addiction-based model was established by Griffiths (Griffiths, 2005) referred to as *the component model of addiction*, which is also applicable to addictive behaviour and lists

- salience (addictive activity dominates thinking, feeling and behaviour),
- mood modification (engaging in addictive activity to destress or escape from unpleasant moods),
- tolerance (requiring increasing amounts of the addictive activity to achieve the desired effect),
- withdrawal symptoms (unpleasant feelings due to disruption or reduction of the addictive activity or inability to engage in),
- conflict (inter- and intrapersonal conflicts due to concerns about the addictive activity) and finally
- relapse (tendency to reverse to patterns of addictive activity even after long periods of abstinence) as common symptoms.

Although this model is considered quite influential as it represents a kind of inspiring symptom-driven template for developing assessment instruments, it does not provide an idea about the developmental mechanisms of addictive processes (Young and Brand, 2017). General neurobiologically-driven explanatory models of addictive processes that account for both substance-use disorders as well as addictive behaviour such as the *reward deficiency syndrome* (Blum et al., 1996), the *incentive sensitization theory* (Robinson and Berridge, 1993), the model of *impaired response inhibition and salience attribution* (iRISA) (Goldstein and Volkow, 2011) have been established (see ☛section 1.5).

One of the first models driven by psychological mechanisms to explicitly explain IUD is referred to as the *cognitive-behavioral model of pathological internet use*, proposed by Davis (Davis, 2001). The model is based on internet-specific maladaptive cognitions moderated by psychopathological predispositions, such as depression or social anxiety as well as reinforcing situational cues, to play an essential role in developing and maintaining IUD. Maladaptive cognitions and social isolation subsequently promote pathological patterns of generalized or specific pathological internet use resulting in behavioural symptoms which in turn close the vicious circle to maladaptive cognitions. Models focussing on specific pathological internet use have also been established for disordered gaming. A well-recognized model in that course is the *cognitive-behavioral model of internet gaming disorder* by Dong and Potenza (Dong and Potenza, 2014) which includes cognitive, motivational, and decision making aspects. They centre immediate reward-seeking motivation, which interacts with decision making processes and which is affected by executive control, the need for stress reduction and reward sensation to explain addictive gaming patterns processes that further enhance reward sensation and inhibit executive control. Partly based on these former models, Brand et al. (Brand et al., 2016) introduced the currently most recognized *interaction of person-affect-cognition-execution model (I-PACE)* to explain the process of developing and maintaining specific IRAB related to communication, gambling, gaming, pornography use and shopping (see ☛Figure 3).

Figure 3: I-PACE model by Brand et al., 2016



Note: Reproduced without adaptation from Brand et al. (Brand et al., 2016, p. 255), published under the terms of the Creative Commons Attribution-NonCommercial-No Derivatives License (CC BY NC ND) and used with kind permission of the Copyright Clearance Center on behalf of Elsevier Ltd. (see ☛Appendix D).

According to the I-PACE model, specific internet-use disorders arise from interactions of individual core characteristics (biopsychological and psychopathological vulnerabilities, personality aspects such as impulsivity or low conscientiousness, social cognitions such as loneliness or social support and specific motives for using games, gambles, social media, pornography, or shopping facilities online) and neurobiological aspects as well as moderating variables (coping style, cognitive biases related to the internet) and mediators (affective and cognitive responses causing cue reactivity and craving combined with impaired impulse control). Conditioning processes strengthen these linkages as the addictive process progresses. As such, the I-PACE model encompasses predisposing, moderating and mediating variables and is suggested to influence therapy by grasping the role of modifiable variables (Young and Brand, 2017).

Another model introducing attributes of specific internet elements was introduced by Douglas et al. (Douglas et al., 2008), named *Internet Addiction Model* (IAM). The model differentiates between *push factors* (psychological motivations and needs to use certain areas on the internet such as escapism or compensating for unpleasant feelings) and *pull factors* (certain characteristics of the internet and its associated applications with inherent addictive potential, such as communication facilities or applications to engage in gaming, gambling or pornography, but also affordability due to the low costs). The IAM assumes that *pull factors* moderate the linkage between psychological motivations and needs (*push factors*) and adverse outcomes of excessive engagement on the internet.

A model that goes beyond the focussed consideration of intrapersonal aspects was introduced by Bronfenbrenner and is referred to as the ecological system theory (Bronfenbrenner, 2000). The model provides a holistic framework for the understanding of human development as it emphasizes the interrelations of individuals and their environments at several levels: (1) the microsystem, including family, peers, school and neighbourhood having the most direct, immediate and influential impact on individuals, (2) the mesosystem, involving relations between microsystems, for example, adolescents' school experiences impacting family life and vice versa, (3) the exosystem, consisting of external environments that may directly or indirectly affect individuals such as governmental policies and media, (4) the macrosystem, including the broader sociocultural context in which individuals are embedded including laws, societal norms and values, and finally (5) the chronosystem, reflecting time and changes encompassing the individual adolescent's history including experiences like parental divorce, relocation as well as sociohistorical events. In the context of the examination of IA parts of the model have been applied (e.g. (Hsieh et al., 2021)) driven by the endeavour to understand addictive behaviour as the result of an individual's experiences, which were gained in the interplay of all dimensions. In their 3-wave longitudinal study Hsieh et al. showed that, apart from intrapersonal and behavioural aspects, environmental characteristics such as community violence, neglect and negative school experiences contribute to the development of IA. Consequently, for future studies they suggested to take a more holistic view and consider *"… the whole interconnected system rather than just the behavior itself …"* (Hsieh et al., 2021, p. 11).

According to the I-PACE model by Brand et al. (Brand et al., 2016) and Bronfenbrenner's microsystem of his ecological system theory (Bronfenbrenner, 2000), the current state of research on the associations of IRAB with internet use patterns, personality aspects, psychopathologies as comorbidities, sociodemographic and psychosocial aspects as well as characteristics of the family environment is discussed below.

1.8.2 Internet use patterns

Internet use is obviously related to IRAB since it is the constitutive foundation of developing addictive use patterns. Their influential importance in the course of developing IRAB has been noted in several reviews (Anderson et al., 2017b, Kuss et al., 2014). Some aspects of internet use patterns have been shown to increase the risk to tip over into IRAB.

Usage time is of course strongly linked to IRAB, since loss of control and the development of tolerance and thus the associated increase in utilization is a constitutive aspect of addiction per se. Therefore, increased utilisation time is considered a relevant outcome of IRAB as shown in a longitudinal study by Lemmens et al., in which higher scores of addictive gaming at baseline predicted higher gaming time at follow-up (Lemmens et al., 2011a). On the other hand longitudinal evidence was shown for utilization time predicting IRAB in a systematic review (Mihara and Higuchi, 2017) and in a meta-analysis (Zhuang et al., 2023), thus a bidirectional relation can be assumed. Usage time, in turn, is of course also related with the growing ease of availability and accessibility of DMD and the internet as part of various digitisation initiatives in recent years (World Health Organization, 2015).

Specific internet-based applications have been found to increase the risk of addictive derailment. Online gambling and online gaming are evidenced by their inclusion in both manuals of psychiatric disorders DSM-5 and ICD-11. Additionally social media use, pornography use, and shopping are most commonly considered in this context (Brand et al., 2020, Rumpf et al., 2021).

The age of onset of regular internet use is discussed as a relevant risk factor for establishing IRAB. Associations of IRAB and earlier initiation of regular internet use were shown in cross-sectional studies (Tsitsika et al., 2014, Koyuncu et al., 2014). A large scale dataset retrieved from the *Programme for International Student Assessment* (PISA) from 2018 including more than 300,000 school students aged 15 or 16 years from 52 countries showed earlier initial age of internet use to be associated with heavy internet use, regardless the geographical area (López-Bueno et al., 2023). Analogue, problematic gaming and earlier initial age of regular gaming onset were shown to be associated (Nakayama et al., 2020, Beard et al., 2017, Rho et al., 2017). In line, a study focussing on early engagement in social media showed that the earlier usage of Instagram or Snapchat (two highly prominent social networks among adolescents) was initiated, the more problematic digital behaviour emerged. Moreover, the detrimental effect of early exposure was mitigated by parental restriction

(Charmaraman et al., 2022). Moreover, longitudinal evidence of the association of IRAB and earlier initiation of internet use was recently shown by Kim et al. (Kim et al., 2023). Although the evidence from previous studies seems to be quite convergent, to the best of the author’s knowledge the age of onset has not been considered in meta-analysis on IRAB yet.

Using DMD as a pre-sleep activity is a widespread routine among adolescents (Hale et al., 2018, Lederer-Hutsteiner et al., 2024) that delays bedtimes (Hale and Guan, 2015, Lederer-Hutsteiner et al., 2024). Delayed bedtimes even extends past midnight, which occurs to a considerable extent, is linked to insomnia and mediates the relation of IRAB and insomnia (Lederer-Hutsteiner et al., 2024). Finally, late-night internet use was found to be positively linked to IRAB as shown in a cross-sectional study among students aged 16–18 years (Nalwa and Anand, 2003).

1.8.3 Personality traits

Personality traits as largely universal, stable and time-invariant aspects that shape the ways an individual perceives, feels, thinks and acts (McCrae and Costa, 1997) are considered as relevant predisposing risk factors of addictive behaviour in general. While this link has been studied broadly, for example, related to addictive smoking or alcohol use, the association to IRAB has been examined to a lesser extent (Müller et al., 2013). Steadily consistent associations of IRAB have been shown with high neuroticism, high impulsivity, low conscientiousness and high shyness (Brand et al., 2016). In line, low social skills jointly with self-esteem and loneliness predicted IGD in a two-wave longitudinal study with a six month follow-up among Dutch adolescents (Lemmens et al., 2011b). All factors were confirmed in a recent meta-analysis of longitudinal studies on IGD, which also added extraversion and agreeableness as significant protective factors (Zhuang et al., 2023). Lower extraversion, agreeableness and conscientiousness as well as higher neuroticism have also been shown as risk factors of IGD in a series of five meta-analysis, each focussing on one of the five personality traits (Chew, 2022).

These findings were confirmed in a systematic review of longitudinal studies on general problematic internet use among adolescents in terms of neuroticism, social skills, self-esteem and loneliness, but opposed in terms of extraversion since higher amounts of this trait were related to more problematic internet use (Anderson et al., 2017b). This result supposes specific personality profiles depending on the specific online behaviour. Indeed, in a study comparing personality traits and their associations with addictive internet use in general, addictive gaming and addictive social networking showed higher neuroticism and lower conscientiousness to be specifically related to general addictive internet use, lower conscientiousness und lower openness to be specifically related to addictive gaming and higher extraversion and higher neuroticism related to addictive use of social networks (Wang et al., 2015).

1.8.4 Comorbid symptoms

Mental comorbidities to IRAB, in particular depression, generalized anxiety and social phobia and attention deficit disorder (with or without hyperactivity) have been consistently shown in many studies, reviews and meta-analyses (Ho et al., 2014, Carli et al., 2013, Zhuang et al., 2023, Busch and McCarthy, 2021) and consequently constitute a rather valid linkage. Other mental health disorders such as autism spectrum disorder (Heffler et al., 2020, Ruckwongpatr et al., 2022) or obsessive-compulsive disorder (Andreassen Schou et al., 2016) have also been linked to early-life exposure to digital media and IRAB, respectively. However, it was shown that the strengths of the association of digital media use and mental health issues heavily depends on how specifically digital media use is mapped in the analysis. A highly recognized paper showed a negative significant, albeit negligibly tiny linkage without any practical relevance when mapping for digital media use generally (Orben and Przybylski, 2019). However, a replication based on the same dataset and statistical approach found a much stronger negative linkage of mental health issues specifically related to social media use among female adolescents (Twenge et al., 2022).

Regarding directionality, both directions have been identified. With respect to depression several studies have been carried out showing consistent findings in terms of relatedness of depression and IA but inconsistencies regarding the directionality of the causal effect. A longitudinal study involving a random-intercept cross-lagged panel among Chinese middle school students indicate a unidirectional relationship of depressive symptoms at an earlier point in time predicting internet addiction at a later point in time, but not vice versa. The effect was found to be more pronounced among males and moderated by positive coping strategies (Yi and Li, 2021). On the other hand, a cross-lagged panel among Chinese university students showed a bidirectional association (Yang et al., 2022). Considering attention deficit disorder, meta-analyses solely including observational studies have shown a clear link between attention deficit and hyperactivity and IA (Wang et al., 2017, Augner et al., 2023). A recent longitudinal study across three waves among Chinese adolescents revealed a bidirectional association of attention deficit and hyperactivity and IA with no gender differences regarding these relations (Wang et al., 2024). Conversely, a 2-year prospective study among junior high school students in Taiwan (Ko et al., 2009) showed a unidirectional link with ADHD being the strongest predictor of IA among a set of psychiatric symptoms such as depression and social phobia. Regarding conduct problems reflected by aggressive and/or antisocial behaviour, associations to IRAB have been identified in several studies as depicted in a systematic review of epidemiological research on IA (Kuss et al., 2014). Since the vast majority of the included studies were cross-sectional, causal and directional claims could not be addressed. A more recent systematic review focusing on conduct problems and their linkages with problematic gambling and gaming also shows a consistent association of conduct problems with both problematic gambling and gaming. Considering longitudinal effects (19 of the included 71 studies were longitudinal) the authors summarize that the evidence for conduct problems as a risk factor was clearer for problematic gambling than problematic gaming (Richard et al., 2020). Conversely, a meta-analysis by Greitemeyer and Mügge including 98 studies with a total of 36,965 participants showed the linkage of playing video games and prosocial behaviour to be moderated by the games' content. Violent content increased aggressive behaviour and prosocial content increased prosocial behaviour (Greitemeyer and Mügge, 2014).

With respect to sleep disorders a number of meta-analyses provide solid evidence of a close relation between IRAB and sleep impairments (Alimoradi et al., 2019, Li et al., 2020, Zhang et al., 2022a). In parts, disordered sleep is also explained by the widespread adolescent routine of using DMD at bedtime as a pre-sleep activity or even after midnight (on a subsequent school day), negatively impacting both sleep quantity and sleep quality (Brautsch et al., 2022, de Sa et al., 2023, Hale and Guan, 2015, Lund et al., 2021, Lederer-Hutsteiner et al., 2024). Evidence related to directional questions of the linkage of IRAB and impaired sleep was found in a meta-analysis based exclusively on longitudinal studies by Pagano et al., 2023 (Pagano et al., 2023), indicating a negative association of utilization time of DMD preceding sleep health but not vice versa. On the other hand, the meta-analysis also showed a negative association of sleep health preceding dysfunctional use of DMD at a later point in time. The already cited meta-analysis by Zhuang et al., 2023 based exclusively on longitudinal studies indicates a moderate pooled association for depression, anxiety and attention deficit being antecedents of IGD (Zhuang et al., 2023). On the other hand, Gentile et al., 2011 (Gentile et al., 2011) conclude that depression and anxiety acted as outcomes of pathological gaming in their two-year longitudinal study among elementary and secondary school students in Singapore. In summary, regarding the interplay of psychological/psychiatric comorbid symptoms and IRAB issues of directionality seem to be complex and by no means straightforward as concluded by Anderson et al., 2017 (Anderson et al., 2017b) in their systematic review of longitudinal studies showing evidence of a bidirectional relation between problematic internet use and mental health in general.

Corresponding bidirectionality is also suggested in Brand et al.'s I-PACE model (Brand et al., 2016) (see ☛section 1.8.1), in which predisposing psychopathologies channel IRAB, which in turn feeds back to psychopathologies and reinforces them.

1.8.5 Sociodemographic aspects

Regarding age, synthesized data from meta-analyses and findings from reviews conclude that the vast majority of studies highlight adolescents and young adults as more vulnerable for IRAB since high prevalences and younger age are widely associated (Nakayama et al., 2017, Mihara and Higuchi, 2017, Lozano-Blasco et al., 2022b). The same holds true within studies focusing on adolescents explicitly, as shown in a recent meta-analyses displaying younger adolescents as the most vulnerable for developing IRAB (Lozano-Blasco et al., 2022a).

Research on gender differences in IRAB is generally challenged by a potential confounding with cultural aspects (Chen et al., 2017, Kuss et al., 2014), higher problem awareness among female subjects (Liu et al., 2011) and also inconsistent measurement approaches (sex vs. gender, dimensionality issues). Although most authors argue that gender per se does not add any contribution in explaining addictive behaviour (Lozano-Blasco et al., 2022a), a systematic review of epidemiological research on IRAB from 2014 concludes that male adolescents clearly showed higher prevalences of IRAB than female adolescents (the same result applied to adults) (Kuss et al., 2014). Several mediators of the relationship between gender and IRAB have been suggested such as socio-emotional needs (Lozano-Blasco et al., 2022a) or specific online applications such as online gaming and pornography which are prone to dysfunctional use and typically preferred by male subjects (Kuss et al., 2014). The above-mentioned overrepresentation of male subjects regarding IRAB may be biased by the fact that the review by Kuss et al., 2014 only included studies till 2013, when social media, typically preferred by female adolescents, did not play such an important role in adolescents' internet use as it does nowadays. A review on addictive behaviour in social networking sites concludes that female adolescents show higher or similar prevalences than male subjects (Kuss and Griffiths, 2017). Another systematic review, carried out four years later, by Busch and McCarthy indicate that female subjects are more vulnerable for problematic smartphone use than males, although they also note inconsistencies of the corresponding results (Busch and McCarthy, 2021). To put it in a nutshell, it seems that gender differences regarding IRAB in general seem to be levelling out, but may be present in specific applications.

With regard to the relation between variables that constitute socioeconomic status such as parental level of education or family income and IRAB, research findings seem to have changed over time. While a review from 2014 outlines an association of IRAB among adolescents from families with higher levels of income (Kuss et al., 2014), a more recent meta-analysis of IA among adolescents from 2022 (Lozano-Blasco et al., 2022a) notes inconsistent findings and highlight studies with positive and negative associations. It is plausible to assume that this levelling is related to progresses in narrowing the digital divide as income still influences accessibility to internet use (Paccoud et al., 2021), but has become less decisive (Arellano et al., 2016).

Consequently, among sociodemographic aspects age, gender and socioeconomic status are taken into account within this thesis.

1.8.6 Psychosocial aspects

Psychosocial aspects reflecting intra- und inter-personal characteristics and their relations to IRAB are among the most researched aspects in the field of interest (Kuss et al., 2014, Zhuang et al., 2023). Meta-analyses on that issue showed, that personal factors are more closely related to IRAB than social factors (Fumero et al., 2018, Koo and Kwon, 2014).

Boredom has been discussed in reviews (Kuss et al., 2014), has been explored in meta-analyses focussing on that specific issue (Camerini et al., 2023), and was found as a mediator of the relation between symptoms of depression as well as anxiety and problematic smartphone use (Elhai et al., 2018). The relation of proneness to boredom to IA in turn has been shown to be fully mediated by attentional bias (focussing and maintaining attention to cues associated with addictive behaviour (Field and Cox, 2008)) towards triggers of social media (Cannito et al., 2023).

Self-esteem is a highly evidenced protective factor of IRAB as shown in reviews (Kuss et al., 2014), but also in a meta-analysis exclusively based on longitudinal studies (Zhuang et al., 2023). Since measures of self-esteem are not included in the dataset used within this thesis, self-efficacy is used as an evidenced proxy-variable as indicated by Lane et al. (Lane et al., 2004) and Stroiney (Stroiney, 2005). However, self-efficacy was also shown to be a significant protective factor of IA in a meta-analysis by Koo and Kwon (Koo and Kwon, 2014).

General social support is another protective factor clearly shown in a meta-analysis exclusively investigating this variable and its relation to IA (Lei et al., 2018), but also in Zhuang et al.'s meta-analyses based on longitudinal studies (Zhuang et al., 2023). Lacking social support has also been shown to impact adolescents' emotional dysregulation, which in further consequence was positively linked to IA (Mo et al., 2018). Moderating effects of the association of social support and IA by gender are inconsistent. While the study by Mo et al. (Mo et al., 2018) showed a stronger linkage among female adolescents, the meta-analysis by Lei et al. (Lei et al., 2018) indicated the opposite effect. Parental support was shown to be negatively related to IRAB in a Chinese middle school sample involving 966 participants (Li et al., 2014). In contrast, a recent Australian large-scale 4-year longitudinal study involving four survey waves showed a positive association of adolescents' perceived parental support and IRAB over time. This result was also surprising for the authors, who speculated *"… that refraining from mediation may be popular with youth and even lead them to perceive their parents as being more supportive. However, parental refraining is associated with increased CIU [compulsive internet use]"* (Donald et al., 2024, p. 308). Peer relationship was also negatively associated with small effect size with IRAB, as shown in Zhuang et al.'s meta-analyses based on longitudinal studies (Zhuang et al., 2023). Conversely, the Australian longitudinal study did not yield any evidence to suggest a corresponding relation (Donald et al., 2024).

Prosocial behaviour defined as the intention to benefit others voluntarily while avoiding antisocial and aggressive behaviour (Martí-Vilar et al., 2019) has been negatively linked to problematic internet use in cross-sectional studies (Guo et al., 2021) as well as to IGD (Lemmens et al., 2015), indicating either a protective effect on or a detrimental result of IRAB. On a longitudinal level a meta-analysis showed a moderate effect of aggression predicting IGD (Zhuang et al., 2023). A randomized control trial also highlights the importance of the screen content used as the authors conclude that *"… intervention to reduce exposure to screen violence and increase exposure to prosocial programming can positively impact child behavior."* (Christakis et al., 2013, p. 431). In line and already mentioned before, a meta-analysis including cross-sectional, longitudinal and experimental studies concludes that violent content in video games increase aggressive behaviour and prosocial content increase prosocial behaviour (Greitemeyer and Mügge, 2014).

School climate was shown to account for IGD, as it was negatively associated with the extent of IGD-symptoms and mediated by maladaptive cognitions related to internet use in a Chinese sample of 1,164 school students aged 14 to 25 years (Zhang et al., 2022b).

Finally, it should be noted that loneliness would be another characteristic of interest to be included. The association of loneliness and IA has been confirmed in meta-analyses exclusively focussing on that specific linkage (Ge et al., 2023, Wang and Zeng, 2024). Since the vast majority of included studies were cross-sectional, the issue of directionality remains unclear. Considering causality a longitudinal study showed a bidirectional relation of loneliness and IA (Tian et al., 2021). Unfortunately, the dataset used within this thesis does not include any specific measures on loneliness.

1.8.7 Family environmental aspects

Most theories and empirical research related to IRAB predominantly involve measures on individual level such as comorbidities or personality traits. This is partly justified by findings from meta-analyses which indicate that intrapersonal aspects show stronger relations to IRAB (Fumero et al., 2018) and IGD (Zhuang et al., 2023) than interpersonal and environmental characteristics. However, these findings may be biased by an under-examination of interpersonal and environmental aspects in that context as noted in a systematic review of longitudinally research trends on problematic internet use among adolescents (Anderson et al., 2017b). Considering health determinants for example, according to Bronfenbrenner’s ecological systems theory (Bronfenbrenner, 2000) or according to Dahlgren and Whitehead’s model of health determinants (Dahlgren and Whitehead, 1991), it becomes obvious that individuals’ health is influenced by several higher order layers outside of their psychobiological constitution and specific lifestyles or rather massively interact with them such as social and community network, living, educational and working conditions as well as general political, socioeconomic and cultural conditions at a macro level. Thus, it is likely that, for example, the cultural framework and community environment an individual is embedded in contribute to well-being and mental health and therefore also to addictive processes. Community environment has been shown as a significant correlate of IGD in a meta-analysis by Ji et al. (Ji et al., 2022). A regional and thus presumably also cultural effect was shown in Zhuang et al.’s meta-analysis of longitudinal research on IGD indicating that depressive symptoms predicted IGD more strongly among Asian populations than non-Asian ones (Zhuang et al., 2023).

With respect to the dataset used within this thesis, only small contributions can be provided to an understanding of environmental associations with IRAB as just a few measures such as parental regulative rules and parental amount of DMD-usage were included.

Regarding parental regulative rules as a potential framework for adolescents’ internet use, inconsistent findings have been carried out. A large scale study among 25 European countries involving about 19,000 adolescents between 11 and 16 years showed restrictive parental mediation to be related with lower excessive internet use of their children (Kalmus et al., 2015). In line, a Korean study showed parental rules to be associated with reduced online time, particularly among adolescents showing low self-control. However no association was found with respect to IRAB (Lee, 2013). This was also confirmed in Zhuang et al.'s meta-analysis based on longitudinal studies for IGD (Zhuang et al., 2023). Another meta-analysis focussing on the relation of problematic internet use and parenting also showed a similar effect (Lukavska et al., 2022). Restrictive parental mediation was shown to generally positively affect adolescents' internet use, but was in no overall association with excessive internet use patterns. The linkage between restrictive parental mediation and excessive internet use patterns was also moderated by adolescents' age with older individuals showing more excessive use the more restrictive parental mediation has been. However, it remains unclear if parental rules are the cause of excessive use patterns among children or vice-versa, in the sense of a parental interventional measure.

The extent of parental DMD usage has been shown to be very closely related to children's screen time in a study of 2,965 Portuguese families (Jago et al., 2012).

1.9 Research questions

To the best of the author's knowledge, no population-representative and up-to-date epidemiological database regarding the phenomenon of IRAB is available in Austria. However, service providers within the healthcare and youth work system, at least in Styria, report a rise in requests for counselling related to excessive use of DMD or the internet, mostly from concerned parents. Thus, the extent of this phenomenon, the contribution of specific use patterns and applications and the associated intrapersonal, interpersonal and environmental correlates remain unclear. This lack of knowledge considerably limits health and addiction policy planning processes both at the levels of prevention and treatment.

1.9.1 Characteristics of DMD and internet use

According to ☛section 1.8.2 several characteristics of DMD and internet use such as availability, accessibility and usage time (World Health Organization, 2015, Mihara and Higuchi, 2017, Zhuang et al., 2023, Lemmens et al., 2011a), specific DMD like smartphones and internet applications like social media use, gaming, gambling, shopping, or pornography use (Rumpf et al., 2021, Brand et al., 2020), bedtime use (Lederer-Hutsteiner et al., 2024, Nalwa and Anand, 2003) as well as the initial age of engaging in regular DMD and internet use (Tsitsika et al., 2014, Koyuncu et al., 2014, López-Bueno et al., 2023, Nakayama et al., 2020, Beard et al., 2017, Rho et al., 2017, Charmaraman et al., 2022) have been consistently reported as being associated with IRAB. Population-representative data on these issues are not yet available in Austria, limiting an estimation of the overall extent of these usage patterns overall and of sociodemographic subgroups specifically. Sociodemographic differentiation is carried out by gender, age and socioeconomic status throughout all analyses to provide a foundation for target-specific and tailored prevention policies.

- Research question 1: Which and how many DMD do school students own and how does this differ across sociodemographic subgroups?
- Research question 2: Which DMD are dominant in usage among school students and how does this differ across sociodemographic subgroups?
- Research question 3: Which internet applications are dominant in usage among school students and how does this differ across sociodemographic subgroups?
- Research question 4: How much leisure time do school students spend with DMD and how does this differ across sociodemographic subgroups?
- Research question 5: To what extent are DMD integrated in bedtime routines among school students and how does this differ across sociodemographic subgroups?
- Research question 6: What is the initial age of engaging in internet use and how does this differ across sociodemographic subgroups?

1.9.2 Prevalence estimation

According to ☛section 1.7, population-representative prevalence estimates on the issue of IRAB are generally scarce (Rumpf et al., 2019, Király and Demetrovics, 2021) and not yet available on a current database in Austria. This lack of valid data severely restricts the planning of evidence-based prevention and treatment resources, which may be indicated since several studies showed sharply rising prevalence rates in course of the restrictions of the COVID-19 pandemic, for example in Germany (Paulus et al., 2022, Werner et al., 2021, Neumann and Lindenberg, 2022) as well as Asia (Fung et al., 2021, Lin, 2020). For the same reason as mentioned above, the sociodemographic differentiation is carried out by gender, age and socioeconomic status throughout all analyses.

- Research question 7: How many school students in Styria are positively screened for addictive behaviour related to any kind of digital media devices (DRAB) and any kind of internet-based applications (ARAB) and how does this differ across sociodemographic subgroups?
- Research question 8: How many school students in Styria are positively screened for addictive behaviour related to specific digital media devices and specific internet-

based applications, respectively and how does this differ across sociodemographic subgroups?

1.9.3 Correlates of IRAB

The results of previous research, summarized in ☛section 1.8, demonstrate that specific internet applications and use patterns (references are outlined above in ☛section 1.9.1) as well as personality aspects and comorbidities (Anderson et al., 2017b, Brand et al., 2016, Zhuang et al., 2023, Chew, 2022, Wang et al., 2015, Busch and McCarthy, 2021, Ho et al., 2014, Carli et al., 2013), sociodemographic characteristics (Busch and McCarthy, 2021, Lozano-Blasco et al., 2022a, Lozano-Blasco et al., 2022b, Mihara and Higuchi, 2017, Paccoud et al., 2021), psychosocial (Greitemeyer and Mügge, 2014, Kuss et al., 2014, Zhuang et al., 2023, Koo and Kwon, 2014, Camerini et al., 2023, Elhai et al., 2018, Li et al., 2014, Martí-Vilar et al., 2019, Zhang et al., 2022b) and family environmental aspects (Kalmus et al., 2015, Jago et al., 2012) contribute to the explanation of IRAB. Consequently, these aspects are subjected to examination by the following questions. IRAB was differentiated into DRAB and ARAB to contribute to the question whether DRAB is a distinct phenomenon that has to be distinguished from ARAB (Davazdahemami et al., 2016) or whether both may be considered interrelated in terms of their associated correlates (Billieux, 2012).

- Research question 9: Which digital media devices and internet-based applications show the strongest associations with the extent of symptoms of DRAB and ARAB, respectively?
- Research question 10: Which usage patterns, personality dimensions, comorbidities, sociodemographic characteristics, psychosocial and family environmental aspects as potential risk and protective factors are associated with the extent of symptoms of DRAB and ARAB? Are there characteristic correlates that are distinct for DRAB and ARAB?
- Research question 11: Which correlates are specific for addictive behaviour related to gaming and social media?

2 Materials and methods

Materials and methods have already been described in a publication by Lederer-Hutsteiner et al., 2024 (Lederer-Hutsteiner et al., 2024) based on the same dataset as this thesis. Therefore, there may be some textual overlaps in same parts of this section. Where this is the case, reference is made to this publication.

The dataset of this thesis is used with kind permission by Gesundheitsfonds Steiermark, who assigned a commissioned work to the research company x-sample, in the context of which the data was collected. The author of the current dissertation thesis is also affiliated with x-sample and was responsible for the planning and implementation of the data collection. Thus, all information on study design, methods and materials is provided first-hand. A positive vote from the Ethics Committee of the Medical University of Graz for using the data within this thesis was received on March, 3rd 2022 (see ☛Appendix B).

2.1 Study design and survey setting

The study design of this thesis is cross-sectional and the data is based on a population-representative survey within schools. School-based surveys are considered superior to other methods for collecting cross-sectional data among children and adolescents. Smit et al. (Smit et al., 2002) highlight for example (1) lower costs compared to other methods, (2) good opportunities to protect anonymity, which is generally an important issue, but takes on added significance in surveys with highly personal content, such as the one processed within this thesis, (3) good response rates (4) the availability of an accessible large number of potential participants and (5) good coverage of adolescents from families with lower socioeconomic status or minority groups, which enhances generalizability. Kristjansson et al. (Kristjansson et al., 2013) also note on the potential to include higher level class- or school-based contextual information as another advantage. Additionally, it should be mentioned that school-based surveys provide good options to systematically draw samples supported by well-documented and unbiased official population data. As potential disadvantages of school-based surveys Smit et al. (Smit et al., 2002) note that (1) they should be kept in a manageable format to minimize the efforts for the schools, (2) they are linked to cluster sampling and (3) potentially result in a non-coverage of truants or students absent on the survey day. Therefore, (1) the data collection process was designed with the objective of reducing the administrative burden on the schools, (2) cluster sampling is taken into account in course of standard error estimation (see ☛section 2.8.4) and (3) a potential bias due to non-coverage of absentees is discussed in ☛section 2.5 and explicitly examined in ☛section 2.8.2.

2.2 Study population

The population of interest is defined as students from Styrian schools

- of all educational regions within Styria,
- including all school types (except extra occupational forms),
- from grade 7 to grade 13.

Educational regions were set up according to the definitions provided by the Styrian directorate of education as “Liezen”, “Obersteiermark Ost”, “Obersteiermark West”, “Oststeiermark”, “Steirischer Zentralraum”, “Südoststeiermark” and “Südweststeiermark”. The addressed school types were defined according to the definitions of Statistics Austria as “pre-vocational year”, “vocational school”, “new secondary school”, “academic secondary school”, “higher technical and vocational colleges” and “intermediate technical and vocational schools”. The age of the addressed students ranges from 12 years (as the minimum age in grade 7) up to 19 years (as the regular maximum age in grade 13). The age of repeaters or of students attending vocational schools can be higher, which was taken into account during data cleaning (see ☛section 2.6).

Given this defined population, Statistics Austria provided data of all 3,537 Styrian school classes nesting a total of 72,947 students (38,071 male and 34,876 female), which met these definitions. Information was provided at a class-based level containing school name and school class, type of school, educational region, grade and the totals of male and female students for each class. The class- and student-based population characteristics are depicted in ☛Table 3.

Table 3: Class-and student-based population characteristics

Educational Region	School type	Grade 7/8 CTc	Grade 7/8 CTm	Grade 7/8 CTf	Grade 9/10 CTc	Grade 9/10 CTm	Grade 9/10 CTf	Grade 11+ CTc	Grade 11+ CTm	Grade 11+ CTf
Liezen	AHS	19	183	237	10	91	138	11	85	154
	BS	0	0	0	0	0	0	0	0	0
	BMS/BHS	0	0	0	32	302	437	34	305	442
	MS	61	574	512	0	0	0	0	0	0
	POLY	0	0	0	9	110	48	0	0	0
Obersteier-mark Ost	AHS	38	455	503	32	266	430	31	213	367
	BS	0	0	0	14	105	152	38	339	377
	BMS/BHS	0	0	0	69	816	725	79	864	632
	MS	85	897	750	0	0	0	0	0	0
	POLY	0	0	0	15	199	90	0	0	0
Obersteier-mark West	AHS	23	244	269	18	149	256	17	109	226
	BS	0	0	0	43	585	96	108	1422	233
	BMS/BHS	0	0	0	40	382	512	44	337	461
	MS	71	655	577	0	0	0	0	0	0
	POLY	0	0	0	7	89	28	0	0	0
Oststeier-mark	AHS	40	473	527	32	271	439	30	258	367
	BS	0	0	0	32	263	251	77	628	581
	BMS/BHS	0	0	0	58	667	784	62	612	678
	MS	135	1,359	1,270	0	0	0	0	0	0
	POLY	0	0	0	20	280	119	0	0	0
Steirischer Zentralraum	AHS	163	1,988	2,144	167	1,778	2,175	160	1571	1,904
	BS	0	0	0	72	976	437	202	2,379	998
	BMS/BHS	0	0	0	134	1,577	1,974	147	1,372	1,818
	MS	215	2,547	2,142	0	0	0	0	0	0
	POLY	0	0	0	26	364	174	0	0	0
Südost-steiermark	AHS	0	0	0	14	101	229	14	85	209
	BS	0	0	0	73	481	686	170	1,442	1,532
	BMS/BHS	0	0	0	31	230	485	33	150	486
	MS	68	631	617	0	0	0	0	0	0
	POLY	0	0	0	11	173	74	0	0	0
Südwest-steiermark	AHS	16	190	238	18	164	272	16	128	237
	BS	0	0	0	35	757	95	101	1,926	145
	BMS/BHS	0	0	0	51	690	603	49	627	443
	MS	103	963	1,018	0	0	0	0	0	0
	POLY	0	0	0	14	194	73	0	0	0

Note: AHS: Academic secondary school. BS: vocational school. BMS/BHS: Intermediate technical and vocational schools and Higher technical and vocational colleges, respectively. MS: New secondary school. POLY: Pre-vocational year. CTc: Count of school classes. CTm: Count of male students. CTf: Count of female students.

2.3 Sampling design

The sample design is a one-stage cluster sample, where the classes are defined as cluster and selection units. A stratification has been applied prior to randomly drawing classes in order to control for school type, educational region and grade according to the class-based population data. Additionally, gender was balanced resulting in equal proportions of male and female students in the total sample. A sample size of 2,000 students was intended, thus, 201 school classes out of 116 schools were sampled at random. The number of sampled school classes was determined assuming a class-based participation rate of 50% and an average of 20 students per school class.

2.4 Data collection

School-based surveys as a widespread form of collecting data among adolescents are linked to some requirements related to survey preparation and data collection. An administrative framework in this context is discussed in Kristjansson et al. (Kristjansson et al., 2013) and involves (1) institutional approval, (2) evaluation of the eligibility of sampled schools, (3) providing information for sampled schools, (4) securing support from the school principal, (5) ensuring that a supervising teacher is assigned to the sampled school class, (6) preparation and delivery of all survey materials, (7) ensuring at least passive consent from parents and finally (8) acknowledging the school's effort. Each of these aspects in the context of data collection within this thesis is discussed below.

Institutional approval for data collection was provided by the Styrian directorate of education, which is the official public authority in school matters. In addition, the Styrian directorate of education also directly announced its support of the project to the principals of the sampled schools. Furthermore, as outlined above, ethical approval for using the data within this dissertation thesis was obtained by the Ethics Committee of the Medical University of Graz (see ☛Appendix B). The eligibility of schools and school classes was guaranteed as all schools were sampled according to the population framework's official data by Statistics Austria. To provide information about the study's objectives and procedures, every principal was contacted by telephone. In that course, 13 principals rejected participation primarily due to a lack of supervising capacities related to the massive administrative tasks with respect to the COVID-19 pandemic or due to too many requests for surveys from other researchers. Four principals offered participation of nine additional school classes in the survey. Eventually, principals' support from 103 schools involving a total of 188 classes was secured and confirmed by a subsequent e-mail. Whenever possible, a teacher was pre-assigned to the supervising role in the survey process. Considering preparation and delivery of the survey materials, one envelope per school class was prepared containing the following documents:

- Cover letter to the principal including the study outline
- Implementation guide for supervising teachers
- Letter of approval from the Styrian directorate of education
- Parents' information letter to be distributed prior to the survey

- Class-specific login data for the online survey

All 188 envelopes were sent to the schools by post on March, 22nd 2022. One week later, an e-mail was sent to all participating schools asking for confirmation of the receipt. In the rare cases that schools did not receive the envelopes all documents were re-sent via e-mail. Students conducted the survey in class setting under supervision of a teacher at the online platform www.onlineumfragen.com. The deadline for implementation was set at May, 27th 2022, so the supervising teachers could choose any suitable time within around two months to carry out the survey. The teachers were instructed that all students of each sampled class should participate, given that they were present in school on the survey day. Teachers were also instructed that all school classes had to be surveyed in class setting and in presence mode, and not when distance learning was in-use. Considering consent, passive consent was ensured as all parents received information letters prior to the survey, where they were informed about the study's outline and explicitly informed about the survey's voluntary nature and that they could easily refuse their child's participance. Additionally, the initial question of the survey was about gathering informed consent from each student. If this was refused, the survey was terminated (see ☛section 2.6). After completion, each school principal received an e-mail expressing gratitude and acknowledging their support and efforts.

2.5 Response rate

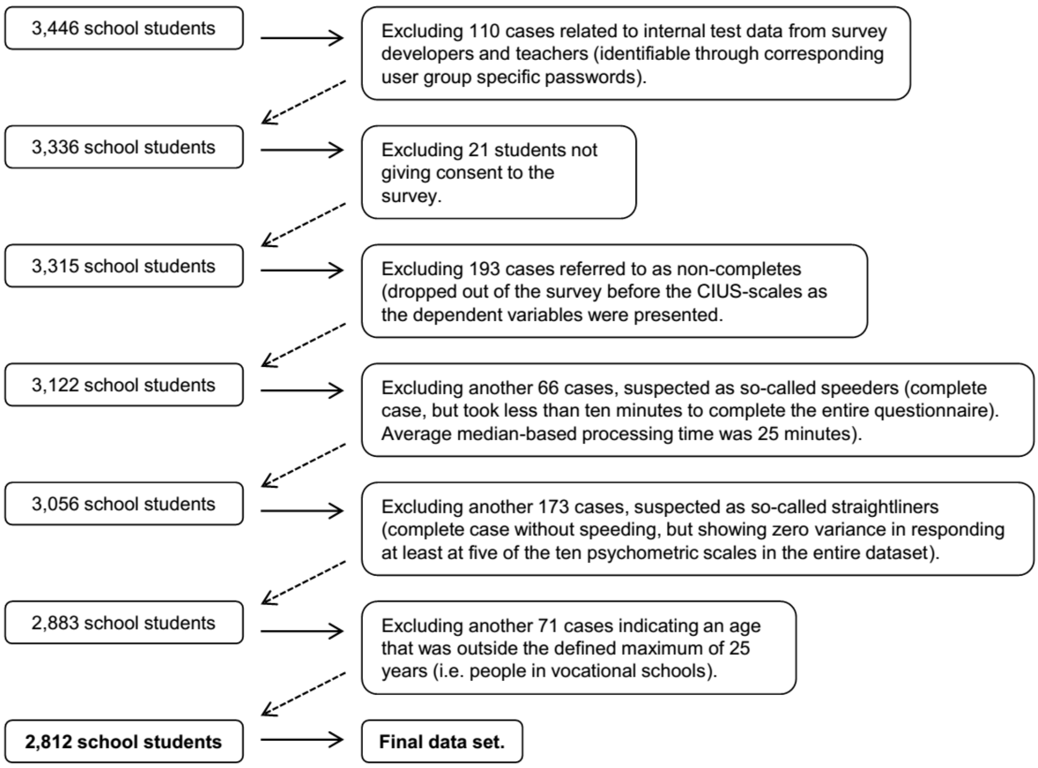
School students from 175 out of the 201 randomly selected school classes finally provided data. The response rate based on school classes was 87.1%, which can be rated as very good (Lederer-Hutsteiner et al., 2024). Non-participating school classes are distributed across all educational regions, school types and grades, but not entirely proportionally according to the study population (see ☛section 2.8.1 for corresponding calibration procedures).

To account for a potential selection bias that could result from the fact that school students who were absent on the day of the survey may have higher prevalence rates, after completion of the survey all supervising teachers were asked to provide the number of school students who were absent and therefore did not participate on the day of the survey. Additionally, they were also asked to estimate the number of students for which they suspect IRAB among all absent school students. Teachers from 64 out of 175 participating school classes provided the relevant information. A total of 141 absent school students were reported and of these, 39 were subjectively estimated by their teachers to show IRAB, yielding a prevalence rate of 27.7% among the reported absentees (for further considerations on that issue see ☛section 2.8.2).

2.6 Data cleaning procedures and final sample size

Originally, the dataset included a total of 3,446 participants. In order to enhance data quality, several procedures related to data cleaning have been applied (see ☛Figure 4) resulting in a final total sample size of 2,812 students, which were taken into account throughout the statistical analyses.

Figure 4: Flow chart of data cleaning



Note: Own illustration.

125 Students who indicated a non-binary gender were also asked to provide a corresponding specification in an open text format. This information was used to assess potential mischievous responding. Highly likely invalid responses such as “Kampfhelikopter” (attack helicopter), “Bratpfanne” (frying pan) or “Bisexueller Senf” (bisexual mustard) were classified as mischievous responses. Among the 125 students who indicated a different gender, 76 provided such answers as shown above and consequently their gender was set as missing data. 49 students provided valid specifications of non-binary gender such as

"Inter", "Non binary", "LGBTQ" or "Transgender". To account for findings from Robinson-Cimpian, 2014 (Robinson-Cimpian, 2014), according to which students who, for the fun of it, indicate a non-binary gender are prone to generally respond mischievously, their scores on ARAB as the major outcome variable were compared with students absent of mischievous responses on gender. Since the means do not differ ($T(2{,}809) = 0.810$; $p = 0.418$), students with mischievous responses on gender were not excluded from the dataset, but their gender was set as missing.

2.7 Measures and classification

With reference to the research questions (see ☛section 1.9) the statistical analyses will involve several measures that are introduced in this section. All measures were compiled in an online questionnaire in German language. Prior to administration, a pre-test with seven students aged 13-17 years in an individual setting, another 23 students in a group setting (involving a whole school class of grade 7 with students aged 13 years) and a German-teaching teacher was conducted. The purpose of these pre-tests was twofold: firstly, to ensure comprehensibility and secondly, to get a clue about the average and a potential maximum processing time. Following the implementation of minor adjustments to the wording of individual items, the questionnaire was deemed suitable for data collection involving a total of 141 individual items. The processing time (median-based) was found to be 25 minutes (Lederer-Hutsteiner et al., 2024).

The dependent variables in this thesis are IRAB (differentiated into DRAB and ARAB) generally as well as DRAB and ARAB related to specific DMD and applications, respectively. Other measures, which act as correlates or covariates, are assigned to the superordinate dimensions of internet use patterns, personality aspects, comorbid symptoms, sociodemographic, psychosocial and family environmental aspects.

2.7.1 Internet-related addictive behaviour

Internet-related addictive behaviour (IRAB)

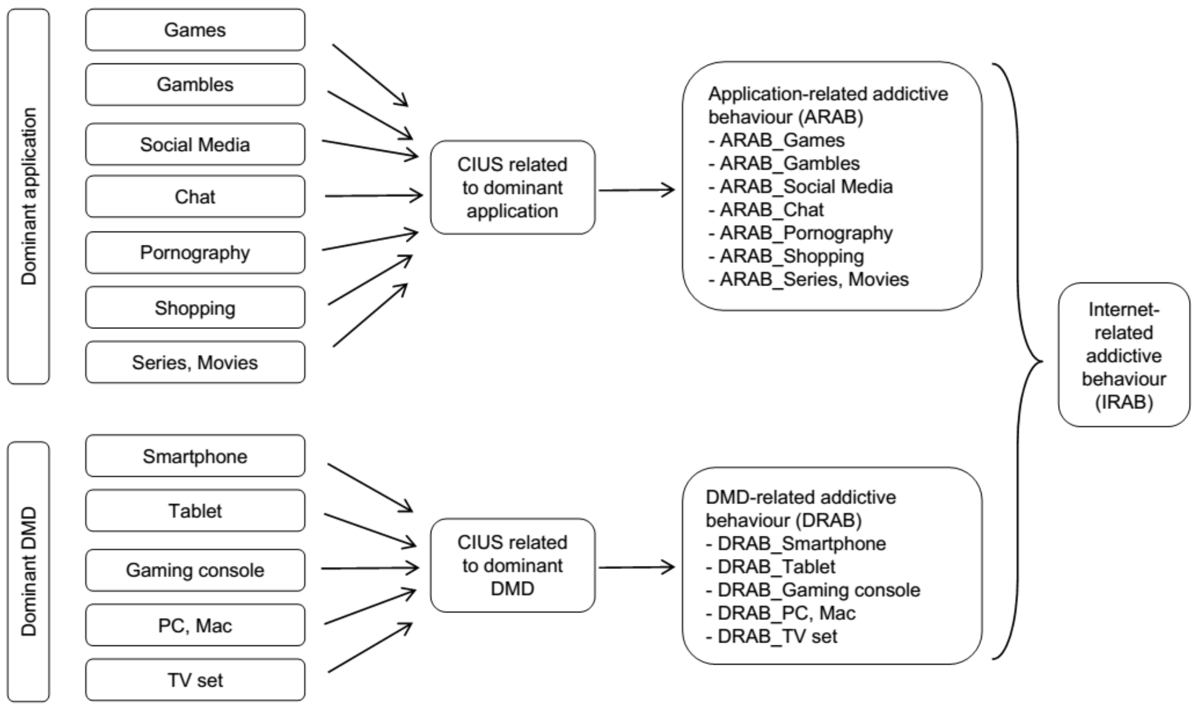
As described in Lederer-Hutsteiner et al. (Lederer-Hutsteiner et al., 2024) IRAB was operationalized using the German self-reporting seven-item short form of the Compulsive Internet Use Scale (CIUS) (Bischof et al., 2016) and its validation study by Besser et al. (Besser et al., 2017). CIUS was chosen as it is theoretically well-founded (based on diagnostic DSM-IV-criteria for behavioural addictions and dependence), well-validated

(Lopez-Fernandez et al., 2019, Laconi et al., 2019, Meerkerk et al., 2009) as also highlighted in a review of assessment instruments for IRAB (Laconi et al., 2014) and widely recognized (Király and Demetrovics, 2021). CUIS covers the diagnostic criteria disrupted control as well as functional impairment (interpersonal conflict, conflicts due to neglect of daily obligations), which are widely consented as central in that context (Billieux et al., 2015, Saunders et al., 2017, Rumpf et al., 2018a, Billieux et al., 2017) (☛section 1.6) as well as mental preoccupation and using the internet to cope with unpleasant moods. In order to estimate prevalences a validated cut-off score showing good specificity and sensitivity is crucial in course of classification, which was done by Besser et al. (Besser et al., 2017) through fully structured and standardized diagnostic interviews according to the Munich-Composite International Diagnostic Interview (M-CIDI) (Wittchen et al., 1995) with 188 positively screened students of two German vocational schools. This cut-off-validation was another important reason to choose CIUS.

Within CIUS, students had to rate the following seven items of the original form (Meerkerk et al., 2009) on a five-point Likert scale (0 = *"Never"* to 4 = *"Very often"*): *"How often do you find it difficult to stop using the Internet when you are online?"*, *"How often are you short of sleep because of the Internet?"*, *"How often have you unsuccessfully tried to spend less time on the Internet?"* (each of these refer to the criteria loss of control), *"How often do others (e.g., parents, friends, partner) say you should use the Internet less?"*, *"How often do you neglect your daily obligations (work, school, or family life) because you prefer to go on the Internet?"* (both refer to the criteria conflict), *"How often do you look forward to your next Internet session?"* (refers to preoccupation) and *"How often do you go on the Internet when you are feeling down?"* (refers to coping). The CIUS-score was carried out as a sum score of all seven items ranging from 0 to 28 with higher scores indicating more IRAB-symptoms and thus a higher severity. Sum scores were only calculated in case of valid responses to all items. Classification was carried out by the cut-off score of 13 proposed by Besser et al. (Besser et al., 2017), which showed a high specificity of 0.97 and therefore reduces the risk of false positive classifications. According to this procedure students were finally classified as *"No noticeable IRAB"* (showing scores ranging from 0 to 12) and *"IRAB"* (showing scores ranging from 13 to 28). The internal consistency based on the data of this thesis is good (α = 0.82, ω = 0.82) and equals the result found by Bischof et al. (Bischof et al., 2016).

CIUS provides a generic measure to evaluate IRAB, however, it does not specify the associated DMD or internet application that the addictive behaviour is related to. Therefore CIUS was queried twice: initially with reference to DMD (yielding DRAB) by asking for the leisure-dominating DMD prior to the presentation of the CIUS scale and later on with reference to internet applications (yielding ARAB) by querying the leisure-dominating internet application prior to the presentation of the CIUS scale. “Dominating” was defined in the sense of spending the most *active* time with this DMD and internet application, respectively. Emphasising *“active”* was necessary to account for the fact that, for example, an excessive gamer might spend the most time with passively streaming music as a background (as lots of young people do with headphones), while gaming is clearly the activity that is actively exercised. All students were then instructed to relate all seven CIUS-questions to this aforementioned DMD and internet application, respectively. An overview of the measurement model of the dependent variable is illustrated in ☛Figure 5.

Figure 5: Measurement model of the dependent variables



Note: Own illustration.

2.7.2 Internet use patterns

Number of personally owned DMD

The number of personally owned DMD was assessed by asking *“Which of the following digital devices that you can use to access the Internet do you own? Only devices that belong to you are meant here.”* Students could select the following items: *“Smartphone”*, *“Tablet”*, *“Gaming console”*, *“Computer”*, *“TV set”* and *“Other digital device”*. In case of students having selected *“Other digital device”* they could specify the corresponding device. Each selected or additionally specified item scored one point. All personally owned DMD were summed up to a total score.

Leisure-dominant DMD

As outlined above, the leisure-dominating DMD was queried by asking *“Which of these devices do you spend the most active time with in your leisure time? By ‘active time’ we mean the following: If, for example, you spend most of your time listening to music in the background on your smartphone, but are actually actively playing something on your gaming console, you would click on ‘gaming console’ in this case.”* The students could choose between *“Smartphone”*, *“Tablet”*, *“Gaming console”*, *“Computer”*, and *“TV set”*.

Leisure-dominant internet application

The leisure dominant internet application was assessed as described above for DMD by asking: *“Which of these internet applications do you spend the most active time with in your leisure time? By ‘active time’ we mean the following: If, for example, you spend most of your time listening to music in the background on your smartphone, but are actually actively playing something or using social media, you would click on ‘Games’ or ‘Social media’ in this case.”* The students could choose between *“Reading and writing e-mails”*, *“Search for information”*, *“Chatting and writing messages”*, *“Publication of own contributions”*, *“Discussion forums”*, *“Watch films/series”*, *“Listen to music/podcasts”*, *“Downloads”*, *“Games”*, *“Gambles”*, *“Erotic/sex/porn”*, *“Social networks”*, *“Shopping”*, *“Selling”* and *“Other activity”*. In case of students having selected *“Other activity”* they could specify the corresponding activity.

Daily usage time of DMD

Usage time was measured by asking: *“How many hours do you spend using these digital devices in your leisure time on a typical school day?”* and in a subsequent question: *“How many hours do you spend using these digital devices in your leisure time on a typical school-free day?”* For each question, students were able to enter the number of hours for each device. As simultaneous use of multiple DMD is not taken into account in the data, a pure sum score would lead to an overestimation of the usage times. Thus, only the maximum value was used for each question. The average daily total usage time within a typical week was calculated as follows: multiplying the maximum value on a typical school day by 5 plus multiplying the maximum value on a typical school-free day by 2 and dividing this term by 7.

Usage of DMD as a pre-sleep activity on evenings with subsequent school day

DMD use as a pre-sleep activity was measured by asking: *“If you have school the next day, how often do you usually use one of these devices directly before falling asleep?”* The term *“devices”* has been defined in the previous question. The students could indicate, if pre-sleep usage usually occurs on 0, 1, 2, 3, 4 or on 5 of five such days yielding a score that ranges from 0 to 5. Higher scores indicate a greater amount of pre-sleep use of DMD on subsequent school days (Lederer-Hutsteiner et al., 2024).

Usage of DMD after midnight on evenings with subsequent school day

DMD usage after midnight was queried by asking: *“If you have school the next day, how often do you usually use one of these devices after midnight?”* The assignment of values is as described above. As schools in Austria typically start at 8 a.m. at the latest, midnight was chosen as reference to deduce how many students are clearly unable to get eight hours of sleep as recommended by the American Academy of Sleep Medicine (Paruthi et al., 2016) (see also (Lederer-Hutsteiner et al., 2024)).

Position of the smartphone during bedtime

The position of the smartphone during bedtime was queried by asking: *“Where does your smartphone usually lie when you sleep at night? Reception mode means that messages, notifications and calls can arrive.”* The students could choose from one of the following options: *“Right next to me or in bed (in reception mode and not silent)”*, *“Right next to me or in bed (in reception mode, but silent)”*, *“Right next to me or in bed (not in reception mode or completely switched off)”*, *“Somewhere else in my room”*, *“Outside my room”*.

Initial age of regular internet use

To assess the initial age of regular internet use the students were asked *“How old were you when you started to use the internet regularly in your leisure time?”* and they could indicate the corresponding age in an open format.

2.7.3 Personality traits

Big Five dimensions of personality

The big five dimensions of personality were measured using the 10 Item Big Five Inventory (BFI-10) established by Rammstedt et al. (Rammstedt, 2013), who provided a short form of the well-recognized Big Five Inventory by John et al. (John, 1991). For each of the five dimensions referred to as openness, conscientiousness, extraversion, agreeableness and neuroticism, students rated two items on a 5-point Likert scale (0 = *"Does not apply at all"* to 4 = *"Fully applies"*), resulting in a total of 10 items. One item per dimension was positively polarised, the other item reversely scored (indicated with "R" subsequently). The following items are included: (1) *"I see myself as someone who is reserved"* (R, dimension extraversion), (2) "*I see myself as someone who is generally trusting*" (dimension agreeableness), (3) *"I see myself as someone who tends to be lazy"* (R, dimension conscientiousness), (4) *"I see myself as someone who is relaxed, handles stress well"* (R, dimension neuroticism), (5) *"I see myself as someone who has few artistic interests"* (R, dimension openness), (6) *"I see myself as someone who is outgoing, sociable"* (dimension extraversion), (7) *"I see myself as someone who tends to find fault with others"* (R, dimension agreeableness), (8) *"I see myself as someone who does a thorough job"* (dimension conscientiousness), (9) *"I see myself as someone who gets nervous easily"* (dimension neuroticism) and (10) *"I see myself as someone who has an active imagination"* (dimension openness). The students were instructed to indicate the extent to which these statements apply to them. The five scores were carried out as means of the two items per dimension ranging from 0 to 4 with higher scores indicating a stronger expression of the corresponding dimension. Sum scores were only calculated in case of valid responses to all items of a specific dimension. The internal consistency based on the data of this thesis is as follows (based on the Spearman-Brown coefficient ρ for the assessment of 2-item subscales (Eisinga et al., 2013)): openness ($\rho = 0.40$), conscientiousness ($\rho = 0.44$), extraversion ($\rho = 0.54$), agreeableness ($\rho = 0.13$), neuroticism ($\rho = 0.38$). The consequences of this unacceptably low internal consistency are discussed in the section that summarizes the evaluation of all measures (☛2.7.8).

2.7.4 Comorbid symptoms

Insomnia

As already described in Lederer-Hutsteiner et al. (Lederer-Hutsteiner et al., 2024) insomnia was measured by Insomnia Severity Index (ISI) in German translation (Gerber et al., 2016), which is a self-reporting format to assess sleep problems. Students had to rate the extent of their impairments related to (1) falling as well as (2) staying asleep, (3) early waking, (4) their sleep satisfaction, (5) their sleep-related concerns and (6) sleep-related interference with well-being and performance during the last two weeks. Self-reporting assessment was based on a five-point Likert-scale ranging from 0 to 4 with higher scores indicating more sleep problems. The item *"How noticeable to others do you think is your* *sleep problem in terms of impairing the quality of your life?"* of the original 7-item scale was removed due to severe confusion and multiple interpretations among adolescents as has been shown during pretesting. The score was calculated as a sum score of all six items ranging from 0 to 24 with higher values indicating a higher insomnia severity. Sum scores were only calculated in case of valid responses to all items. The internal consistency based on the data of this thesis is acceptable (α = 0.79, ω = 0.79). The classification of individual students' insomnia severity was carried out by proportionally adjusted cut-off scores according to Gerber et al.'s (Gerber et al., 2016) validated thresholds, taking into account the reduced maximum score due to removing one item. Students were classified as "No clinically significant insomnia" (scores ranging from 0 to 6), "Subthreshold insomnia" (scores ranging from 7 to 12), "Clinically significant moderate insomnia" (scores ranging from 13 to 18) and "Clinically significant severe insomnia" (scores ranging from 19 to 24).

Generalized anxiety

This measurement has also been already described in Lederer-Hutsteiner et al. (Lederer-Hutsteiner et al., 2024) and is partly adopted as follows: generalized anxiety was measured using the German self-reporting form of the Generalized Anxiety Disorder Screener (GAD-7) (Lowe et al., 2008) and its validation in a sample of paediatric patients with anxiety disorder (confirmed by structured interviews) (Mossman et al., 2017). GAD-7 is based on diagnostic criteria for Generalized Anxiety Disorder embedded in DSM-IV and assesses the severity of anxiety symptoms. GAD-7 consists of 7 items, which are self-rated on 4-point Likert-scales (0 = *"Not at all"*, 1 = *"Several days"*, 2 = *"More than half the days"* and 3 = *"Nearly every day"*). School students rated (1) *"Feeling nervous, anxious or on edge"*, (2) *"Not being able to stop or control worrying"*, (3) *"Worrying too much about different things"*, (4) *"Trouble relaxing"*, (5) *"Being so restless that it is hard to sit still"*, (6) *"Becoming easily annoyed or irritable"* and (7) *"Feeling afraid as if something awful might happen"*. The scores of all 7 items were summed with higher scores indicating a higher severity of anxiety disorder (scores ranging from 0 to 21). Sum scores were only calculated for participants with valid responses to all 7 items. The internal consistency in the present study is excellent (α = 0.90, ω = 0.90). Classification is based on a cut-off score of 11, which showed the best compromise between sensitivity (0.97) and specificity (1.00) as suggested by Mossman et al. (Mossman et al., 2017). Two groups were differentiated: "No noticeable anxiety disorder" (score from 0 to 10) and "At least moderate anxiety disorder" (score from 11 to 21).

Strengths and Difficulties

Strengths and difficulties were measured by using the widely recognized Strengths and Difficulties Questionnaire (SDQ) in German translation and self-reporting form (Klasen et al., 2003). SDQ operationalizes adolescent's behavioural as well as internalizing problems along the four dimensions "emotional problems", "conduct problems", "hyperactivity/inattention" and "peer relationship problems". Additionally, the strengths-related subscale "prosocial behaviour" is included. SDQ includes a total of 25 items (five items per subscale), which were self-rated by the students on a 3-point scale (0 = *"Not true"*, 1 = *"Somewhat true"* and 2 = *"Certainly true"*).

The items and their subscale-assignment are as follows (reversely scored items are indicated with "R"): (1) *"I try to be nice to other people. I care about their feelings"* (prosocial behaviour), (2) *"I am restless, I cannot stay still for long"* (hyperactivity/inattention), (3) *"I get a lot of headaches, stomach-aches or sickness"* (emotional problems), (4) *"I usually share with others (food, games, pens etc.)"* (prosocial behaviour), (5) *"I get very angry and often lose my temper"* (conduct problems), (6) *"I am usually on my own. I generally play alone or keep to myself"* (peer relationship problems), (7) *"I usually do as I am told"* (R, conduct problems), (8) *"I worry a lot"* (emotional problems), (9) *"I am helpful if someone is hurt, upset or feeling ill"* (prosocial behaviour), (10) *"I am constantly fidgeting or squirming"* (hyperactivity/inattention), (11) *"I have one good friend or more"* (R, peer relationship problems), (12) *"I fight a lot. I can make other people do what I want"* (conduct problems), (13) *"I am often unhappy, down-hearted or tearful"* (emotional problems), (14) *"Other people my age generally like me"* (R, peer relationship problems), (15) *"I am easily distracted, I find it difficult to concentrate"* (hyperactivity/inattention), (16) *"I am nervous in new situations. I easily lose confidence"* (emotional problems), (17) *"I am kind to younger children"* (prosocial behaviour), (18) *"I am often accused of lying or cheating"* (conduct problems), (19) *"Other children or young people pick on me or bully me"* (peer relationship problems), (20) *"I often volunteer to help others (parents, teachers, children)"* (prosocial behaviour), (21) *"I think before I do things"* (R, hyperactivity/inattention), (22) *"I take things that are not mine from home, school or elsewhere"* (conduct problems), (23) *"I get on better with adults than with people my own age"* (peer relationship problems), (24) *"I have many fears, I am easily scared"* (emotional problems) and (25) *"I finish the work I'm doing. My attention is good"* (R, hyperactivity/inattention).

The score of each subscale was carried out as a sum score, preceded by recoding the five inversely polarized items (7, 11, 14, 21 and 25). The higher the score, the higher the extent of the corresponding subscale's construct (scores ranging from 0 to 10 each). Sum scores were only calculated if a student showed valid responses to all items per subscale. In addition to the four difficulties-related subscales (excluding prosocial behaviour), SDQ also provides a total difficulties index indicating an overall psychosocial constitution of each student by adding the values of all difficulties-related subscales (scores ranging from 0 to 40). The internal consistency of each subscale based on the data of this thesis is as follows: emotional problems (α = 0.77, ω = 0.77), conduct problems (α = 0.55, ω = 0.56), hyperactivity/inattention (α = 0.61, ω = 0.57), peer relationship problems (α = 0.50, ω = 0.48), prosocial behaviour (α = 0.74, ω = 0.74), total difficulties index (α = 0.78, ω = 0.77). The consequences of low internal consistencies of some subscales are discussed in the section that summarizes the evaluation of all measures (☛section 2.7.8). The classification of the total difficulties index was carried out as follows: (“Normal”: scores from 0–15; “Borderline”: 16-19; “Abnormal”: 20–40).

2.7.5 Sociodemographic characteristics

Age

The students’ age was queried by the question *“Your age?”* and an open field for the corresponding entry.

Gender

Gender was queried by the question *“Your gender?”* and students could choose between “Male”, “Female” and “Different gender”. Students who chose “Different gender” could provide a specification in an open text field. This information was used to assess mischievous responses which were then set as missing data (see in detail ☛section 2.6).

Socioeconomic status

The index of socioeconomic status (SES) was established by asking students about the educational background of their father and mother (*“What is your father's highest level of education?”, “What is your mother's highest level of education?”*) as well as their parent’s financial situation (*“How do your parents come along with the money they have available?”*) Both questions could be answered on a 5-point Likert scale on which higher values indicate higher formal education and financial resources, respectively. Regarding the parent’s educational background the higher value of both parents was used. The SES-index was then calculated as a sum score ranging from 0–8. The index was only calculated if a student provided valid information on both indicators.

2.7.6 Psychosocial characteristics

Proneness to boredom

Proneness to boredom was measured using the Boredom Proneness Scale (BPS) established by Farmer and Sundberg (Farmer and Sundberg, 1986). On a 4-point Likert-scale (0 = *"I do not agree at all"* to 3 = *"I fully agree"*) the students rated their tendency to feel bored according to the following items of the subscale "time": (1) *"Time always seems to be passing slowly"*, (2) *"I often find myself at loose ends, not knowing what to do"*, (3) *"Much of the time I just sit around doing nothing"* and (4) *"I find it hard to entertain myself"*. The scores of all four items were summed with higher scores indicating a higher proneness to boredom (scores ranging from 0 to 12). Sum scores were only calculated for participants with valid responses to all four items. The internal consistency in the present study is good (α = 0.79, ω = 0.80).

Self-efficacy

Self-efficacy was measured according to "Allgemeine Selbstwirksamkeit Kurzskala" (ASKU) developed by Beierlein et al. (Beierlein et al., 2012) as a generalized concept referring to the students' self-reported abilities to cope with daily difficulties and barriers and to successfully overcome critical challenges on their own. Generalized self-efficacy across situations was shown to be associated with self-esteem (Lane et al., 2004, Stroiney, 2005). On a 5-point Likert-scale (ranging from 0 = *'Doesn't apply at all'* to 4 = *'Applies completely'*) school students rated their expectation of being able to cope with difficulties as well as critical challenges in (daily) life on the following items: (1) *"I can rely on my own abilities in difficult situations."*, (2) *"I am able to solve most problems on my own."* and (3) *"I can usually solve even challenging and complex tasks well."* The scores of all 3 items were added with higher scores indicating a higher self-efficacy (scores ranging from 0 to 12). Sum scores were only calculated in case of valid responses to all 3 items. The internal consistency in the present study is good (α = 0.85, ω = 0.85).

Parental support

Parental support was measured using the scale „Unterstützung durch die Eltern" (SKU) established by Roth et al. (Roth et al., 2003). The scale addresses both the parents' understanding of their children's needs (as perveived by the students) as wells as the students' understanding of their parents' demands. On a 4-point Likert-scale (ranging from 0 = *"Not true at all"* to 3 = *"Exactly true")* the students rated the following items: (1) *My parents listen to me when I have problems.*", (2) *"I usually find the criticism I get from my parents to* *be helpful."*, (3) *"My parents stick by me, even when I've done something stupid"*, (4) *"My parents' demands of me are usually justified"* and (5) *"I don't need to hide my true thoughts and feelings from my parents"*. The scores of all 5 items were added with higher scores indicating more perceived parental support (scores ranging from 0 to 15). Sum scores were only calculated in case of valid responses to all 5 items. The internal consistency in the present study is good (α = 0.85, ω = 0.85).

Social support

Social support was measured using the Berliner Social Support Scale (BSSS) established by Schulz and Schwarzer (Schulz and Schwarzer, 2003). On a 4-point Likert-scale (ranging from 0 = *"Not true at all"* to 3 = *"Exactly true")* the students assessed the emotional and instrumental support they perceived to be available along the following items, whereas items 1 to 4 refer to the subscale emotional support and items 5 to 8 refer to the subscale instrumental support: (1) *"There are people who truly like me"*, (2) *"Whenever I am not feeling well, other people show me that they are fond of me"*, (3) *"Whenever I am sad, there are people who cheer me up"*, (4) *"There is always someone there for me when I need comforting"*, (5) *"I know some people who I can always rely on"*, (6) *"When I am worried, there is someone who helps me"*, (7) *"There are people who offer me help when I need it"* and (8) *"When things get too much for me, there are others to help me"*. The scores of all 4 items per subscale were added with higher scores indicating more emotional and instrumental support, respectively (scores ranging from 0 to 12 in each subscale). Sum scores were only calculated in case of valid responses to all 4 items per subscale. The internal consistency in the present study is excellent for both subscales (emotional support: α = 0.89, ω = 0.90), (instrumental support: α = 0.91, ω = 0.91).

Concerns related to the extent of DMD or internet use

Concerns related to the extent of internet use were measured by the following three items, for each of which the students were asked to indicate dichotomously whether they apply to them (0 = "Does not apply"; 1 = "Applies"): (1) *"I spend so much time on the internet or with digital devices that I sometimes worry"*, (2) *"I spend so much time on the internet or with digital devices that I've been thinking lately that I should seek help"* and (3) *"I spend so much time on the internet or with digital devices that I've been to a counselling session or I am currently doing so."* The scores of all three items were added. Higher scores indicate more concerns related to the extent of using DMD or the internet.

Well-being in school class

Well-being in school class was queried by the item *"I usually feel comfortable among my classmates."* On a 4-point Likert-scale (ranging from 0 = *"Doesn't apply at all"* to 3 = *"Applies completely"*) students could rate the extent to which this statement applies to them. Higher scores indicate more subjective well-being in school-class.

2.7.7 Family environmental aspects

Parental rules

As already described in Lederer-Hutsteiner et al. (Lederer-Hutsteiner et al., 2024) parental rules were measured unidimensionally by asking *"Have your parents established rules about how much time you are allowed to use DMD in your leisure time?"*. The students could respond with *"Yes"* (coded as 1) or *"No"* (coded as 0).

Extent of parental DMD usage

An index of the extent of parental DMD usage was established by asking *"Think about a typical Sunday for your family. On such a Sunday, how much time do your parents spend at home using digital devices?"*. The students should indicate their father's and mother's extent of DMD usage, respectively. Both questions could be answered on a 5-point Likert scale (0 = *"Very little time"* to 4 = *"Very much time"*) on which higher values indicate a higher extent. The index was then calculated as a mean score ranging from 0–4.

Siblings

The students were asked: *"Are you an only child or do you have siblings?"* and indicated *"Only child"* (coded as 0) or *"Siblings"* (coded as 1).

2.7.8 Overview and evaluation of internal consistency of measures

All variables and measures used within this thesis are summarized in the following ☛Table 4. Cronbach's Alpha and McDonalds's Omega are shown to assess internal consistency of each scale. For the assessment of the 2-item subscales of personality the less biased Spearman-Brown coefficient ρ (Eisinga et al., 2013) is indicated. The two measures of internet-related addictive behaviour (DRAB and ARAB) show acceptable and good internal consistencies, respectively. Personality factors, on the other hand, show unacceptable internal consistencies and will therefore not be considered in the course of the statistical analyses. The internal consistencies of comorbid symptoms are good, with the exception of most of the SDQ-subscales. As a consequence, the problem-related SDQ-subscales will be excluded from all analyses and instead only the total difficulties score as a proxy variable for the overall psychosocial constitution, as well as the prosocial behaviour subscale, both showing acceptable internal consistencies, will be taken into account. Regarding psychosocial characteristics all measures show good and excellent internal consistencies, respectively.

Table 4: Overview of all involved measures

Variable	Measure	Internal Consistency
Internet-related addictive behaviour		
DRAB	CIUS referred to dominant DMD and internet	α = 0.76, ω = 0.76 (7 Items)
ARAB	application, respectively	α = 0.82, ω = 0.82 (7 Items)
Internet use pattern		
DMDCOUNT	Self-constructed item	n.a.
DOMDMD	Self-constructed item	n.a.
DOMAPP	Self-constructed item	n.a.
DMDTIME	Self-constructed item	n.a.
PRESLEEP	Self-constructed item	n.a.
AFTERMID	Self-constructed item	n.a.
POSIT	Self-constructed item	n.a.
INITAGE	Self-constructed item	n.a.
Personality factors		
EXTRAVERSION	BFI-10, subscale extraversion	ρ = 0,54 (2 Items^{1R})
AGREEABLENESS	BFI-10, subscale agreeableness	ρ = 0,13 (2 Items^{1R})
CONSCIENTIOUSNESS	BFI-10, subscale conscientiousness	ρ = 0,44 (2 Items^{1R})
NEUROTICISM	BFI-10, subscale neuroticism	ρ = 0,38 (2 Items^{1R})
OPENNESS	BFI-10, subscale openness	ρ = 0,40 (2 Items^{1R})
Comorbid symptoms		
INSOMNIA SYMPTOMS	ISI	α = 0.79, ω = 0.79 (6 Items)
ANXIETY	GAD-7	α = 0.90, ω = 0.90 (7 Items)
EMOTIONAL PROBLEMS	SDQ, subscale emotional problems	α = 0.77, ω = 0.77 (5 Items)
CONDUCT PROBLEMS	SDQ, subscale conduct problems	α = 0.55, ω = 0.56 (5 Items^{1R})
HYPERACTIVITY/INATTENTION	SDQ, subscale hyperactivity/inattention	α = 0.61, ω = 0.57 (5 Items^{2R})
PEER PROBLEMS	SDQ, subscale peer problems	α = 0.50, ω = 0.48 (5 Items^{2R})
PROSOCIAL BEHAVIOUR	SDQ, subscale prosocial behaviour	α = 0.74, ω = 0.74 (5 Items)
PSYCONST	SDQ, total difficulties score	α = 0.78, ω = 0.77 (20 Items)
Sociodemographic characteristics		
AGE	Self-constructed item	n.a.
GENDER	Self-constructed item	n.a.
SOCIOECONOMIC STATUS	Self-constructed item	n.a.
Psychosocial characteristics		
PRONENESS TO BOREDOM	BPS	α = 0.79, ω = 0.80 (4 Items)
SELF-EFFICACY	ASKU	α = 0.85, ω = 0.85 (3 Items)
PARENTAL SUPPORT	SKU	α = 0.85, ω = 0.85 (5 Items)
EMOTIONAL SUPPORT	BSSS, subscale emotional support	α = 0.89, ω = 0.90 (4 Items)
INSTRUMENTAL SUPPORT	BSSS, subscale instrumental support	α = 0.91, ω = 0.91 (4 Items)
IRABCONC	Self-constructed item	n.a.
WELLBEING IN SCHOOL CLASS	Self-constructed item	n.a.
Family environmental aspects		
PARENTAL RULES	Self-constructed item	n.a.
PARENTUSE	Self-constructed item	n.a.
SIBLINGS	Self-constructed item	n.a.

Note: DRAB: Device-related addictive behaviour. ARAB: Application-related addictive behaviour. DMDCOUNT: Number of personally owned digital media devices. DOMDMD: Leisure-dominant digital media device. DOMAPP: Leisure-dominant internet application. DMDTIME: Daily usage time of digital media devices. PRESLEEP: Count of days using DMD as a pre-sleep activity on evenings with subsequent school day. AFTERMID: Count of days using digital media devices after midnight on evenings with subsequent school day. POSIT: Position of the smartphone during bedtime. INITAGE: Initial age of regular internet use. ANXIETY: Generalized anxiety symptoms. PEER PROBLEMS. Peer relationship problems. PSYCONST: overall psychosocial constitution. IRABCONC: Concerns related to the extent of internet use. PARENTUSE: Extent of parental use of digital media devices. α (Cronbach's Alpha). ω (McDonald's Omega). ρ (Spearman-Brown). n.a: not applicable. 1R, 2R: The count of reversed items is indicated as 1R or 2R. No indication means absence of reversed items.

2.8 Statistical analyses

2.8.1 Calibration

As already shown in ☛section 2.5 a very good participation rate of 87.1% of all 201 sampled school classes was achieved in the survey. However, the resulting sample loss consisting of 26 non-participating school classes and also individual students that were absent on the day of the survey are potential risks for mismatches between the student sample's and the underlying study population's structure that may jeopardize the sample's representativeness. To compensate for the observed mismatches between the sample's and population's structure, calibration weights were assigned based on an assessment of congruency between the sample and population. The assessment was carried out according to ☛Table 5 using educational region, school type, grades and gender as structural characteristics on students' level.

Table 5: Comparison of structural characteristics between study sample and population

Educational region	School type	Grade	Gender	POPc	SAMc	POP%	SAM%	Weight
Steirischer Zentralraum	AHS	Sec1	Male	1,988	65	2.73	2.55	1.07
	AHS	Sec2	Male	3,349	71	4.59	2.79	1.65
	POLY, BS	Sec1	Male	0	0	0.00	0.00	n.a.
	POLY, BS	Sec2	Male	3,719	133	5.10	5.22	0.98
	BMS/BHS	Sec1	Male	0	0	0.00	0.00	n.a.
	BMS/BHS	Sec2	Male	2,949	95	4.04	3.73	1.08
	MS	Sec1	Male	2,547	46	3.49	1.81	1.93
	MS	Sec2	Male	0	0	0.00	0.00	n.a.
Other regions	AHS	Sec1	Male	1,545	47	2.12	1.85	1.15
	AHS	Sec2	Male	1,920	19	2.63	0.75	3.53
	POLY, BS	Sec1	Male	0	0	0.00	0.00	n.a.
	POLY, BS	Sec2	Male	8,993	295	12.33	11.58	1.06
	BMS/BHS	Sec1	Male	0	0	0.00	0.00	n.a.
	BMS/BHS	Sec2	Male	5,982	239	8.20	9.38	0.87
	MS	Sec1	Male	5,079	198	6.96	7.77	0.90
	MS	Sec2	Male	0	0	0.00	0.00	n.a.
	AHS	Sec1	Female	2,144	83	2.94	3.26	0.90
Steirischer Zentralraum	AHS	Sec2	Female	4,079	160	5.59	6.28	0.89
	POLY, BS	Sec1	Female	0	0	0.00	0.00	n.a.
	POLY, BS	Sec2	Female	1,609	72	2.21	2.83	0.78
	BMS/BHS	Sec1	Female	0	0	0.00	0.00	n.a.
	BMS/BHS	Sec2	Female	3,792	170	5.20	6.67	0.78
	MS	Sec1	Female	2,142	60	2.94	2.36	1.25
	MS	Sec2	Female	0	0	0.00	0.00	n.a.

(Continued)

Table 5: (Continued)

Educational region	School type	Grade	Gender	POPc	SAMc	POP%	SAM%	Weight
Other regions	AHS	Sec1	Female	1,774	47	2.43	1.85	1.32
	AHS	Sec2	Female	3,324	61	4.56	2.39	1.90
	POLY, BS	Sec1	Female	0	0	0.00	0.00	n.a.
	POLY, BS	Sec2	Female	4,580	269	6.28	10.56	0.59
	BMS/BHS	Sec1	Female	0	0	0.00	0.00	n.a.
	BMS/BHS	Sec2	Female	6,688	253	9.17	9.93	0.92
	MS	Sec1	Female	4,744	164	6.50	6.44	1.01
	MS	Sec2	Female	0	0	0.00	0.00	n.a.
			TOTAL	**72,947**	**2,547***	**100,00**	**100,00**	

Note: AHS: Academic secondary school. BS: vocational school. BMS/BHS: Intermediate technical and vocational schools and Higher technical and vocational colleges, respectively. MS: New secondary school. POLY: Pre-vocational year. Sec1: Secondary school, level 1 (grades 5 to 8). Sec2: Secondary school, level 2 (grades 9+). POPc: Count of students in population. SAMc: Count of students in sample. POP%: Percentage of students in population. SAM%: Percentage of students in sample. Weight: Calibration weight calculated by dividing POP% by SAM%. n.a: not applicable. * The sample size shown is smaller than the actual sample size because students with missing values on gender or non-binary gender are not included.

The comparison of the population's and sample's percentages depicted in ☛Table 5 shows a high degree of congruency in many strata. However, some expected under- and over-coverages are also evident. The maximum under-coverage is observed among male students attending academic secondary schools of grades 9+ located outside the central region of Styria. Students of this stratum were assigned the maximum weight of 3.53, indicating that each student carrying these characteristics will be treated as 3.53 students in course of the statistical analyses. The maximum over-coverage relates to female students attending vocational or pre-vocational schools outside the central region of Styria. Each female student sharing these characteristics was assigned the minimal weight of 0.59.

2.8.2 Absentee bias

As already mentioned in ☛section 2.1, school-based surveys among adolescents are potentially at risk of biasing estimates due to non-coverage of absent students (Smit et al., 2002). A high number of absentees may result in biased estimates, assuming that the reason for absence is related to the examined variables. To put it in a nutshell, if the reason for absence is linked to a weaker psychosocial constitution among absentees or that they have overslept as a result of intensively using DMD at night, higher prevalences are therefore to be assumed in this subgroup, which are not reflected in the data. Since the survey was carried out on a single day in class-setting and in presence mode only, absent students had no chance to participate and provide data. Basically, it would be possible to make up the survey for absentees, but this would greatly increase the schools' workload and thus reduce their willingness to participate. As a compromise, after the survey had been carried out the teachers were asked to indicate the number of absent pupils and also to estimate how many of them they thought exhibited IRAB. Recognising that this can only serve as a rough estimate that is by no means comparable to the screening of the present students, this procedure may nevertheless be considered as a compromise to minimize the schools' efforts, but still take into account a potential bias. As already shown in ☛section 2.5, supervising teachers from 64 out of 175 participating school classes provided the relevant information. A total of 141 school students absent on the day of the survey were reported and of these, 39 were subjectively estimated by their teachers to show IRAB, yielding a prevalence rate of 27.66% among the reported absentees. A comparison of this prevalence rate with the one observed among the surveyed students was carried out by calculating 95%-confidence intervals shown in ☛Table 6. The prevalences of absent and surveyed students do not differ significantly as both 95%-confidence intervals overlap. Thus, a substantial bias due to non-coverage of absent students can be excluded, assuming that (1) teachers' assessments of the extent to which their students use DMD are largely valid and (2) provided that the 64 classes from which this information was received are a representative sample of all 175 classes.

Table 6: Comparison of prevalence estimates of surveyed and absent students

Subgroup	**Prevalence IRAB**	**95%-CI**
Surveyed students	32.58%	30.58%; 34.65%
Absent students	27.66%	21.77%; 33.55%*

Note: * 95%-confidence interval was calculated using finite population correction.

2.8.3 Multiple imputation

Missing data is a common issue, especially in empirically driven social sciences (van Ginkel et al., 2020), where questionnaire-based approaches to data collection are often used. ☛Table 9 in ☛section 3.1 shows some high values for missing data (particularly for socioeconomic status, but also for some psychometric measures such as anxiety or psychosocial constitution), cumulating to total rate of 48.56% of cases with missingness on at least one of the variables involved. Since missing data is obvious, there are several options to address it in statistical analyses. In order to avoid potential selection biases and loss of statistical power associated for example with listwise deletion, several approaches have been developed. Decisions in this regard depend on mechanisms and patterns associated with missingness. According to Little and Rubin (Little and Rubin, 2002) three mechanisms need to be taken into account: missing completely at random (MCAR), missing at random (MAR) and missing not at random (MNAR). Under MCAR conditions, cases with missingness are considered as a random subsample of the entire dataset, neither associated with unobserved, nor observed data and as such their exclusion would yield a loss of statistical power through the reduction of sample size, but would not bias estimates (Graham, 2009). Under MAR conditions, missingness is linked to observed but not to unobserved data. Finally, under MNAR, missingness is linked to unobserved data.

To examine MAR conditions, i.e. associations of missingness patterns with any of the observed data, a couple of binary logistic regression analyses have been carried out and showed significant linkages of several central observed variables that are involved in the regression models carried out in the results section. For example,

- missingness on daily usage time of DMD is significantly linked to anxiety (b = 0.153 (0.072); p = 0.033) and female gender (b = 2.263 (1.052); p = 0.031) and
- missingness on count of days using DMD after midnight is significantly associated with daily usage time of DMD (b = -0.233 (0.087); p = 0.008).

Based on these results, there is evidence for missing values to be assumed as MAR and as a consequence, a simple exclusion of cases with missing data would result in biased estimates. In order to address this issue multiple imputation (MI) was carried out using the fully conditional specification (FCS) approach (Van Buuren et al., 2006) and predictive mean matching (PMM) with 5 cases in each match set (k = 5), i.e. each imputed value is the mean of five randomly chosen observed values of other cases whose predicted values are the most closest to the predicted values of the case for which data is to be imputed. To account for the high cumulative rate of cases with missingness mentioned above, a total of m = 50 datasets were created. MI was carried out using all variables on single item level involved in the statistical analyses.

2.8.4 Design effect and multilevel regression

The complex clustered sampling approach used in the sampling process of this thesis needs to be taken into account, since the students were not drawn by simple random sampling on individual level. Instead of single students, classes as clusters in which students are nested were drawn in multiple strata. As described in Hox et al., 2018 (Hox et al., 2018), this typically violates the assumption of independent observations, which would justify the calculation of standard errors, confidence intervals and p-values based on simple random sampling. Sampling approaches applying classes as clusters as selection units are typically faced with the fact that students within the same class show a bigger homogeneity of observed characteristics compared to students of different classes within the same strata (Bacher, 2009). As a consequence, measures from students within the same class are more correlated (referred to as intraclass correlation, ICC) and provide less information than measures from students from different classes of the same strata resulting in biased standard error estimation (Hox et al., 2018). This effect referred to as the design effect was introduced by Kish, 1965 (Kish, 1965) and is defined as the ratio of the standard error of a certain estimator given a complex sample design to the standard error of the same estimator under simple random sampling conditions. The design effect is taken into account in any calculations of confidence intervals assigned to descriptive parameters such as proportions and means. In the context of inferential statistics, multilevel approaches are applied to appropriately adjust standard error estimates (Hox et al., 2018).

2.8.5 Assumptions of regression analysis

To test for outliers, standardised residuals were calculated and values below -3.29 or above 3.29 were defined as outliers according to Tabachnik et al. (Tabachnick et al., 2013). Multicollinearity was tested by tolerance and variance inflation factor (VIF) as outlined by Myers (Myers, 1990) and Menard (Menard, 1995), recommending that VIF should remain below the value of 10 and tolerance above 0.2. Potential autocorrelations were tested using Durbin Watson statistics, following the rule proposed by Durbin and Watson (Durbin and Watson, 1950), according to which values should be close to the value of 2 and not below 1 or above 3. Normally distributed residuals were examined by the histograms as well as by P-P plots of standardised residuals. Homoscedasticity and linearity were examined by scatterplots of standardised predicted values on the x-axis and standardised residuals on the y-axis. Homoscedasticity was also tested using Koenker-test statistic (Daryanto, 2020), which is a studentized version of the Breusch-Pagan-test and outperformed other heteroscedasticity-tests (e.g. White's test, Breusch-Pagan-test) in a respective simulation study by Lyon and Tsai (Lyon and Tsai, 1996).

☛Table 7 show the results of the examination of the assumptions of regression analysis, indicating no problems with linearity, multicollinearity and autocorrelations. However, several outliers were detected. One outlier is indicated in case of the model with the outcome variable DMDCOUNT, 17 for DMDTIME, 13 for PRESLEEP, 20 for INITAGE, 3 for DRAB and 3 for ARAB (see the note of ☛Table 7 for a description of the variable labels). Outliers have been excluded from the corresponding analyses. Two other issues relate to non-normally distributed residuals and heteroscedasticity as indicated for some variables in ☛Table 7. According to Gelman et al., 2020 (Gelman et al., 2020) violations of normally distributed residuals are ignorable, since individual data points are not predicted within this thesis. With regard to heteroscedasticity and a resulting potential bias in the estimation of standard errors, three randomly chosen datasets (datasets 5, 22 and 32) from the multiple imputation dataset were analysed using multilevel linear regression and cluster robust standard errors based on Liang and Zeger (Liang and Zeger, 1986) and Bell and McCaffrey (Bell and McCaffrey, 2002) and implemented in the R-package “CR2”. A comparison of these analyses with a model without the robustness-adjustment of standard errors shows that in none of these three datasets did the robust estimators differ substantially from the ones that were yielded by the unadjusted model. Moreover, all p-values indicated the same classification of significance. Therefore, all analyses were carried out without robustness-adjustment of standard errors, since robust estimators are not implemented within multilevel and multiple imputed datasets (to the best of the author’s knowledge neither in R nor in SPSS).

Table 7: Examination of the assumptions of regression analysis

DEPVAR	OUT	COLL	INDEP	NORM	HOMO	LIN
DMDCOUNT	SRmin = -3.365 SRmax = 2.884	TOLmin = 0.971 VIFmax = 1.029	DW = 1.970	OK	LM = 1.079 p = 0.782	OK
DMDTIME	SRmin = -2.320 SRmax = 7.159	TOLmin = 0.971 VIFmax = 1.030	DW = 1.861	OK	LM = 5.614 p = 0.132	OK
PRESLEEP	SRmin = -3.864 SRmax = 0.994	TOLmin = 0.972 VIFmax = 1.029	DW = 1.897	Left skewed	LM = 48.936 p < 0.001	OK
AFTERMID	SRmin = -1.592 SRmax = 2.274	TOLmin = 0.972 VIFmax = 1.028	DW = 1.816	Right skewed	LM = 13.964 p = 0.003	OK
INITAGE	SRmin = -6.002 SRmax = 2.330	TOLmin = 0.972 VIFmax = 1.029	DW = 1.965	OK	LM = 44.205 p < 0.001	OK
DRAB	SRmin = -3.312 SRmax = 3.088	TOLmin = 0.234 VIFmax = 4.281	DW = 1.881	OK	LM = 80.806 p < 0.001	OK
ARAB	SRmin = -4.427 SRmax = 3.791	TOLmin = 0.242 VIFmax = 4.294	DW = 1.869	OK	LM = 116.127 p < 0.001	OK

Note: Unimputed, unweighted dataset. DEPVAR: dependent variable in the regression model. OUT: outliers COLL: collinearity. INDEP: uncorrelated residuals. NORM: normally distributed errors. HOMO: homoscedasticity. LIN: linearity. SR: standardised residuals. TOL: Tolerance. VIF: variance inflation factor. DW: Durbin-Watson: LM: Studentized Lagrange multiplier. DMDCOUNT: Number of personally owned digital media devices. DMDTIME: Daily usage time of digital media devices. PRESLEEP: Count of days using DMD as a pre-sleep activity on evenings with subsequent school day. AFTERMID: Count of days using digital media devices after midnight on evenings with subsequent school day. INITAGE: Initial age of regular internet use. DRAB: Device-related addictive behaviour. ARAB: Application-related addictive behaviour. The independent variables used in the examination can be seen in the results-section (☛section 3.2 and ☛section 3.4).

2.8.6 Software

Multiple imputation was carried out using IBM SPSS Version 29, *Multiple Imputation Module*.

The sample’s multilevel structure and the resulting design effect is taken into account in any calculations of confidence intervals assigned to descriptive parameters such as proportions and means by using IBM SPSS Version 29, *Complex Samples Module*, by using IBM SPSS Version 29, *Linear Mixed Models Module* in the context of multilevel linear regression and by using the R-package *lme4, Version 1.1-35.5* in the context of multilevel logistic regression.

3 Results

3.1 Characteristics of the sample

By applying population-adjusted calibration weights (discussed in ☛section 2.8.1) the sociodemographic characteristics of the sample are shown in ☛Table 8. The sample consists of 2,812 students attending Styrian schools from grade 7 onwards. 7.7% show missing values on gender, 47.3% are males, 43.3% females and 1.7% assign themselves a non-cis-gender. Since this subgroup consists of only 49 students, they are excluded from all inferential statistical analyses in order to avoid suppressing potentially practically relevant differences between cis- and non-cis-students due to excessively wide confidence intervals of non-cis-students. On average, the students are 15.76 years of age (SD = 2.20. MIN = 12. MAX = 25), 5.8% show missing values regarding age. 27.6% of the students attend academic secondary schools, followed by higher or intermediate technical and vocational colleges (26.3%), vocational schools (23.3%), new secondary schools (19.9%) and prevocational year (2.9%). Most students attend schools located in the central region of Styria (39.0%), followed by East-Styria (17.3%), Southwest-Styria (16.3%), Southeast-Styria (11.9%), Upper-Styria West (6.3%), Upper-Styria East (5.7%) and Liezen (3.5%).

Table 8: Sociodemographic characteristics of the sample

Variable	N (%)
Gender	
Male	1,329 (47.27%)
Female	1,218 (43.30%)
Different gender	49 (1.74%)
Missings	216 (7.68%)
Age	
Mean (SD); Median (IQR)	15.76 (2.20); 16.00 (3.00)
Minimum	12
Maximum	25
Missings	163 (5.81%)
School type	
New secondary school	559 (19.87%)
Academic secondary school	776 (27.58%)
Prevocational year	83 (2.94%)
Vocational school	654 (23.26%)
HTVC or ITVC	741 (26.34%)
Missings	0 (0.00%)
Educational region of attended school	
Liezen	99 (3.53%)
Upper-Styria East	161 (5.74%)
Upper-Styria West	177 (6.28%)
East-Styria	485 (17.25%)
Central region of Styria	1,097 (39.00%)
Southeast-Styria	334 (11.87%)
Southwest-Styria	459 (16.33%)
Missings	0 (0.00%)

Note: n=2,812 (unimputed, weighted dataset). The table shows frequencies and percentages in parentheses, except for age. SD: Standard deviation. IQR: Interquartile range. HTVC: Higher technical and vocational colleges. ITVC: Intermediate technical and vocational colleges.

Table 9: Descriptive statistics of all measures involved in the analyses

Variable	N (%)	Mean (SD); Median	95%-CI
Internet-related addictive behaviour			
DRAB (scores from 0 – 28)		11.50 (5.30); 11.00	11.23; 11.76
Missings	*1 (0.00%)*		
ARAB (scores from 0 – 28)		10.04 (5.71); 10.00	9.77; 10.31
Missings	*1 (0.00%)*		
r = 0.843 (0.831; 0.853); p < 0.001			
Internet use pattern			
DMDCOUNT		3.58 (1.15); 4.00	3.52; 3.63
Missings	*0 (0.00%)*		
DOMDMD			
Smartphone	2,165 (76.97%)		74.83%; 78.99%
Tablet	71 (2.54%)		1.97%; 3.26%
Gaming console	133 (4.73%)		4.00%; 5.58%
Computer/Laptop	380 (13.50%)		11.80%; 15.39%
TV	63 (2.24%)		1.76%; 2.84%
Missings	*1 (0.00%)*		
DOMAPP			
Reading and writing e-mails	16 (0.55%)		0.31%; 1.00%
Search für information	27 (0.97%)		0.66%; 1.44%
Chatting and writing messages	341 (12.13%)		11.02%; 13.35%
Publication of own contributions	15 (0.55%)		0.34%; 0.88%
Discussion forums	3 (0.10%)		0.03%; 0.31%
Watch films/series	422 (15.00%)		13.72%; 16.37%
Listen to music/podcasts	330 (11.75%)		10.66%; 12.93%
Downloads	14 (0.49%)		0.29%; 0.81%
Games	416 (14.80%)		13.18%; 16.58%
Gambles	6 (0.21%)		0.09%; 0.48%
Erotic/sex/porn	76 (2.70%)		2.12%; 3.45%
Social networks	1,078 (38.35%)		36.13%; 40.62%
Shopping	15 (0.52%)		0.33%; 0.82%
Selling	7 (0.26%)		0.12%; 0.56%
Other activity	44 (1.58%)		1.14%; 2.19%
Missings	*1 (0.00%)*		
DMDTIME		5.04 (2.83); 4.57	4.88; 5.20
Missings	*83 (2.94%)*		
PRESLEEP (scores from 0 – 5)		4.22 (1.42); 5.00	4.16; 4.28
Missings	*86 (3.07%)*		
AFTERMID (scores from 0 – 5)		1.66 (1.82); 1.00	1.58; 1.75
Missings	*200 (7.10%)*		
POSIT			
In bed (reception mode, not silent)	494 (17.56%)		16.17%; 19.05%
In bed (reception mode, silent)	992 (35.28%)		33.46%; 37.13%
In bed (flight mode or switched off)	393 (13.97%)		12.64%; 15.40%
Somewhere else in my room	568 (20.20%)		18.77%; 21.71%
Outside my room	327 (11.63%)		10.13%; 13.31%
Missings	*39 (1.37%)*		
INITAGE		11.55 (2.14); 12.00	11.44; 11.66
Missings	*163 (5.78%)*		
Comorbid symptoms			
INSOMNIA (scores from 0 – 24)		7.53 (5.23); 7.00	7.29; 7.77
No insomnia	1,256 (44.66%)		42.66%; 46.68%
Subthreshold insomnia	855 (30.39%)		28.79%; 32.05%
Moderate insomnia	352 (12.52%)		11.25%; 13.92%
Severe insomnia	100 (3.57%)		2.88%; 4.41%
Missings	*249 (8.86%)*		
ANXIETY (scores from 0 – 21)		6.88 (5.53); 6.00	6.59; 7.18
No	1,809 (64.34%)		61.79%; 66.80%
Yes	658 (23.39%)		21.50%; 25.39%
Missings	*345 (12.27%)*		
PSYCONST (scores from 0 – 40)		13.97 (6.08); 13.00	13.63; 14.30
Normal	1,432 (50.94%)		48.46%; 53.41%
Borderline	441 (15.67%)		14.39%; 17.04%
Abnormal	458 (16.30%)		14.90%; 17.80%
Missings	*481 (17.09%)*		

(Continued)

Table 9: (Continued)

Variable	N (%)	Mean (SD); Median	95%-CI
Sociodemographic characteristics			
AGE		15.76 (2.20); 16.00	15.61; 15.91
Missings	*163 (5.81%)*		
GENDER			
Male	1,329 (47.27%)		43.71%; 50.86%
Female	1,218 (43.30%)		39.68%; 47.00%
Different gender	49 (1.74%)		1.29%; 2.34%
Missings	*216 (7.68%)*		
SES (scores from 0 – 8)		6.11 (1.50); 6.00	6.04; 6.18
Missings	*661 (23.51%)*		
Psychosocial characteristics			
BOREDOM (scores from 0 – 12)		4.33 (3.02); 4.00	4.19; 4.48
Missings	*294 (10.46%)*		
SELFEFF (scores from 0 – 12)		8.37 (2.60); 9.00	8.24; 8.51
Missings	*189 (6.71%)*		
PARSUPP (scores from 0 – 15)		10.80 (3.53); 12.00	10.64; 10.97
Missings	*334 (11.88%)*		
EMOSUPP (scores from 0 – 12)		9.87 (2.82); 11.00	9.73; 10.00
Missings	*221 (7.84%)*		
INSTSUPP (scores from 0 – 12)		9.79 (2.96); 11.00	9.65; 9.93
Missings	*210 (7.47%)*		
PROBEHAV (scores from 0 – 10)		7.72 (2.13); 8.00	7.62; 7.83
Missings	*329 (11.72%)*		
CONCERNS (scores from 0 – 3)		0.32 (0.65); 0.00	0.29; 0.35
Missings	*220 (7.81%)*		
WELLCLASS (scores from 0 – 3)		2.23 (0.84); 2.00	2.18; 2.27
Missings	*243 (8.64%)*		
Family environmental aspects			
PARENTAL RULES			
No	2,227 (79.20%)		77.05%; 81.21%
Yes	498 (17.71%)		15.77%; 19.82%
Missings	*87 (3.09%)*		
PARENTUSE (scores from 0 – 4)		1.59 (1.05); 1.50	1.55; 1.64
Missings	*171 (6.09%)*		
SIBLINGS			
No	376 (13.39%)		12.20%; 14.67%
Yes	2,273 (80.83%)		79.21%; 82.35%
Missings	*163 (5.78%)*		

Note: Note: n=2,812 (unimputed, weighted dataset). DRAB: Device-related addictive behaviour. ARAB: Application-related addictive behaviour. DMDCOUNT: Number of personally owned digital media devices. DOMDMD: Leisure-dominant digital media device. DOMAPP: Leisure-dominant internet application. DMDTIME: Daily usage time of digital media devices. PRESLEEP: Count of days using DMD as a pre-sleep activity on evenings with subsequent school day. AFTERMID: Count of days using digital media devices after midnight on evenings with subsequent school day. POSIT: Position of the smartphone during bedtime. INITAGE: Initial age of regular internet use. INSOMNIA: insomnia severity (ISI-score) ANXIETY: Generalized anxiety disorder (GAD-7-score). PSYCONST: overall psychosocial constitution (SDQ total difficulties score). SES: Socioeconomic status. BOREDOM: Proneness to boredom. SELFEFF: Self-efficacy. PARSUPP: Parental support. EMOSUPP: Emotional support. INSTSUPP: Instrumentals support. PROBEHAV: Prosocial behaviour. CONCERNS: Concerns related to the extent of internet use. WELLCLASS: Wellbeing in school class. PARENTUSE: Extent of parental use of digital media devices. r: correlation coefficient.

3.2 Results related to characteristics of DMD and internet use

According to research questions (RQ) 1 to 6 (☛section 1.9.1) this section shows gender-, age- and SES-specific characteristics of DMD and internet use.

RQ1: count of DMD in own possession

According to ☛Table 10 the examined students own an average of 3.58 DMD (SD: 1.14; 95%-CI: 3.52 – 3.63). With regard to the distribution of individual DMD, it can be observed that almost all students own a smartphone (99.0%), followed by computers/laptops (85.9%), TV's (70.5%), gaming consoles (55.2%) and tablets (45.0%). ☛Table 11 shows that the equipment with DMD is rather homogeneous across classes, only little variation can be observed ($ICC_{adjusted}$ = 0.052). Of the three predictors in the model, a significant association is only found for gender, when controlling for age and SES. Female students own, on average, fewer DMD than males (b = -0.326; 95%-CI: -0.420; -0.233). Age and SES are not linked to the number of owned DMD.

RQ2: dominant DMD in use

As shown in ☛Table 12, among the DMD considered, such as smartphone, tablet, gaming console, PC/laptop and TV, a clear dominance of smartphones in terms of leisure-related usage is observed across all three considered sociodemographic subgroups. For 77.0% (95%-CI: 74.85%; 79.01%) of the students, the smartphone is the dominant DMD, followed by 13.5% (95%-CI: 11.81%; 15.40%) who mainly use PC/laptop and 4.7% (95%-CI: 4.00%; 5.58%) who predominantly use gaming consoles. Tablets and TVs have only a minor relevance in this regard.

Considering gender specificity (see ☛Table 13), it is observed that smartphones are much more dominant among female students compared to males (OR = 5.113; 95%-CI: 4.035; 6.482), whereas gaming consoles (OR = 0.090; 95%-CI: 0.048; 0.168) and PC/laptops (OR = 0.146; 95%-CI: 0.105; 0.204) show the opposite effect. Tablets and TVs, which are used much less frequently in leisure time, show no association with gender. Considering the students' age, it is observed that smartphone use becomes more dominant the older the students are (OR = 1.129; 95%-CI: 1.065; 1.196). On the other hand, tablets (OR = 0.801; 95%-CI: 0.676; 0.951), gaming consoles (OR = 0.818; 95%-CI: 0.743; 0.902) and PC/laptops (OR = 0.919; 95%-CI: 0.851; 0.993) show the opposite effect. Socioeconomic status is only associated with a dominance of PC/laptops. The higher the SES, the more often PC/laptops are dominant in leisure-related usage (OR = 1.110; 95%-CI: 1.005; 1.225).

☛Table 13 also shows that leisure-related dominance of tablets (although only rarely occurring) is quite heterogeneous across classes ($ICC_{adjusted}$ = 0.257). Moreover, the dominance of PC/laptops and TVs vary substantially across school classes. Since the data does not include any information about specific class characteristics, such as those related to tablet classes or IT-specific focal points, no further examination can be carried out in that respect.

RQ3: dominant internet-based application in use

☛Table 14 displays the five most dominant internet-based applications among students. Social media is clearly the one with the highest rate of being dominant in leisure-related usage across all three considered sociodemographic subgroups (38.4% of the total sample; 95%-CI: 36.14%; 40.63%). In this regard, social media is followed by streaming movies and series (15.0%; 95%-CI: 13.73%; 16.37%), gaming (14.8%; 95%-CI: 13.18%; 16.58%), chatting (12.1%; 95%-CI: 11.02%; 13.35%) and listening to music (11.8%; 95%-CI: 10.67%; 12.93%). Other applications with recognized addictive potential are dominant for significantly fewer students (engaging in porn content at 2.7%, shopping at 0.5% and gambling at 0.2%). However, it should be noted that this doesn't mean that only 0.2% of the students basically engage in online gambling – it just means that, for that 0.2%, gambling is their main leisure-related online activity.

☛Table 15, depicting the results of multilevel logistic regression analyses, shows gender to be associated with a dominance of social media, gaming, chatting and listening to music. While the odds of using social media (OR = 2.555; 95%-CI: 2.138; 3.053), chatting (OR = 1.380; 95%-CI: 1.087; 1.752) and listening to music (OR = 1.469; 95%-CI: 1.146; 1.885) as the dominant online activity are higher for female students compared to male, the odds of gaming are substantially higher for male students (OR = 0.091; 95%-CI: 0.064; 0.127). Age is associated with listening to music, gaming and social media. The odds using social media and listening to music as the dominant online activity are the higher the older students are. However, with respect to gaming the inverse association was observed (OR = 0.802; 95%-CI: 0.747; 0.861).

While the dominance of certain DMD varied substantially across school classes, the dominance of specific internet applications is much more homogeneous across classes (maximum $ICC_{adjusted}$ = 0.078 for gaming; see ☛Table 15).

RQ4: daily leisure-related usage time of the dominant DMD

☛Table 16 shows an average of 5.04 hours (SD: 2.83; 95%-CI: 4.88 – 5.20) of daily usage. This estimate just refers to leisure-related usage (school-related usage is not included) and to the most used device (additional usage time of other DMD was not taken into account, as the data does not provide an indication of simultaneous use of multiple DMD). It can therefore be reasonably assumed that both the total, as well as the leisure-related usage time are in fact higher.

Usage times vary substantially across school classes, as indicated by $ICC_{adjusted}$ = 0.113 (☛Table 17). Moreover, the regression analysis also indicates that female students show a higher level of leisure-related usage time of more than half an hour than males (b = 0.548; 95%-CI [0.326; 0.770]) and that usage time is negatively associated with SES (b = -0.186; 95%-CI [-0.258; -0.114]). The students' age is not linked to usage times.

RQ5: bedtime routines; count of school days using DMD as a pre-sleep activity

☛Table 18 indicates that students spend an average of 4.22 school days (SD: 1.42; 95%-CI: 4.16 – 4.28) per week using DMD as a pre-sleep activity, i.e. on evenings with subsequent school day. Since a school week in Austria consists of five such days, this means that pre-sleep activity occurs on almost every single school day.

Pre-sleep activity is very homogeneous across classes ($ICC_{adjusted}$ = 0.023) as shown in ☛Table 19. Age is positively associated with the extent of pre-sleep activity with DMD, which means that older students show this behaviour more frequently (b = 0.110; 95%-CI [0.082; 0.137]). SES on the other hand is negatively linked to corresponding pre-sleep activity, indicating that students with lower SES show more pre-sleep activity (b = -0.079; 95%-CI [-0.117; -0.041]). However, there is no relation to gender.

RQ5: bedtime routines; count of school days using DMD after midnight

The measurement of after-midnight DMD usage was carried out in the same way as for the extent of pre-sleep activity. ☛Table 20 shows an average of 1.66 school days (SD: 1.82; 95%-CI: 1.58 – 1.75) per week on which students use DMD after midnight on evenings with subsequent school day.

As with pre-sleep activity, after midnight usage is not substantially varied between school classes ($ICC_{adjusted}$ = 0.065), positively linked to age (b = 0.100; 95%-CI [0.060; 0.140]), negatively associated with SES (b = -0.103; 95%-CI [-0.152; -0.054]) and not related to gender (see ☛Table 21).

RQ6: initial age of regularly using the internet during leisure time

☛Table 23 shows significant associations of the initial age of regularly using the internet during leisure time with gender, age and SES. 21.8% of the variance of the initial age of regular internet use can be explained by these three sociodemographic variables. School classes do not provide a substantial contribution in variance explanation ($ICC_{adjusted}$ = 0.032). Male students start their engagement in regular internet use half a year earlier than female students (b = 0.499; 95%-CI [0.348; 0.650]). Moreover, ☛Table 22 displays a steady decline of the onset of regular internet use with decreasing current age, indicating that the entry to the internet occurs at increasingly earlier time points. The results of multilevel regression analysis shown in ☛Table 23 indicate that the onset declines by nearly half a year for each year of younger current age (b = 0.420; 95%-CI [0.380; 0.459]). With regard to SES, no relation with the onset of regular internet use was observed.

Table 10: Count of DMD in own possession; descriptive statistics

	N	Mean (SD); Median	95%-CI
Total	2,811	3.58 (1.14); 4.00	3.52; 3.63
Gender	2,546		
Male	1,328	3.74 (1.14); 4.00	3.66; 3.82
Female	1,218	3.39 (1.13); 3.00	3.33; 3.46
Age	2,648		
12, 13, 14 years	856	3.60 (1.21); 4.00	3.48; 3.71
15, 16 years	818	3.58 (1.12); 4.00	3.50; 3.66
17, 18 years	722	3.56 (1.08); 4.00	3.48; 3.65
19+ years	252	3.63 (1.21); 4.00	3.49; 3.79
SES	2,150		
Scores 0 – 4	296	3.55 (1.20); 4.00	3.43; 3.68
Scores 5 – 8	1,854	3.61 (1.12); 4.00	3.54; 3.67

Note: Unimputed, weighted dataset. Different gender excluded due to too few cases (see ☛section 3.1), outlier excluded (see ☛section 2.8.5). Unit of analysis: Count of DMD. The table shows means, standard deviations, medians and 95%-confidence interval of the mean. SD: standard deviation. CI: confidence intervall. MIN: 0. MAX: 7. Proportions of single DMD among students: Smartphone: 99.0%. Tablet: 45.0%. Gaming console: 55.2%. Computer/Laptop: 85.9%. TV: 70.5%. Additional DMD: 2.3% (primarily Smartwatch or Virtual Reality Accessories).

Table 11: Count of DMD in own possession; multilevel linear regression coefficients

	b(SE) pooled	95%-CI (b) pooled	β pooled
Fixed effects			
Intercept	3.673 (0.227)***	3.229; 4.117	0.119
Gender	-0.326 (0.048)***	-0.420; -0.233	-0.232
Age	-0.004 (0.012)	-0.028; 0.021	0.001
Ses	0.020 (0.015)	-0.010; 0.050	-0.015
Random effects	**σ^2 pooled**	**95%-CI (σ^2) pooled**	
Variance of class-intercept	0.067 (0.016)	0.035; 0.098	

Note: Imputed dataset; m = 50. Different gender excluded due to too few cases (see ☛section 3.1), outlier excluded (see ☛section 2.8.5). Multilevel linear regression (Level 1: students. Level 2: school classes). Unit of analysis: Count of DMD. Pooled variance estimate of Level 1-residuals = 1.210. Pooled ICC adjusted/conditional = 0.052/0.051. Pooled R^2 marginal/conditional based on (Nakagawa and Schielzeth, 2013) = 0.021/0.073.
Gender: (Male = 0. Female =1). Age: Students' age. Ses: Socioeconomic status. b: Pooled unstandardized coefficient. SE: Pooled standard error. 95%-CI: Pooled 95%-confidence interval of b. β: Pooled standardized coefficient according to Gelman (Gelman, 2008) by dividing numeric variables by two standard deviations to provide a better comparison with binary variables). σ^2: Variance. * p < 0.05. ** p < 0.01. *** p < 0.001.

Table 12: Dominant DMD in use; descriptive statistics

	N	*SMA % (95%-CI)*	*TABL % (95%-CI)*	*CONS % (95%-CI)*	*PC/LAP % (95%-CI)*	*TV % (95%-CI)*
Total	2,811	77.00 (74.85; 79.01)	2.54 (1.97; 3.26)	4.73 (4.00; 5.58)	13.50 (11.81; 15.40)	2.24 (1.76; 2.84)
Gender*DOMDMD	2,546					
Male	1,328	66.63 (63.68; 69.45)	2.12 (1.30; 3.45)	8.25 (6.89; 9.86)	20.81 (18.09; 23.82)	2.19 (1.51; 3.18)
Female	1,218	89.39 (87.38; 91.11)	3.05 (2.27; 4.09)	0.84 (0.47; 1.49)	4.45 (3.42; 5.76)	2.28 (1.56; 3.30)
Age*DOMDMD	2,648					
12, 13, 14 years	856	71.96 (68.66; 75.05)	3.55 (2.37; 5.28)	6.79 (5.24; 8.74)	15.28 (12.75; 18.20)	2.43 (1.56; 3.76)
15, 16 years	818	78.38 (74.04; 82.17)	2.75 (1.83; 4.10)	4.62 (3.37; 6.32)	12.94 (9.85; 16.81)	1.30 (0.75; 2.26)
17, 18 years	722	82.45 (79.10; 85.36)	1.59 (0.78; 3.23)	2.34 (1.49; 3.66)	11.10 (8.77; 13.94)	2.52 (1.68; 3.78)
19+ years	252	80.07 (74.21; 84.87)	0.76 (0.46; 1.25)	4.12 (2.25; 7.43)	11.79 (7.35; 18.39)	3.27 (1.54; 6.79)
SES*DOMDMD	2,151					
Scores 0 – 4	296	79.98 (75.40; 83.88)	1.31 (0.63; 2.69)	6.60 (4.12; 10.40)	10.52 (7.87; 13.92)	1.59 (0.76; 3.32)
Scores 5 – 8	1,855	77.36 (75.03; 79.53)	2.54 (1.9; 3.40)	3.66 (2.93; 4.57)	14.34 (12.37; 16.56)	2.10 (1.52; 2.88)

Note: Unimputed, weighted dataset. Different gender excluded due to too few cases (see ☛section 3.1). The table shows total and row percentages in relation to valid cases and 95%-confidence interval. 95%-CI: 95%-confidence interval. SMA: Smartphone. TABL: Tablet. CONS: Gaming console. PC/LAP: Computer/Laptop. TV: TV. DOMDMD: Dominant DMD in use.

Table 13: Dominant DMD in use; multilevel binary logistic regression coefficients

	SMA b (SE); OR (95%-CI(OR))	**TABL** b (SE); OR (95%-CI(OR))	**CONS** b (SE); OR (95%-CI(OR))	**PC/LAP** b (SE); OR (95%-CI(OR))	**TV** b (SE); OR (95%-CI(OR))
Fixed effects					
Intercept	-0.842 (0.557);	-2.276 (1.62);	1.446 (0.890);	-0.765 (0.732);	-5.138 (1.300)***;
	0.431; (0.145, 1.284)	0.103; (0.004, 2.457)	4.245 (0.741; 24.308)	0.466; (0.111, 1.954)	0.006; (0.001, 0.075)
Gender	1.632 (0.121)***;	0.271 (0.287);	-2.413 (0.322)***;	-1.922 (0.169)***;	0.085 (0.285);
	5.113; (4.035, 6.482)	1.312; (0.747, 2.303)	0.090 (0.048; 0.168)	0.146; (0.105, 0.204)	1.089; (0.623, 1.902)
Age	0.121 (0.029)***;	-0.221 (0.087)*;	-0.201 (0.050)***;	-0.084 (0.039)*;	0.064 (0.065);
	1.129; (1.065, 1.196)	0.801; (0.676, 0.951)	0.818 (0.743; 0.902)	0.919; (0.851, 0.993)	1.066; (0.938, 1.212)
Ses	-0.061 (0.041);	0.198 (0.122);	-0.125 (0.070);	0.104 (0.051)*;	-0.003 (0.099);
	0.941; (0.868, 1.020)	1.219; (0.960, 1.584	0.883 (0.770; 1.012)	1.110; (1.005, 1.225)	0.997; (0.821, 1.210)
Random effects	**Pooled σ2**	**Pooled σ2**	**Pooled σ2**	**Pooled σ2**	**Pooled σ2**
Var. class-intercept	0.233	1.140	Not applicable[!]	0.523	0.730

Note: Imputed dataset; m = 50. Different gender excluded due to too few cases (see ☛section 3.1). Multilevel binary logistic regressions (Level 1: students. Level 2: school classes). SMA-model: Pooled ICC adjusted = 0.066. Pooled R^2 marginal/conditional based on (Nakagawa and Schielzeth, 2013) = 0.174/0.229. TABL-model: Pooled ICC adjusted = 0.257. Pooled R^2 marginal/conditional based on (Nakagawa and Schielzeth, 2013) = 0.083/0.319. CONS-model: Pooled R^2 (Cox & Snell) = 0.045. Pooled R^2 (Nagelkerke) = 0.148. PC/LAP-model: Pooled ICC adjusted = 0.137. Pooled R^2 marginal/conditional based on (Nakagawa and Schielzeth, 2013) = 0.206/0.315. TV-model: Pooled ICC adjusted = 0.182. Pooled R^2 marginal/conditional based on (Nakagawa and Schielzeth, 2013) = 0.007/0.187.

[!] The CONS-model was analysed by ignoring the multilevel structure due to singularity issues of the level 2-variable.

Gender: (Male = 0. Female =1). Age: Students' age. Ses: Socioeconomic status. b: Pooled log-odds. SE: Pooled standard error. OR: Odds ratio (exp(b)). 95%-CI (OR): Pooled 95%-confidence interval of OR. σ^2: Variance. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$. SMA: Smartphone as dominant DMD. TABL: Tablet as dominant DMD. CONS: Gaming as dominant DMD. PC/LAP: Computer/Laptop as dominant DMD. TV: TV as dominant DMD.

Table 14: Dominant internet-based application in use; descriptive statistics

	N	CHAT % (95%-CI)	FILM % (95%-CI)	AUDIO % (95%-CI)	GAME % (95%-CI)	SMEDIA % (95%-CI)
Total	2,811	12.14 (11.02; 13.35)	15.00 (13.73; 16.37)	11.75 (10.67; 12.93)	14.80 (13.18; 16.58)	38.36 (36.14; 40.63)
Gender*DOMAPP	2,546					
Male	1,328	10.74 (9.18; 12.53)	15.35 (13.66; 17.22)	10.23 (8.72; 11.98)	24.81 (21.87; 28.01)	29.52 (26.50; 32.74)
Female	1,218	14.00 (12.45; 15.71)	15.42 (13.46; 17.60)	13.75 (11.99; 15.72)	3.49 (2.50; 4.85)	49.62 (46.70; 52.55)
Age*DOMAPP	2,648					
12, 13, 14 years	856	12.13 (10.17; 14.41)	15.29 (12.95; 17.95)	10.01 (8.48; 11.79)	21.23 (18.37; 24.4)	33.34 (28.90; 38.11)
15, 16 years	818	10.61 (8.75; 12.81)	15.07 (12.55; 17.99)	12.05 (9.81; 14.72)	13.82 (11.30; 16.81)	41.57 (37.95; 45.29)
17, 18 years	722	14.33 (11.86; 17.20)	14.82 (12.73; 17.18)	12.36 (10.41; 14.61)	9.18 (7.09; 11.81)	43.02 (39.14; 46.99)
19+ years	252	12.58 (9.72; 16.13)	12.28 (8.52; 17.39)	14.17 (9.99; 19.71)	11.60 (7.51; 17.49)	37.34 (31.03; 44.11)
SES*DOMAPP	2,151					
Scores 0 – 4	296	14.21 (11.00; 18.17)	16.01 (12.54; 20.24)	13.30 (9.88; 17.68)	13.33 (10.07; 17.45)	34.05 (28.75; 39.79)
Scores 5 – 8	1,855	11.88 (10.42; 13.51)	14.83 (13.44; 16.33)	11.18 (9.93; 12.55)	13.93 (12.01; 16.11)	41.62 (39.30; 43.98)

Note: Unimputed, weighted dataset. Different gender excluded due to too few cases (see ☛section 3.1). The table shows total and row percentages in relation to valid cases and 95%-confidence interval. 95%-CI: 95%-confidence interval. Row percentages do not sum to 100% since just the five most dominant internet-based applications are shown. CHAT: Chatting and writing messages. FILM: Watch films/series. AUDIO: Listen to music/podcasts. GAME: Games. SMEDIA: Social media. DOMAPP: Dominant internet-based application in use. Other internet-based applications with addictive potential are dominant for (in %): engaging in porn content: 2.70 (2.12; 3.45), gambling: 0.21 (0.10; 0.49), shopping: 0.52 (0.33, 0.82).

Table 15: Dominant internet-based application in use; multilevel binary logistic regression coefficients

	CHAT b (SE); OR (95%-CI(OR))	FILM b (SE); OR (95%-CI(OR))	AUDIO b (SE); OR (95%-CI(OR))	GAME b (SE); OR (95%-CI(OR))	SMEDIA b (SE); OR (95%-CI(OR))
Fixed effects					
Intercept	-2.059 (0.536)***; 0.128; (0.045, 0.365)	-1.415 (0.548)**; 0.243; (0.083, 0.711)	-3.343 (0.577)***; 0.035; (0.011, 0.109)	2.514 (0.653)***; 12.352; (3.438, 44.389)	-2.231 (0.422)***; 0.107; (0.047, 0.246)
Gender	0.322 (0.122)**; 1.380; (1.087, 1.752)	-0.108 (0.117); 0.898; (0.678, 1.131)	0.385 (0.127)**; 1.469; (1.146, 1.885)	-2.402 (0.174)***; 0.091; (0.064, 0.127)	0.938 (0.091)***; 2.555; (2.138, 3.053)
Age	0.009 (0.028); 1.009; (0.955, 1.065)	-0.033 (0.029); 0.968; (0.915, 1.023)	0.081 (0.029)**; 1.084; (1.025, 1.147)	-0.221 (0.036)***; 0.802; (0.747, 0.861)	0.064 (0.022)**; 1.066; (1.021, 1.114)
Ses	-0.029 (0.040); 0.971; (0.898, 1.051)	0.028 (0.041); 1.028; (0.949, 1.113)	-0.029 (0.043); 0.972; (0.894, 1.057)	-0.029 (0.045); 0.972; (0.889, 1.062)	0.047 (0.030); 1.048; (0.989, 1.111)
Random effects	**Pooled σ2**	**Pooled σ2**	**Pooled σ2**	**Pooled σ2**	**Pooled σ2**
Var. class-intercept	0.028	0.100	0.063	0.279	0.114

Note: Imputed dataset; m = 50. Different gender excluded due to too few cases (see ☛section 3.1). Multilevel binary logistic regressions (Level 1: students. Level 2: school classes). CHAT-model: Pooled ICC adjusted = 0.009. Pooled R^2 marginal/conditional based on (Nakagawa and Schielzeth, 2013) = 0.009/0.017. FILM-model: Pooled ICC adjusted = 0.030. Pooled R^2 marginal/conditional based on (Nakagawa and Schielzeth, 2013) = 0.003/0.033. AUDIO-model: Pooled ICC adjusted = 0.019. Pooled R^2 marginal/conditional based on (Nakagawa and Schielzeth, 2013) = 0.021/0.039. GAME-model: Pooled ICC adjusted = 0.078. Pooled R^2 marginal/conditional based on (Nakagawa and Schielzeth, 2013) = 0.314/0.368. SMEDIA-model: Pooled ICC adjusted = 0.033. Pooled R^2 marginal/conditional based on (Nakagawa and Schielzeth, 2013) = 0.065/0.096.

Gender: (Male = 0. Female =1). Age: Students' age. Ses: Socioeconomic status. b: Pooled log-odds. SE: Pooled standard error. OR: Odds ratio (exp(b)). 95%-CI (OR): Pooled 95%-confidence interval of OR. σ^2: Variance. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$. CHAT: Chatting as dominant application. FILM: Streaming film as dominant application. AUDIO: Listening to music as dominant application. GAME: Gaming as dominant application. SMEDIA: Social media as dominant application.

Table 16: Daily leisure-related usage time of dominant DMD; descriptive statistics

	N	Mean (SD); Median	95%-CI
Total	2,713	5.04 (2.83); 4.57	4.88; 5.20
Gender	2,469		
Male	1,296	4.66 (2.63); 4.29	4.45; 4.86
Female	1,173	5.21 (2.52); 5.00	5.03; 5.39
Age	2,564		
12, 13, 14 years	833	4.57 (2.55); 4.00	4.30; 4.84
15, 16 years	786	5.31 (2.74); 5.00	5.08; 5.54
17, 18 years	705	5.06 (2.34); 4.71	4.84; 5.28
19+ years	240	5.01 (3.08); 4.39	4.45; 5.56
SES	2,097		
Scores 0 – 4	284	5.93 (2.71); 5.86	5.61; 6.26
Scores 5 – 8	1,813	4.73 (2.36); 4.43	4.59; 4.88

Note: Unimputed, weighted dataset. Different gender excluded due to too few cases (see ☛section 3.1), outlier excluded (see ☛section 2.8.5). Unit of analysis: Daily hours. The table shows means, standard deviations, medians and 95%-confidence interval of the mean. SD: standard deviation. CI: confidence intervall.

Table 17: Daily leisure-related usage time of dominant DMD; multilevel linear regression coefficients

	b(SE) pooled	95%-CI (b) pooled	β pooled
Fixed effects			
Intercept	5.266 (0.598)***	4.093; 6.438	-0.060
Gender	0.548 (0.113)***	0.326; 0.770	0.096
Age	0.038 (0.033)	-0.026; 0.102	0.030
Ses	-0.186 (0.037)***	-0.258; -0.114	-0.104
Random effects	**σ^2 pooled**	**95%-CI (σ^2) pooled**	
Variance of class-intercept	0.776 (0.138)	0.505; 1.047	

Note: Imputed dataset; m = 50. Different gender excluded due to too few cases (see ☛section 3.1), outlier excluded (see ☛section 2.8.5). Multilevel linear regression (Level 1: students. Level 2: school classes). Unit of analysis: Daily hours. Pooled variance estimate of Level 1-residuals = 6.118. Pooled ICC adjusted/conditional = 0.113/0.110. Pooled R^2 marginal/conditional based on (Nakagawa and Schielzeth, 2013) = 0.025/0.135.
Gender: (Male = 0. Female =1). Age: Students' age. Ses: Socioeconomic status. b: Pooled unstandardized coefficient. SE: Pooled standard error. 95%-CI: Pooled 95%-confidence interval of b. β: Pooled standardized coefficient according to Gelman (Gelman, 2008) by dividing numeric variables by two standard deviations to provide a better comparison with binary variables). σ^2: Variance. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

Table 18: Count of school days using DMD as a pre-sleep-activity; descriptive statistics

	N	Mean (SD); Median	95%-CI
Total	2,712	4.22 (1.42); 5.00	4.16; 4.28
Gender	2,469		
Male	1,281	4.23 (1.39); 5.00	4.14; 4.32
Female	1,188	4.24 (1.40); 5.00	4.15; 4.33
Age	2,567		
12, 13, 14 years	833	3.87 (1.65); 5.00	3.72; 4.02
15, 16 years	792	4.30 (1.36); 5.00	4.21; 4.40
17, 18 years	702	4.55 (1.02); 5.00	4.48; 4.62
19+ years	241	4.44 (1.09); 5.00	4.31; 4.58
SES	2,108		
Scores 0 – 4	285	4.50 (1.10); 5.00	4.36; 4.63
Scores 5 – 8	1,823	4.21 (1.43); 5.00	4.13; 4.29

Note: Unimputed, weighted dataset. Different gender excluded due to too few cases (see ☛section 3.1), outlier excluded (see ☛section 2.8.5). Unit of analysis: Count of school days. The table shows means, standard deviations, medians and 95%-confidence interval of the mean. SD: standard deviation. CI: confidence interval.

Table 19: Count of school days using DMD as a pre-sleep-activity; multilevel linear regression coefficients

	b(SE) pooled	95%-CI (b) pooled	β pooled
Fixed effects			
Intercept	2.937 (0.264)***	2.419; 3.455	-0.010
Gender	0.075 (0.056)	-0.035; 0.184	0.027
Age	0.110 (0.014)***	0.082; 0.137	0.175
Ses	-0.079 (0.020)***	-0.117; -0.041	-0.090
Random effects	**σ^2 pooled**	**95%-CI (σ^2) pooled**	
Variance of class-intercept	0.042 (0.019)	0.005; 0.078	

Note: Imputed dataset; m = 50. Different gender excluded due to too few cases (see ☛section 3.1), outlier excluded (see ☛section 2.8.5). Multilevel linear regression (Level 1: students. Level 2: school classes). Unit of analysis: Count of school days. Pooled variance estimate of Level 1-residuals = 1.751. Pooled ICC adjusted/conditional = 0.023/0.022. Pooled R^2 marginal/conditional based on (Nakagawa and Schielzeth, 2013) = 0.044/0.066.
Gender: (Male = 0. Female =1). Age: Students' age. Ses: Socioeconomic status. b: Pooled unstandardized coefficient. SE: Pooled standard error. 95%-CI: Pooled 95%-confidence interval of b. β: Pooled standardized coefficient according to Gelman (Gelman, 2008) by dividing numeric variables by two standard deviations to provide a better comparison with binary variables). σ^2: Variance. * p < 0.05. ** p < 0.01. *** p < 0.001.

Table 20: Count of school days using DMD after midnight; descriptive statistics

	N	Mean (SD); Median	95%-CI
Total	2,612	1.66 (1.82); 1.00	1.58; 1.75
Gender	2,376		
Male	1,224	1.69 (1.85); 1.00	1.57; 1.82
Female	1,152	1.58 (1.75); 1.00	1.47; 1.68
Age	2,476		
12, 13, 14 years	794	1.39 (1.78); 0.00	1.26; 1.52
15, 16 years	764	1.75 (1.81); 1.00	1.61; 1.89
17, 18 years	686	1.81 (1.79); 1.00	1.66; 1.95
19+ years	231	1.98 (1.93); 1.00	1.68; 2.29
SES	2,045		
Scores 0 – 4	272	2.28 (1.86); 2.00	2.08; 2.47
Scores 5 – 8	1,772	1.50 (1.74); 1.00	1.41; 1.59

Note: Unimputed, weighted dataset. Different gender excluded due to too few cases (see ☛section 3.1), outlier excluded (see ☛section 2.8.5). Unit of analysis: Count of school days. The table shows means, standard deviations, medians and 95%-confidence interval of the mean. SD: standard deviation. CI: confidence intervall.

Table 21: Count of school days using DMD after midnight; multilevel linear regression coefficients

	b(SE) pooled	95%-CI (b) pooled	β pooled
Fixed effects			
Intercept	0.646 (0.384)	-0.108; 1.400	-0.007
Gender	0.014 (0.077)	-0.136; 0.165	0.004
Age	0.100 (0.021)***	0.060; 0.140	0.123
Ses	-0.103 (0.025)***	-0.152; -0.054	-0.091
Random effects	**σ^2 pooled**	**95%-CI (σ^2) pooled**	
Variance of class-intercept	0.204 (0.047)	0.112; 0.295	

Note: Imputed dataset; m = 50. Different gender excluded due to too few cases (see ☛section 3.1), outlier excluded (see ☛section 2.8.5). Multilevel linear regression (Level 1: students. Level 2: school classes). Unit of analysis: Count of school days. Pooled variance estimate of Level 1-residuals = 2.937. Pooled ICC adjusted/conditional = 0.065/0.063. Pooled R^2 marginal/conditional based on (Nakagawa and Schielzeth, 2013) = 0.026/0.089.
Gender: (Male = 0. Female =1). Age: Students' age. Ses: Socioeconomic status. b: Pooled unstandardized coefficient. SE: Pooled standard error. 95%-CI: Pooled 95%-confidence interval of b. β: Pooled standardized coefficient according to Gelman (Gelman, 2008) by dividing numeric variables by two standard deviations to provide a better comparison with binary variables). σ^2: Variance. * p < 0.05. ** p < 0.01. *** p < 0.001.

Table 22: Initial age of regularly using the internet during leisure time; descriptive statistics

	N	Mean (SD); Median	95%-CI
Total	2,630	11.55 (2.14); 12.00	11.44; 11.66
Gender	2,400		
Male	1,239	11.45 (2.26); 12.00	11.27; 11.63
Female	1,161	11.79 (1.77); 12.00	11.68; 11.91
Age	2,503		
12, 13, 14 years	799	10.52 (1.68); 11.00	10.37; 10.67
15, 16 years	790	11.52 (1.88); 12.00	11.36; 11.69
17, 18 years	685	12.40 (1.94); 13.00	12.24; 12.56
19+ years	229	13.27 (2.07); 14.00	12.93; 13.61
SES	2,056		
Scores 0 – 4	280	11.69 (2.20); 12.00	11.46; 11.92
Scores 5 – 8	1,775	11.69 (1.87); 12.00	11.58; 11.80

Note: Unimputed, weighted dataset. Different gender excluded due to too few cases (see ☛section 3.1), outlier excluded (see ☛section 2.8.5). Unit of analysis: Age in years. The table shows means, standard deviations, medians and 95%-confidence interval of the mean. SD: standard deviation. CI: confidence intervall.

Table 23: Initial age of regularly using the internet during leisure time; multilevel linear regression coefficients

	b(SE) pooled	95%-CI (b) pooled	β pooled
Fixed effects			
Intercept	4.542 (0.376)***	3.804; 5.281	-0.044
Gender	0.499 (0.077)***	0.348; 0.650	0.117
Age	0.420 (0.020)***	0.380; 0.459	0.437
Ses	0.045 (0.027)	-0.007; 0.098	0.034
Random effects	**σ^2 pooled**	**95%-CI (σ^2) pooled**	
Variance of class-intercept	0.101 (0.040)	0.022; 0.180	

Note: Imputed dataset; m = 50. Different gender excluded due to too few cases (see ☛section 3.1), outlier excluded (see ☛section 2.8.5). Multilevel linear regression (Level 1: students. Level 2: school classes). Unit of analysis: Age in years. Pooled variance estimate of Level 1-residuals = 3.097. Pooled ICC adjusted/conditional = 0.032/0.025. Pooled R^2 marginal/conditional based on (Nakagawa and Schielzeth, 2013) = 0.218/0.243.

Gender: (Male = 0. Female =1). Age: Students' age. Ses: Socioeconomic status. b: Pooled unstandardized coefficient. SE: Pooled standard error. 95%-CI: Pooled 95%-confidence interval of b. β: Pooled standardized coefficient according to Gelman (Gelman, 2008) by dividing numeric variables by two standard deviations to provide a better comparison with binary variables). σ^2: Variance. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

3.3 Results related to prevalence estimation

According to research questions 7 and 8 (☛section 1.9.2) the results of this section reflect gender-, age- and SES-specific prevalences of DRAB and ARAB in general as well as prevalences with regard to specific DMD and internet-related applications. As a reminder, DRAB and ARAB were measured using the generic CIUS (with a value of 13 as the cut-off) related to the specific DMD and internet-based application, respectively that is dominant in usage (for more details on the measurement approach see ☛section 2.7.1).

RQ7: prevalences of DRAB and ARAB

☛Table 24 shows the observed prevalences of DRAB and ARAB. 40.5% (95%-CI: 38.34 – 42.73) of the students show DRAB and 32.6% (95%-CI: 30.57 – 34.65) show ARAB, related to any of the examined DMD and internet-based applications, respectively.

Multilevel binary logistic regression analyses (see ☛Table 25) show that prevalences are very homogeneous across classes with only little variation observed for DRAB ($ICC_{adjusted}$ = 0.033) as well as for ARAB ($ICC_{adjusted}$ = 0.029). All three sociodemographic variables gender, age and socioeconomic status are consistently associated with both DRAB and ARAB. Female students show almost twice the odds of being classified as DRAB (OR = 1.908; 95%-CI: 1.597; 2.280) and even slightly higher odds of being classified as ARAB (OR = 1.938; 95%-CI: 1.611; 2.330). The odds of DRAB and ARAB decrease by 7.2% and 6.0%, respectively with each one-unit increase of age (OR_{DRAB} = 0.928; 95%-CI: 0.888; 0.969. OR_{ARAB} = 0.940; 95%-CI: 0.899; 0.983) as well as by 11.5% and 6.2%, respectively with each one-unit increase of SES (OR_{DRAB} = 0.885; 95%-CI: 0.834; 0.938. OR_{ARAB} = 0.901; 95%-CI: 0.849; 0.956).

RQ8: prevalences of specific DRABs and ARABs

☛Table 26 displays the prevalences of DRAB, related to specific DMD. DRAB refers by far the most frequently to smartphones. 32.3% (95%-CI: 30.18 – 34.47) of the students show smartphone-related DRAB, followed by a further 5.3% (95%-CI: 4.49 – 6.30), who show DRAB related to personal computers or laptops and 1.6% (95%-CI: 1.17 – 2.17) showing DRAB related to gaming consoles. DRAB related to TV has a comparatively negligible prevalence.

While DRAB in general (i.e. independent of the related specific DMD) is rather homogeneously distributed across school classes as already mentioned above, the situation is quite different for specific DRABs. Referring to ☛Table 27, tablet-related addictive behaviour (DRAB_TABL), for example, varies pretty substantially across school classes as indicated by the respective adjusted ICC of 0.316. Substantial ICCs are also observed for gaming console-related addictive behaviour (DRAB_CONS) ($ICC_{adjusted}$ = 0.230) and PC/laptop-related addictive behaviour (DRAB_PC/LAP) ($ICC_{adjusted}$ = 0.149). Smartphone-related addictive behaviour (DRAB_SMA) on the other hand, is highly homogeneously distributed across school classes ($ICC_{adjusted}$ = 0.016). Several associations of addictive behaviours with gender are observed suggesting specificity with certain DMD. While female adolescents show more than three times the odds of being classified as smartphone-related addictive behaviour (DRAB_SMA) (OR = 3.293; 95%-CI: 2.735; 3.967), the opposite is clearly indicated for gaming console-related addictive behaviour (DRAB_CONS) (OR = 0.069; 95%-CI: 0.021; 0.233) as well as for PC/laptop-related addictive behaviour (DRAB_PC/LAP) (OR = 0.152; 95%-CI: 0.092; 0.253), both assigned with higher odds among male students. Age is only associated with tablet-related addictive behaviour (DRAB_TABL) (OR = 0.678; 95%-CI: 0.495; 0.929) indicating higher prevalences among younger students and SES with smartphone-related addictive behaviour (DRAB_SMA) (OR = 0.886; 95%-CI: 0.834; 0.941) indicating higher prevalences among students with lower SES.

☛Table 28 shows prevalences of ARAB, related to specific internet-based applications. The prevalence of ARAB related to social media is clearly the highest among the examined students. 13.8% (95%-CI: 12.31 – 15.48) of the students show social media-related ARAB, followed by a further 4.9% (95%-CI: 4.03 – 5.91) of the students, who show gaming-related ARAB and 4.7% (95%-CI: 4.09 – 5.28) showing ARAB related to streaming of series and films. Although comparatively much rarer, 1.0% (95%-CI: 0.71 – 1.47) show porn-related ARAB.

As with certain specific DRAB-models, also some specific ARABs (see ☛Table 29) show variation between school classes. While porn-related addictive behaviour (ARAB_PORN) and gaming-related addictive behaviour (ARAB_GAME) vary substantially between school classes ($ICC_{adjusted}$ = 0.409 and 0.184, respectively), chatting-related addictive behaviour (ARAB_CHAT), streaming films-related addictive behaviour (ARAB_FILM) ($ICC_{adjusted}$ = 0.071 and 0.073, respectively) and especially social media-related addictive behaviour (ARAB_SMEDIA) ($ICC_{adjusted}$ = 0.011) are quite homogeneously distributed across classes.
Female students show more than four times the odds of being classified as social media-related addictive behaviour (ARAB_SMEDIA) (OR = 4.354; 95%-CI: 3.313; 5.720), more than two times the odds of being classified as chatting-related addictive behaviour (ARAB_CHAT) (OR = 2.143; 95%-CI: 1.361; 3.374) and more than 1.5 times the odds of being classified as streaming films-related addictive behaviour (ARAB_FILM) (OR = 1.725; 95%-CI: 1.134; 2.622) than males. However, female students show strongly reduced odds for gaming-

related addictive behaviour (ARAB_GAME) (OR = 0.132; 95%-CI: 0.076; 0.229) and for porn-related addictive behaviour (ARAB_PORN) (OR = 0.223; 95%-CI: 0.077; 0.641). Age is only associated with gaming-related addictive behaviour (OR = 0.868; 95%-CI: 0.775; 0.972) and SES with social media-related addictive behaviour (OR = 0.923; 95%-CI: 0.856; 0.994).

Table 24: Prevalences of DRAB and ARAB, respectively; descriptive statistics

	N DRAB	*DRAB % (95%-CI)*	*N ARAB*	*ARAB % (95%-CI)*
Total	2,808	40.51 (38.34; 42.73)	2,808	32.58 (30.57; 34.65)
Gender*DRAB/ARAB	2,543		2,543	
Male	1,327	33.25 (30.51; 36.11)	1,327	25.54 (23.03; 28.23)
Female	1,216	48.22 (45.29; 51.17)	1,216	39.79 (37.06; 42.59)
Age*DRAB/ARAB	2,645		2,645	
12, 13, 14 years	856	43.64 (40.00; 47.35)	856	34.60 (30.99; 38.39)
15, 16 years	817	43.81 (40.24; 47.45)	818	34.95 (31.40; 38.68)
17, 18 years	721	37.36 (33.51; 41.37)	721	30.99 (27.68; 34.52)
19+ years	251	30.43 (23.50; 38.37)	250	23.30 (17.62; 30.14)
SES*DRAB/ARAB	2,149		2,148	
Scores 0 – 4	295	51.63 (47.16; 56.08)	296	44.04 (39.15; 49.05)
Scores 5 – 8	1,854	37.80 (35.17; 40.51)	1,852	30.33 (28.07; 32.68)

Note: Unimputed, weighted dataset. Different gender excluded due to too few cases (see ☛section 3.1), outlier excluded (see ☛section 2.8.5). The table shows total and row percentages in relation to valid cases and 95%-confidence interval. 95%-CI: 95%-confidence interval. DRAB: DMD-related addictive behaviour. ARAB: Internet application-related addictive behaviour.

Table 25: Prevalences of DRAB and ARAB, respectively; multilevel binary logistic regression coefficients

	DRAB b (SE); OR (95%-CI(OR))	**ARAB** b (SE); OR (95%-CI(OR))
Fixed effects		
Intercept	1.149 (0.416)***; 3.155; (1.397, 7.128)	0.450 (0.427); 1.569; (0.679, 3.622)
Gender	0.646 (0.091)***; 1.908; (1.597, 2.280)	0.661 (0.094)***; 1.938; (1.611, 2.330)
Age	-0.075 (0.022)***; 0.928; (0.888, 0.969)	-0.062 (0.023)**; 0.940; (0.899, 0.983)
Ses	-0.123 (0.030)***; 0.885; (0.834, 0.938)	-0.105 (0.030)***; 0.901; (0.849, 0.956)
Random effects	**Pooled σ2**	**Pooled σ2**
Var. class-intercept	0.111	0.097

Note: Imputed dataset; m = 50. Different gender excluded due to too few cases (see ☛section 3.1). Multilevel binary logistic regressions (Level 1: students. Level 2: school classes). DRAB-model: Pooled ICC adjusted = 0.033. Pooled R^2 marginal/conditional based on (Nakagawa and Schielzeth, 2013) = 0.047/0.078. ARAB-model: Pooled ICC adjusted = 0.029. Pooled R^2 marginal/conditional based on (Nakagawa and Schielzeth, 2013) = 0.044/0.072.

Gender: (Male = 0. Female =1). Age: Students' age. Ses: Socioeconomic status. b: Pooled log-odds. SE: Pooled standard error. OR: Odds ratio (exp(b)). 95%-CI (OR): Pooled 95%-confidence interval of OR. σ^2: Variance. * p < 0.05. ** p < 0.01. *** p < 0.001. DRAB: DMD-related addictive behaviour. ARAB: Internet application-related addictive behaviour.

Table 26: Prevalences of specific DRABs; descriptive statistics

	N	DRAB_SMA % (95%-CI)	DRAB_TABL % (95%-CI)	DRAB_CONS % (95%-CI)	DRAB_PC/LAP % (95%-CI)	DRAB_TV % (95%-CI)
Total	2,808	32.29 (30.18; 34.47)	0.95 (0.67; 1.36)	1.59 (1.17; 2.17)	5.33 (4.49; 6.30)	0.35 (0.20; 0.61)
Gender*Spec.DRAB	2,543					
Male	1,327	21.18 (19.05; 23.47)	0.57 (0.25; 1.32)	2.71 (1.88; 3.88)	8.57 (7.06; 10.36)	0.23 (0.07; 0.72)
Female	1,216	44.46 (41.69; 47.26)	1.41 (0.93; 2.14)	0.23 (0.07; 0.72)	1.55 (1.00; 2.40)	0.57 (0.31; 1.03)
Age* Spec.DRAB	2,645					
12, 13, 14 years	856	33.13 (30.08; 36.33)	1.44 (0.77; 2.71)	2.15 (1.23; 3.75)	6.48 (4.89; 8.53)	0.44 (0.21; 0.90)
15, 16 years	817	35.58 (31.62; 39.75)	1.38 (0.89; 2.13)	1.48 (0.85; 2.57)	5.02 (3.75; 6.68)	0.35 (0.11; 1.09)
17, 18 years	721	32.04 (28.62; 35.66)	0.14 (0.02; 0.99)	0.54 (0.20; 1.42)	4.33 (3.06; 6.09)	0.31 (0.10; 0.99)
19+ years	251	23.27 (18.25; 29.17)	0.00 (0.00; 0.00)	3.28 (1.65; 6.40)	3.46 (1.59; 7.36)	0.42 (0.06; 3.04)
SES* Spec.DRAB	2,149					
Scores 0 – 4	295	42.24 (37.94; 46.67)	0.00 (0.00; 0.00)	3.02 (1.65; 5.47)	5.87 (4.12; 8.29)	0.51 (0.12; 2.07)
Scores 5 – 8	1,854	30.35 (27.96; 32.85)	0.96 (0.64; 1.45)	0.98 (0.62; 1.55)	5.21 (4.22; 6.41)	0.30 (0.13; 0.68)

Note: Unimputed, weighted dataset. Different gender excluded due to too few cases (see ☛section 3.1), outlier excluded (see ☛section 2.8.5). The table shows total and row percentages in relation to valid cases and 95%-confidence interval. 95%-CI: 95%-confidence interval. DRAB_SMA: Smartphone-related addictive behaviour. DRAB_TABL: Tablet-related addictive behaviour. DRAB_CONS: Gaming console-related addictive behaviour. DRAB_PC/LAP: Computer/Laptop-related addictive behaviour. DRAB_TV: TV-related addictive behaviour.

Table 27: Prevalences of specific DRABs; multilevel binary logistic regression coefficients

	DRAB_SMA b (SE); OR (95%-CI(OR))	*DRAB_TABL* b (SE); OR (95%-CI(OR))	*DRAB_CONS* b (SE); OR (95%-CI(OR))	*DRAB_PC/LAP* b (SE); OR (95%-CI(OR))
Fixed effects				
Intercept	-0.038 (0.421); 0.963; (0.422, 2.197)	-0.173 (2.730); 0.841; (0.004, 177.505)	-1.487 (1.578); 0.226; (0.010, 4.978)	-1.181 (1.005); 0.307; (0.043, 2.199)
Gender	1.192 (0.095)***; 3.293; (2.735, 3.967)	0.701 (0.505); 2.016; (0.749, 5.430)	-2.671 (0.619)***; 0.069; (0.021, 0.233)	-1.882 (0.259)***; 0.152; (0.092, 0.253)
Age	-0.042 (0.022); 0.959; (0.918, 1.001)	-0.388 (0.161)**; 0.678; (0.495, 0.929)	-0.058 (0.084); 0.944; (0.800, 1.114)	-0.109 (0.054); 0.897; (0.807, 0.998)
Ses	-0.121 (0.031)***; 0.886; (0.834, 0.941)	0.009 (0.183); 1.009; (0.705, 1.443)	-0.270 (0.118)*; 0.764; (0.605, 0.963)	0.048 (0.072); 1.049; (0.910, 1.209)
Random effects	**Pooled σ2**	**Pooled σ2**	**Pooled σ2**	**Pooled σ2**
Var. class-intercept	0.054	1.524	0.980	0.575

Note: Imputed dataset; m = 50. Different gender excluded due to too few cases (see ☛section 3.1). Multilevel binary logistic regressions (Level 1: students. Level 2: school classes). DRAB_SMA-model: Pooled ICC adjusted = 0.016. Pooled R^2 marginal/conditional based on (Nakagawa and Schielzeth, 2013) = 0.108/0.123. DRAB_TABL-model: Pooled ICC adjusted = 0.316. Pooled R^2 marginal/conditional based on (Nakagawa and Schielzeth, 2013) = 0.159/0.426. DRAB_CONS-model: Pooled ICC adjusted = 0.230. Pooled R^2 marginal/conditional based on (Nakagawa and Schielzeth, 2013) = 0.310/0.469. DRAB_PC/LAP-model: Pooled ICC adjusted = 0.149. Pooled R^2 marginal/conditional based on (Nakagawa and Schielzeth, 2013) = 0.196/0.316.
The DRAB_TV-model was ignored due to too few cases.
Gender: (Male = 0. Female =1). Age: Students' age. Ses: Socioeconomic status. b: Pooled log-odds. SE: Pooled standard error. OR: Odds ratio (exp(b)). 95%-CI (OR): Pooled 95%-confidence interval of OR. σ^2: Variance. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$. DRAB_SMA: Smartphone-related addictive behaviour. DRAB_TABL: Tablet-related addictive behaviour. DRAB_CONS: Gaming console-related addictive behaviour. DRAB_PC/LAP: Computer/Laptop-related addictive behaviour.

Table 28: Prevalences of specific ARABs; descriptive statistics

	N	ARAB_CHAT % (95%-CI)	ARAB_FILM % (95%-CI)	ARAB_GAME % (95%-CI)	ARAB_GAMB % (95%-CI)	ARAB_PORN % (95%-CI)	ARAB_SMEDIA % (95%-CI)	ARAB_SHOP % (95%-CI)
Total	2,808	3.32 (2.72; 4.04)	4.65 (4.09; 5.28)	4.88 (4.03; 5.91)	0.11 (0.04; 0.35)	1.02 (0.71; 1.47)	13.82 (12.31; 15.48)	0.15 (0.07; 0.35)
Gender*Spec.ARAB	2,543							
Male	1,327	2.37 (1.60; 3.49)	3.48 (2.75; 4.40)	8.02 (6.38; 10.04)	0.16 (0.04; 0.65)	1.29 (0.83; 1.99)	6.38 (5.08; 7.98)	0.08 (0.01; 0.58)
Female	1,216	4.58 (3.64; 5.75)	6.11 (5.10; 7.30)	1.28 (0.87; 1.90)	0.00 (0.00; 0.00)	0.29 (0.11; 0.81)	22.33 (20.17; 24.66)	0.18 (0.07; 0.46)
Age*Spec.ARAB	2,645							
12, 13, 14 years	856	3.81 (2.61; 5.53)	4.47 (3.48; 5.71)	6.31 (4.65; 8.50)	0.12 (0.02; 0.90)	1.46 (0.82; 2.58)	13.54 (11.11; 16.40)	0.12 (0.02; 0.85)
15, 16 years	818	3.24 (2.44; 4.30)	4.69 (3.70; 5.93)	4.59 (3.42; 6.13)	0.00 (0.00; 0.00)	0.69 (0.28; 1.73)	16.54 (13.82; 19.67)	0.07 (0.01; 0.53)
17, 18 years	721	3.63 (2.57; 5.11)	5.86 (4.72; 7.26)	4.08 (2.92; 5.69)	0.14 (0.02; 0.99)	0.69 (0.28; 1.69)	12.75 (10.39; 15.55)	0.37 (0.12; 1.17)
19+ years	250	3.15 (1.58; 6.18)	1.54 (0.57; 4.09)	2.82 (1.34; 5.83)	0.43 (0.06; 3.06)	1.47 (0.63; 3.39)	9.85 (6.85; 13.96)	0.00 (0.00; 0.00)
SES*Spec.ARAB	2,148							
Scores 0 – 4	296	6.41 (4.26; 9.55)	7.26 (4.96; 10.51)	5.49 (3.89; 7.70)	0.36 (0.05; 2.57)	1.84 (0.85; 3.97)	15.08 (11.70; 19.22)	0.00 (0.00; 0.00)
Scores 5 – 8	1,852	3.12 (2.43; 3.99)	4.48 (3.81; 5.28)	4.44 (3.46; 5.67)	0.11 (0.03; 0.45)	0.77 (0.46; 1.27)	13.97 (12.24; 15.90)	0.06 (0.05; 0.09)

Note: Unimputed, weighted dataset. Different gender excluded due to too few cases (see ☛section 3.1), outlier excluded (see ☛section 2.8.5). The table shows total and row percentages in relation to valid cases and 95%-confidence interval. 95%-CI: 95%-confidence interval. Row percentages do not sum up to 100% since just the most dominant internet-based applications are shown. ARAB_CHAT: Addictive behaviour related to chatting and writing messages. ARAB_FILM: Addictive behaviour related to watching films/series. ARAB_GAME: Addictive behaviour related to gaming. ARAB_GAMB: Addictive behaviour related to gambling. ARAB_PORN: Addictive behaviour related to engaging in erotic/sex/porn-content. ARAB_SMEDIA: Addictive behaviour related to using social media. ARAB_SHOP: Addictive behaviour related to online shopping.

Table 29: Prevalences of specific ARABs; multilevel binary logistic regression coefficients

	ARAB_CHAT b (SE); OR (95%-CI(OR))	ARAB_FILM b (SE); OR (95%-CI(OR))	ARAB_GAME b (SE); OR (95%-CI(OR))	ARAB_PORN b (SE); OR (95%-CI(OR))	ARAB_SMEDIA b (SE); OR (95%-CI(OR))
Fixed effects					
Intercept	-2.791 (0.976)**; 0.061; (0.009, 0.415)	-2.143 (0.934)*; 0.117; (0.019, 0.732)	-0.389 (1.055); 0.677; (0.086, 5.355)	-3.515 (2.288); 0.030; (<0.001, 2.635)	-1.602 (0.541)**; 0.202; (0.070, 0.582)
Gender	0.762 (0.232)***; 2.143; (1.361; 3.374)	0.545 (0.214)*; 1.725; (1.134, 2.622)	-2.022 (0.280)***; 0.132; (0.076, 0.229)	-1.503 (0.540)**; 0.223; (0.077, 0.641)	1.471 (0.139)***; 4.354; (3.313, 5.720)
Age	-0.029 (0.052); 0.972; (0.877, 1.076)	-0.051 (0.051); 0.950; (0.860, 1.050)	-0.141 (0.058)*; 0.868; (0.775, 0.972)	-0.054 (0.119); 0.947; (0.750, 1.196)	-0.043 (0.029); 0.958; (0.906, 1.013)
Ses	-0.097 (0.067); 0.908; (0.795, 1.036)	-0.105 (0.066); 0.900; (0.791, 1.024)	-0.016 (0.074); 0.984; (0.851, 1.138)	-0.119 (0.152); 0.888; (0.659, 1.197)	-0.081 (0.038)*; 0.923; (0.856, 0.994)
Random effects	**Pooled σ2**	**Pooled σ2**	**Pooled σ2**	**Pooled σ2**	**Pooled σ2**
Var. class-intercept	0.252	0.260	0.741	2.276	0.037

Note: Imputed dataset; m = 50. Different gender excluded due to too few cases (see ☛section 3.1). Multilevel binary logistic regressions (Level 1: students. Level 2: school classes). ARAB_CHAT-model: Pooled ICC adjusted = 0.071. Pooled R^2 marginal/conditional based on (Nakagawa and Schielzeth, 2013) = 0.047/0.115. ARAB_FILM-model: Pooled ICC adjusted = 0.073. Pooled R^2 marginal/conditional based on (Nakagawa and Schielzeth, 2013) = 0.032/0.103. ARAB_GAME-model: Pooled ICC adjusted = 0.184. Pooled R^2 marginal/conditional based on (Nakagawa and Schielzeth, 2013) = 0.214/0.358. ARAB_PORN-model: Pooled ICC adjusted = 0.409. Pooled R^2 marginal/conditional based on (Nakagawa and Schielzeth, 2013) = 0.099/0.467. ARAB_SMEDIA-model: Pooled ICC adjusted = 0.011. Pooled R^2 marginal/conditional based on (Nakagawa and Schielzeth, 2013) = 0.147/0.156.

The ARAB_GAMB- and ARAB_SHOP-models were ignored due to too few cases.

Gender: (Male = 0. Female =1). Age: Students' age. Ses: Socioeconomic status. b: Pooled log-odds. SE: Pooled standard error. OR: Odds ratio (exp(b)). 95%-CI (OR): Pooled 95%-confidence interval of OR. σ^2: Variance. * p < 0.05. ** p < 0.01. *** p < 0.001. ARAB_CHAT: Chatting-related addictive behaviour. ARAB_FILM: Film streaming-related addictive behaviour. ARAB_GAME: Gaming-related addictive behaviour. ARAB_PORN: Pornography-related addictive behaviour. ARAB_SMEDIA: Social media-related addictive behaviour.

3.4 Results related to correlates of DRAB and ARAB

According to research questions 9 to 11 (☛section 1.9.3) this section examines associations of specific DMD and internet-based applications, usage characteristics, comorbid symptoms, sociodemographic, psychosocial and family environmental aspects with DRAB and ARAB in general (independent of the specific DMD and application, respectively) as well as specifically related to social media- and gaming-related addictive behaviour.

RQ9: Associations of specific DMD and internet-based applications with the extent of symptoms of DRAB and ARAB, respectively

☛Table 30 shows a comparison of the extent of symptoms of DRAB and ARAB, respectively, each adjusted by the same set of variables. On the whole, DRAB-symptoms are relatively independent of the specific dominant DMD to which the addictive behaviour relates. As such, tablets, gaming consoles and computers/laptops as dominant DMDs yield comparable extents of DRAB-symptoms compared to smartphones as dominant DMDs. However, TVs being dominant in DMD usage show a significantly lower extent of such symptoms ($b = -1.732$; 95%-CI [-2.837; -0.626]).

For the analysis of the ARAB-model in ☛Table 30, only cases where chatting, watching films or engaging in social media, games or pornographic content are the dominant applications were included. As depicted in ☛Table 9 all other applications being dominant in usage are represented by too few cases. ☛Table 30 indicates comparable extents of ARAB-symptoms for watching films/series, gaming and engaging in porn content as dominant applications compared to social media being dominant. Students for whom chatting is the dominant application show significantly lower extents of ARAB-symptoms compared to social media engagement ($b = -0.978$; 95%-CI [-1.520; -0.435]).

RQ10: Associations of usage characteristics, comorbid symptoms, sociodemographic aspects, psychosocial and family environmental aspects with the extent of symptoms of DRAB and ARAB, respectively

☛Table 30 shows that both the extent of DRAB- and ARAB-symptoms are very homogeneously distributed across school classes as the random-effect variable with only minor variation observed ($ICC_{adjusted} = 0.032$ for the DRAB-model and $ICC_{adjusted} = 0.031$ for the ARAB-model).

Both models highly converge in terms of their associated fixed-effect correlates, explaining around 37% of the total variance of DRAB and ARAB, respectively. As already indicated by the low ICC, school classes only add little contribution in explaining additional variance. With very few exceptions, the same correlates are linked to DRAB as well as to ARAB. However, anxiety (the more anxiety the more ARAB-symptoms) and the presence of siblings (more ARAB-symptoms among students with siblings) are associated with ARAB, but not with DRAB. On the other hand, the position of the smartphone during bedtime (more DRAB-symptoms among students who keep their smartphone in bed) is linked to DRAB, but not to ARAB.

With regard to usage characteristics, leisure-related usage time, the extent of pre-sleep and after-midnight DMD-activity are positively, and the initial age of regular internet use is negatively linked to DRAB and ARAB (the earlier the onset, the more DRAB- and ARAB-symptoms). No association is shown in relation to the number of DMD owned.

Considering comorbidities, insomnia and the overall psychosocial constitution are both positively associated with both DRAB and ARAB (the more problematic, the more DRAB- and ARAB-symptoms). Anxiety however, is only associated with ARAB.

In terms of sociodemographic characteristics, age and gender show linkages to the extent of DRAB- and ARAB-symptoms (the younger, the more DRAB- and ARAB-symptoms and female students being more affected than males), but not the students' socioeconomic status.

Among the set of psychosocial characteristics, proneness to boredom and concerns related to the students' extent of internet and DMD use are both positively associated with DRAB- and ARAB-symptoms. Feelings of well-being in school class as well as parental support are also positively linked to DRAB- and ARAB-symptoms (the more parental support and well-being in school class, the more symptoms). Self-efficacy on the other hand, shows a clear negative association (the more self-efficacy the less DRAB- and ARAB-symptoms). However, neither prosocial behaviour nor generally-perceived social support show any association.

With regard to family environmental aspects, both parental regulative rules and parental extent of DMD use are both associated with the extent of DRAB- and ARAB-symptoms (more symptoms in case of existing rules and in case of higher parental DMD usage). Having siblings is only weakly linked to the extent of ARAB-symptoms.

For both models the strongest associations, indicated by the Gelman-adjusted standardised coefficients (Gelman, 2008) of the ARAB-model, are shown for

- being concerned about one's own extent of internet and DMD use (β_{Gelman} = 0.176; b = 1.502; 95%-CI [1.188; 1.817]),
- being in vulnerable overall psychosocial constitution (β_{Gelman} = 0.137; b = 0.129; 95%-CI [0.079; 0.178]),

- having sleep impairments (β_{Gelman} = 0.122; b = 0.133; 95%-CI [0.087; 0.179]),
- higher amounts of usage time (β_{Gelman} = 0.116; b = 0.231; 95%-CI [0.153; 0.310]),
- being more prone to boredom (β_{Gelman} = 0.106; b = 0.200; 95%-CI [0.122; 0.277]),
- being female (β_{Gelman} = 0.101; b = 1.167; 95%-CI [0.714; 1.619]) and
- using DMD after midnight on evenings with subsequent school day (β_{Gelman} = 0.091; b = 0.287; 95%-CI [0.163; 0.411]).

RQ11: Specific correlates for the extent of symptoms of social media- and gaming-related addictive behaviour

☛Table 31 shows only little variation of social media-related addictive behaviour between school classes ($ICC_{adjusted}$ = 0.028). However, gaming-related addictive behaviour is indicated to be substantially more varied. 13.5% of its variance is attributed to school classes ($ICC_{adjusted}$ = 0.135). The fixed effects explain a total of 39.2% of the total variance in the social media-model and 35.2% in the gaming-model.

While there are certain similarities between these models, there are also some distinct features. As with the general DRAB- and ARAB-models, leisure-related usage time, the overall psychosocial constitution, proneness to boredom, self-efficacy and concerns related to the students' extent of internet and DMD use are related to both the extent of symptoms of social media- and gaming-related addictive behaviour. More intensive pre-sleep and after-midnight activity with DMD, insomnia and anxiety on the other hand, are only associated with the extent of symptoms of social media- and not with gaming-related addictive behaviour. A similar linkage is observed with regard to age and gender. Being female, and the younger the students are, the more symptoms of social media- related addictive behaviour are indicated. In the context of gaming, however, no association with age and gender is apparent. Specificity for gaming is shown with regard to parental support (the more support the more symptoms), the parental extent of DMD use (the higher the extent of parental DMD use the more gaming-related symptoms of addictive behaviour are exhibited by their children) and the presence of siblings (students with siblings show more gaming-related symptoms). Referring to the extent of social media-related symptoms no such linkages were identified.

In both models, no association was found between the number of DMD owned, the position of the smartphone during bedtime, the onset of regular internet use, the socioeconomic status, general social support, prosocial behaviour as well as parental regulative rules and the extent of symptoms of addictive behaviour.

Table 30: Extent of symptoms of DRAB and ARAB; multilevel linear regression coefficients

	DRAB b(SE), 95%-CI, β	**ARAB** b(SE), 95%-CI, β
Fixed effects		
Intercept	7.087 (1.19)***; (4.755; 9.42); -0.133	4.992 (1.374)***; (2.298; 7.686); -0.074
Internet use characteristics		
DMDCOUNT	-0.140 (0.076); (-0.290; 0.010); -0.026	-0.055 (0.088); (-0.227; 0.117); -0.012
DOMDMD (ref.: Smartphone)		
Tablet	-0.761 (0.565); (-1.869; 0.347); -0.077	
Gaming console	0.302 (0.420); (-0.521; 1.125); 0.029	
Computer/Laptop	0.306 (0.267); (-0.218; 0.830); 0.029	
TV	-1.732 (0.564)**; (-2.837; -0.626); -0.163	
DOMAPP (ref.: Social media)		
Chatting		-0.978 (0.277)***; (-1.520; -0.435); -0.086
Watching films/series		-0.471 (0.269); (-0.998; 0.056); -0.041
Gaming		-0.025 (0.298); (-0.610; 0.560); -0.002
Engaging in porn content		-0.300 (0.611); (-1.498; 0.898); -0.027
DMDTIME	0.267 (0.035)***; (0.199; 0.335); 0.144	0.231 (0.040)***; (0.153; 0.310); 0.116
PRESLEEP	0.377 (0.069)***; (0.243; 0.512); 0.099	0.373 (0.080)***; (0.216; 0.529); 0.091
AFTERMID	0.290 (0.055)***; (0.182; 0.399); 0.098	0.287 (0.063)***; (0.163; 0.411); 0.091
POSIT	0.468 (0.203)*; (0.071; 0.865); 0.044	0.193 (0.231); (-0.260; 0.645); 0.017
INITAGE	-0.233 (0.047)***; (-0.326; -0.141); -0.094	-0.187 (0.053)***; (-0.291; -0.083); -0.070
Comorbid symptoms		
INSOMNIA	0.129 (0.021)***; (0.089; 0.169); 0.127	0.133 (0.023)***; (0.087; 0.179); 0.122
ANXIETY	0.043 (0.024); (-0.003; 0.089); 0.044	0.079 (0.027)**; (0.026; 0.133); 0.076
PSYCONST	0.098 (0.022)***; (0.055; 0.141); 0.111	0.129 (0.025)***; (0.079; 0.178); 0.137
Sociodemographic characteristics		
AGE	-0.172 (0.052)**; (-0.273; -0.071); -0.072	-0.137 (0.058)*; (-0.250; -0.023); -0.053
GENDER	1.208 (0.200)***; (0.816; 1.600); 0.112	1.167 (0.231)***; (0.714; 1.619); 0.101
SES	0.038 (0.063); (-0.086; 0.162); 0.010	0.021 (0.071); (-0.119; 0.161); 0.005
Psychosocial characteristics		
BOREDOM	0.202 (0.034)***; (0.136; 0.269); 0.115	0.200 (0.040)***; (0.122; 0.277); 0.106
SELFEFF	-0.180 (0.039)***; (-0.256; -0.104); -0.089	-0.155 (0.045)**; (-0.243; -0.067); -0.071
PARSUPP	0.072 (0.030)*; (0.012; 0.131); 0.047	0.111 (0.035)**; (0.043; 0.178); 0.069
EMOSUPP	0.064 (0.063); (-0.059; 0.187); 0.034	-0.016 (0.073); (-0.158; 0.127); -0.008
INSTSUPP	0.032 (0.060); (-0.086; 0.149); 0.017	0.005 (0.070); (-0.132; 0.141); 0.002
PROBEHAV	-0.033 (0.045); (-0.122; 0.056); -0.013	-0.089 (0.054); (-0.194; 0.017); -0.034
CONCERNS	1.396 (0.140)***; (1.121; 1.671); 0.175	1.502 (0.160)***; (1.188; 1.817); 0.176
WELLCLASS	0.379 (0.117)**; (0.149; 0.609); 0.061	0.433 (0.135)**; (0.168; 0.698); 0.065
Family environmental aspects		
PARENTAL RULES	0.764 (0.248)**; (0.277; 1.251); 0.072	0.767 (0.281)**; (0.215; 1.318); 0.067
PARENTUSE	0.286 (0.087)**; (0.116; 0.456); 0.055	0.326 (0.100)**; (0.130; 0.522); 0.059
SIBLINGS	0.379 (0.252); (-0.115; 0.873); 0.037	0.570 (0.209)*; (0.002; 1.138); 0.050
Random effects	**σ^2 pooled**	**σ^2 pooled**
Variance of class-intercept	0.563 (0.197)	0.598 (0.248)

Note: n=2,667 for the DRAB-model. n=2.254 for the ARAB-model (only cases showing social media, chatting, watching films, gaming or engaging in porn as dominant application). (imputed dataset; m = 50; k = 5). Different gender excluded due to too few cases, see ☛section 3.1. Multilevel regression (Level 1: students. Level 2: school classes). Unit of analysis: CIUS-score related to specific DMD and applications, respectively.
Model DRAB: Pooled variance estimate of Level 1-residuals = 17.073. Pooled ICC adjusted/conditional = 0.032/0.020. Pooled R^2 marginal/conditional based on (Nakagawa and Schielzeth, 2013) = 0.371/0.391.
Model ARAB: Pooled variance estimate of Level 1-residuals = 18.917. Pooled ICC adjusted/conditional = 0.031/0.019. Pooled R^2 marginal/conditional based on (Nakagawa and Schielzeth, 2013) = 0.373/0.392.
DMDCOUNT: Count of DMD in own possession. DOMDMD: Dominant DMD in use (dummy-coded). DOMAPP: Dominant internet-based application in use (dummy-coded). DMDTIME: Daily leisure-related usage time of the dominant DMD (in hours). PRESLEEP: Count of school days using DMD as a pre-sleep activity. AFTERMID: Count of school days using DMD after midnight. POSIT: Position of smartphone during bedtime (Not in bed = 0. In bed = 1). INITAGE: Initial age of regular internet use. INSOMNIA: ISI-score. ANXIETY: GAD-score. PSYCONST: Total difficulties SDQ-score. AGE: Students' age (in years). GENDER: Male = 0. Female = 1. Age: SES: Socioeconomic status. BOREDOM: BPS-score. SELFEFF: ASKU-score (self-efficacy). PARSUPP: SKU-score (parental support). EMOSUPP: BSSS-score (emotional support). INSTSUPP: BSSS-score (instrumental support). PROBEHAV: Prosocial behaviour SDQ-score. CONCERNS: Concerns related to the extent of internet use. WELLCLASS: Wellbeing in school class. PARENTAL RULES: Parental rules to regulate DMD use (No rules = 0. Rules = 1). PARENTUSE: Extent of parental DMD use. SIBLINGS: No = 0. Yes = 1. b: Pooled unstandardized coefficient. SE: Pooled standard error. 95%-CI: Pooled 95%-confidence interval of b. β: Pooled standardized coefficient according to Gelman (Gelman, 2008) by dividing numeric variables by two standard deviations to provide a better comparison with binary variables). σ^2: Variance. * p < 0.05. ** p < 0.01. *** p < 0.001.

Table 31: Extent of symptoms of ARAB related to social media and gaming; multilevel linear regression coefficients

	Social media-related addictive behaviour b(SE), 95%-CI, β	**Gaming-related addictive behaviour** b(SE), 95%-CI, β
Fixed effects		
Intercept	7.876 (2.029)***; (3.898; 11.854); -0.078	-0.040 (3.089); (-6.095; 6.015); -0.150
Internet use characteristics		
DMDCOUNT	0.018 (0.127); (-0.231; 0.268); 0.002	0.155 (0.248); (-0.331; 0.641); -0.007
DMDTIME	0.226 (0.060)***; (0.108; 0.344); 0.113	0.279 (0.109)*; (0.066; 0.493); 0.141
PRESLEEP	0.295 (0.126)*; (0.048; 0.542); 0.072	0.310 (0.197); (-0.076; 0.696); 0.081
AFTERMID	0.222 (0.090)*; (0.045; 0.398); 0.071	0.261 (0.161); (-0.055; 0.577); 0.086
POSIT	0.497 (0.345); (-0.179; 1.173); 0.044	-0.004 (0.554); (-1.090; 1.081); -0.003
INITAGE	-0.098 (0.082); (-0.259; 0.064); -0.037	-0.204 (0.125); (-0.449; 0.041); -0.077
Comorbid symptoms		
INSOMNIA	0.149 (0.034)***; (0.083; 0.215); 0.137	0.123 (0.064); (-0.003; 0.248); 0.116
ANXIETY	0.080 (0.039)*; (0.004; 0.156); 0.077	0.071 (0.077); (-0.079; 0.221); 0.072
PSYCONST	0.128 (0.038)**; (0.054; 0.201); 0.136	0.133 (0.060)*; (0.015; 0.250); 0.140
Sociodemographic characteristics		
AGE	-0.339 (0.084)***; (-0.503; -0.175); -0.133	-0.005 (0.151); (-0.302; 0.292); -0.005
GENDER	1.469 (0.328)***; (0.826; 2.113); 0.129	0.246 (0.774); (-1.272; 1.763); 0.016
SES	0.038 (0.109); (-0.175; 0.252); 0.011	0.216 (0.169); (-0.115; 0.548); 0.063
Psychosocial characteristics		
BOREDOM	0.159 (0.059)**; (0.043; 0.275); 0.084	0.220 (0.096)*; (0.032; 0.408); 0.116
SELFEFF	-0.160 (0.069)*; (-0.296; -0.024); -0.073	-0.267 (0.109)*; (-0.480; -0.054); -0.119
PARSUPP	0.033 (0.055); (-0.074; 0.140); 0.021	0.243 (0.086)**; (0.075; 0.411); 0.153
EMOSUPP	0.036 (0.110); (-0.180; 0.253); 0.018	-0.031 (0.166); (-0.356; 0.294); -0.009
INSTSUPP	0.017 (0.106); (-0.190; 0.224); 0.009	0.117 (0.162); (-0.200; 0.435); 0.060
PROBEHAV	-0.047 (0.081); (-0.206; 0.113); -0.018	-0.177 (0.135); (-0.442; 0.087); -0.067
CONCERNS	1.784 (0.252)***; (1.289; 2.279); 0.209	1.045 (0.391)**; (0.280; 1.811); 0.119
WELLCLASS	0.199 (0.197); (-0.187; 0.584); 0.030	0.148 (0.336); (-0.511; 0.806); 0.021
Family environmental aspects		
PARENTAL RULES	0.556 (0.445); (-0.317; 1.429); 0.049	0.621 (0.637); (-0.627; 1.869); 0.049
PARENTUSE	0.174 (0.145); (-0.110; 0.458); 0.032	0.529 (0.257)*; (0.025; 1.034); 0.095
SIBLINGS	0.282 (0.449); (-0.598; 1.163); 0.024	2.085 (0.696)**; (0.721; 3.449); 0.181
Random effects	**σ^2 pooled**	**σ^2 pooled**
Variance of class-intercept	0.544 (0.420)	2.650 (1.293)

Note: n=1,064 for the social media-model (only cases showing social media as dominant application). n=365 for the gaming –model (only cases showing gaming as dominant application). (imputed dataset; m = 50; k = 5). Different gender excluded due to too few cases, see ☛section 3.1. Multilevel regression (Level 1: students. Level 2: school classes). Unit of analysis: CIUS-score related to specific DMD and applications, respectively.
Model social media: Pooled variance estimate of Level 1-residuals = 18.769. Pooled ICC adjusted/conditional = 0.028/0.017. Pooled R^2 marginal/conditional based on (Nakagawa and Schielzeth, 2013) = 0.392/0.409.
Model gaming: Pooled variance estimate of Level 1-residuals = 17.025. Pooled ICC adjusted/conditional = 0.135/0.087. Pooled R^2 marginal/conditional based on (Nakagawa and Schielzeth, 2013) = 0.352/0.439.
DMDCOUNT: Count of DMD in own possession. DMDTIME: Daily leisure-related usage time of the dominant DMD (in hours). PRESLEEP: Count of school days using DMD as a pre-sleep activity. AFTERMID: Count of school days using DMD after midnight. POSIT: Position of smartphone during bedtime (Not in bed = 0. In bed = 1). INITAGE: Initial age of regular internet use. INSOMNIA: ISI-score. ANXIETY: GAD-score. PSYCONST: Total difficulties SDQ-score. AGE: Students' age (in years). GENDER: Male = 0. Female = 1. Age: SES: Socioeconomic status. BOREDOM: BPS-score. SELFEFF: ASKU-score (self-efficacy). PARSUPP: SKU-score (parental support). EMOSUPP: BSSS-score (emotional support). INSTSUPP: BSSS-score (instrumental support). PROBEHAV: Prosocial behaviour SDQ-score. CONCERNS: Concerns related to the extent of internet use. WELLCLASS: Wellbeing in school class. PARENTAL RULES: Parental rules to regulate DMD use (No rules = 0. Rules = 1). PARENTUSE: Extent of parental DMD use. SIBLINGS: No = 0. Yes = 1. b: Pooled unstandardized coefficient. SE: Pooled standard error. 95%-CI: Pooled 95%-confidence interval of b. β: Pooled standardized coefficient according to Gelman (Gelman, 2008) by dividing numeric variables by two standard deviations to provide a better comparison with binary variables). σ^2: Variance. * p < 0.05. ** p < 0.01. *** p < 0.001.

Table 32: Overview of associations yielded by multilevel linear regression

	DRAB	ARAB	Social media-related addictive behaviour	Gaming-related addictive behaviour
Internet use characteristics				
DMDCOUNT				
DOMDMD	✓			
DOMAPP		✓		
DMDTIME	✓	✓	✓	✓
PRESLEEP	✓	✓	✓	
AFTERMID	✓	✓	✓	
POSIT	✓			
INITAGE	✓	✓		
Comorbid symptoms				
INSOMNIA	✓	✓	✓	
ANXIETY		✓	✓	
PSYCONST	✓	✓	✓	✓
Sociodemographic characteristics				
AGE	✓	✓	✓	
GENDER	✓	✓	✓	
SES				
Psychosocial characteristics				
BOREDOM	✓	✓	✓	✓
SELFEFF	✓	✓	✓	✓
PARSUPP	✓	✓		✓
EMOSUPP				
INSTSUPP				
PROBEHAV				
CONCERNS	✓	✓	✓	✓
WELLCLASS	✓	✓		
Family environmental aspects				
PARENTAL RULES	✓	✓		
PARENTUSE	✓	✓		✓
SIBLINGS		✓		✓

Note. Check marks indicate significant associations, empty cells indicate no association. DMDCOUNT: Count of DMD in own possession. DOMDMD: Dominant DMD in use (dummy-coded). DOMAPP: Dominant internet-based application in use (dummy-coded). DMDTIME: Daily leisure-related usage time of the dominant DMD (in hours). PRESLEEP: Count of school days using DMD as a pre-sleep activity. AFTERMID: Count of school days using DMD after midnight. POSIT: Position of smartphone during bedtime (dummy-coded). INITAGE: Initial age of regular internet use. INSOMNIA: ISI-score. ANXIETY: GAD-score. PSYCONST: Total difficulties SDQ-score. AGE: Students' age (in years). GENDER: Male = 0. Female = 1. Age: SES: Socioeconomic status. BOREDOM: BPS-score. SELFEFF: ASKU-score (self-efficacy). PARSUPP: SKU-score (parental support). EMOSUPP: BSSS-score (emotional support). INSTSUPP: BSSS-score (instrumental support). PROBEHAV: Prosocial behaviour SDQ-score. CONCERNS: Concerns related to the extent of internet use. WELLCLASS: Wellbeing in school class. PARENTAL RULES: Parental rules to regulate DMD use (No rules = 0. Rules = 1). PARENTUSE: Extent of parental DMD use. SIBLINGS: No = 0. Yes = 1.

4 Discussion

4.1 Background and objectives

Although the study of the prevalence, risk and protective factors of IRAB has been heavily issued in the last two decades, studies that delved into a comparison of the addictive potential of specific internet-based entities such as DMD or certain internet applications such as social media or games are scarce. However, some studies suggest that excessive social media use and gaming not only attract different sociodemographic subgroups, e.g. related to gender (Kuss et al., 2014, Busch and McCarthy, 2021), but is also associated with distinct individual risk factors, e.g. related to anxiety or depression (Castrén et al., 2022, Andreassen Schou et al., 2016). Referring to prevalence estimates, a ton of studies has been carried out since the initiation of research activities on the issue of IRAB, whereas a substantial proportion did not provide reliable reference points due to substantial methodological limitations e.g. related to sampling or measurement issues, as shown in a systematic review from 2011 that examined the quality of studies based on STROBE-criteria (Moreno et al., 2011) and also more recently in a meta-analysis from 2022 (Lozano-Blasco et al., 2022b). Lacking methodological rigor in that field may also be reflected in the finding of another meta-analysis from 2020 (Pan et al., 2020) that reported prevalence rates from single studies ranging between 1 to 40%. In order to set methodological standards some collaborations have been established meanwhile (Rumpf et al., 2019, Fineberg et al., 2018).

By 2022, during the COVID-19 pandemic, no current database on that issue was available in Styria and also not in Austria, although there were strong claims by school, prevention and treatment professionals reporting various adverse effects and increasing requests for counselling associated with the increase in the use of DMD and internet applications, such as social media or games among adolescents. These claims were supported by studies in Germany which indicated sharply rising prevalence rates of IRAB among adolescents (Paulus et al., 2022, Werner et al., 2021, Neumann and Lindenberg, 2022). Together, the lack of current data or at least reliable prevalence estimates from other studies that might have been considered transferable to Styria or Austria, severely limited the conception and planning of respective prevention and treatment policies.

This dissertation thesis aims to contribute in this respect by providing reliable and population-representative results on the issue of digital media usage and their addictive excesses among adolescents in Styria. First, characteristics of DMD and internet use were described in order to establish knowledge in which specific DMD and internet-based applications adolescents are engaged in, how much leisure time they spend on it, to what extent this engagement is integrated in bedtime routines, to what extent they are equipped with DMDs and when they started to regularly engage in internet activities. Second, prevalence rates of IRAB were estimated based on the well-established measurement CIUS. In this context, a distinction was made between addictive behaviour related to DMD (DRAB) and internet applications (ARAB), respectively. Finally, extensive models were tested to examine the relations of usage patterns, comorbid symptoms, sociodemographic, psychosocial and family environmental aspects and IRAB in general (taking into account the distinction between DRAB and ARAB), as well as for social media- and gaming-related addictive behaviour as specific domains of ARAB.

4.2 Characteristics of DMD and internet use

The following subsection discusses the findings related to research questions 1 to 6 (see ☛section 1.9).

Availability of DMD

Regarding the availability of potential addictive entities such as internet enabling DMD, the findings show that students are highly equipped. On average, they are in possession of 3.58 DMD and almost all students (99%) own an internet-enabling smartphone.

Considering digital divides related to possession of DMDs, which was pointed out to still influence accessibility to internet use of lower income families (Paccoud et al., 2021), no relation was found with respect to SES, which is in line with Arellano et al. (Arellano et al., 2016) who showed that this kind of digital divide has become less decisive related to the accessibility of the internet. Female students were found to own significantly fewer DMD than males, which may reflect still existing gender stereotypes influencing earlier adoption of different kinds of technology in general and specific gaming devices such as gaming consoles in particular by males (Masanet et al., 2021). However, in this context it should be noted that, regardless of gender, almost all students own an internet-enabling smartphone, which puts the notion of a digital gender divide into perspective. Besides, age is not associated with the amount of DMD students own, indicating that younger adolescents have the same access to DMDs and thus potential to access the internet as older ones. However, research showed that digital divides are still present with regard to infrastructural, grid-related aspects of more decentralised regions. In a survey among school students in a Styrian region referred to as “East Styria” (x-sample, 2021) the students of more decentralized civil parishes indicated the mobile internet reception as one of the major aspects that they miss, but are important to them. Not a single student from the larger civil parishes referred to that aspect. However, the amount of DMD in possession is not related to IRAB as the topic of this thesis (for a more detailed discussion see ☛section 4.4).

DMD usage during bedtime

DMD usage during bedtime occurs to a very high extent. Students use them on nearly every evening with subsequent school day (on average on 4.24 of five such evenings per week) as a pre-sleep activity, which was defined as using DMD directly before falling asleep. Pre-sleep activity was found to be positively associated with age (the older students are, the more pre-sleep activity) and negatively with SES (the less SES students have indicated, the more pre-sleep activity). No relation is shown for gender. Another examined aspect of DMD usage during bedtime is after-midnight usage on evenings with subsequent school day, which is shown to occur on average on 1.66 of five such evenings per week and linked to the same sociodemographic characteristics and in the same directions (positively to age and negatively to SES) as pre-sleep activity mentioned above. 28.1% of the students show after-midnight usage of DMD on at least three of five evenings with subsequent school day, i.e. on more than every second day. In addition to linkages of these bedtime routines with IRAB (discussed in ☛section 4.4) they are also associated with insomnia as shown in an article by Lederer-Hutsteiner et al. (Lederer-Hutsteiner et al., 2024) based on the same dataset as this thesis. The article also showed that on average after-midnight usage occurs to a higher extent than what was expected for unimpaired sleep.

Initial age of using the internet

Considering age, the general trend of younger people entering regular digital media use has been observed for some time in many countries (Holloway et al., 2013, Medienpädagogischer Forschungsverbund, 2023b) and is in line with the corresponding results of this thesis. A representative survey in Germany among children and adolescents aged 6 to 19 years indicates a threefold increase (from 6 to 18%) in the proportion of children aged 6 to 7 who possess their own smartphone from 2023 to 2024 (Iconkids, 2024). Another representative monitoring survey even shows respective increases among toddlers. In this survey among a German population of parents with children aged 2 to 5 years, the proportions of toddlers owning a smartphone increased from 4 to 10% between 2020 and 2023, those who own a tablet from 14 to 21% and those who possess a computer or laptop from 19 to 22% (Medienpädagogischer Forschungsverbund, 2023b). This approach strongly contradicts recommendations of a AWMF-registered S2k-guideline carried out recently by the German Society for Paediatrics and Adolescent Medicine, according to which children under the age of 3 should be kept completely away from all passive and active use of screen media and children aged 3 to 6 should be allowed a maximum of 30 minutes on individual days in the presence of their parents. Assuming that possession of smartphones also goes along with access to internet-related applications, these findings are also represented by results of this thesis, according to which the initial age of regularly using the internet is positively associated with the current age indicating that the onset of regular internet use declines by nearly half a year for each year of younger current age. The associations of this trend with IRAB are discussed below in ☛section 4.4.

Dominant DMD, internet-based applications and usage time

Smartphones as the dominant DMD for leisure-related activities among students, as highlighted in the results, aligns with global trends in mobile device usage. In all sociodemographic subgroups smartphones were found to be the most frequently used DMD, with a total of 77.0% of students reporting it as their dominant DMD. This is consistent with research showing that mobile phones are integral to daily activities, especially among young adults (Medienpädagogischer Forschungsverbund, 2023a, Ting and Chen, 2020). In contrast, PCs or laptops (13.5%) and gaming consoles (4.7%) are far less dominant among adolescents. Gender differences were shown, with female students being more likely to dominantly use smartphones, while males were more likely to dominantly use gaming consoles and PCs/laptops due to their higher engagement in gaming activities. This supports prior studies demonstrating that males are more inclined towards video gaming, while females engage more with social media and communication platforms (Andreassen Schou et al., 2016). Although the smartphone also dominates usage across all observed cohorts, age-related differences also emerged and are reflected by increasing smartphone dominance the older the students are. Conversely, a dominance of tablets and gaming consoles was found to appear more frequently among younger students. SES however, has not been found robustly associated with any device.

With regard to the estimates provided for usage times of DMD, it is important to note that they exclusively refer to leisure-related usage (not including school-related usage) and to the dominant DMD only. It is therefore highly likely that both the total, as well as the leisure-related usage times are in fact higher, because additional usage time of other DMD could not be extracted from the data, as they do not provide any indication of simultaneous multitasking DMD use. Multitasking patterns however, were shown to be highly prevalent among adolescents for example by combing television and text messaging or surfing on social networks or by playing computer games and surfing the internet (Ettinger and Cohen, 2020). With this in mind, students show a daily average of around 5 hours of leisure-related DMD use, regardless of their age, but linked to gender an SES. Female students spend on average more than half an hour more time on their preferred DMD than males and usage time increases as the students’ SES decreases. Overall, the findings clearly underscore the central role of smartphones in the students’ leisure-related digital media activities as well as in the students’ leisure time generally.

Referring to specific internet-based applications social media is unequivocally dominant among the examined student population across all three considered sociodemographic subgroups. 38.4% of all students indicate social media to be dominant in usage, followed by streaming movies and series as well as gaming (15.0% each), chatting (12.1%) and listening to music (11.8%). Other applications with recognized addictive potential are dominant for substantially fewer students, e.g. engaging in porn content (2.7%), shopping (0.5%) and gambling (0.2%). However, it should be noted that these quantities do not reflect the totals of students who basically or occasionally engage in these activities, as they just refer to students who indicate these applications as their dominant leisure-related online activity. With respect to gender differences, the odds of using social media as the dominant online activity are higher for female students compared to males. Conversely, the odds for predominantly gaming are substantially higher for male students. Both gender differences have also been shown in previous research (Andreassen Schou et al., 2016). Furthermore, the dominance of social media increases the older students are, while for gaming the inverse association was observed. No association was found for SES.

4.3 Prevalence estimation

The findings discussed in this subsection relate to the research questions 7 and 8 (see ☛section 1.9).

Due to the measurement model (see ☛Figure 5 in ☛section 2.7.1), in which the generic CIUS was processed twice, once related to the dominant DMD and once referred to the dominant internet application, this thesis provides prevalences not only related generally to IRAB, but also specifically for certain DMD (DRAB) and internet applications (ARAB). To the best of the authors’ knowledge no study has been published yet involving a comparable procedure. Most studies either used generic measures of IRAB or involved specific measures such as the *Smartphone Addiction Scale* (SAS) (Kwon et al., 2013) for smartphone use, the *Bergen Social Media Addiction Scale* (BSMAS) (Andreassen et al.,

2012) for social media use or the *Game Addiction Scale* (GAS-7) (Lemmens et al., 2009) for gaming.

Despite existing limitations and without any claim of estimating clinical relevance (discussed in detail in ☛section 4.5), the findings indicate that IRAB as an umbrella term of DRAB and ARAB seems to be a highly widespread phenomenon among adolescents; even more so among female as well as younger and low-SES adolescents. In total, DRAB (addictive behaviour related to any DMD) and ARAB (addictive behaviour related to any internet application) were shown for 40.5% and 32.6%, respectively. Considering specific DRABs, the smartphone was clearly identified as the one DMD by far the most frequently associated with addictive behaviour among the various compared DMD (which is also due to the widespread dominance of smartphones in usage mentioned above). 32.3% of the examined adolescents show smartphone-related addictive behaviour, followed by 5.3%, 1.6%, 1.0% and 0.4% who show PC/laptop-related, gaming console-related, tablet-related and TV-related addictive behaviour, respectively. With respect to specific ARABs, addictive behaviour is most frequently linked to social media (also due to their dominance in usage mentioned above). 13.8% of the adolescents show social media-related addictive behaviour, followed by 4.9%, 4.7%, 3.3%, 1.0%, 0.2% and 0.1% show gaming-related, streaming films/series-related, chatting-related, pornography use-related, shopping-related and gambling-related addictive behaviour, respectively.

Regarding sociodemographic characteristics, female students show more than three times the odds of being classified as smartphone-related addictive behaviour and more than four times the odds of social media-related addictive behaviour compared to male students, which is in line with recent reviews and studies (Busch and McCarthy, 2021, Dailey et al., 2020, Boniel-Nissim et al., 2024). Male students are more prone to show addictive behaviour with gaming consoles and PCs/laptops, which is consistent to their surplus of addictive behaviour related to gaming. Furthermore, male students show more pornography-related addictive behaviour than females. Both areas have been highlighted as linked to male subjects in prior research (Kuss et al., 2014, de Alarcon et al., 2019, Meng et al., 2022, Boniel-Nissim et al., 2024, Andreassen Schou et al., 2016). Although, as already outlined above, low-SES students show higher proportions of DRAB and ARAB in general, the students’ SES is in no association to any prevalence of specific DRABs and ARABs, except for smartphone-related addictive behaviour, which is more prevalent among low-SES students. However, previous research on the association of SES and IRAB is highly inconsistent, showing positive as well as negative associations, as noted in a recent meta-analysis (Lozano-Blasco et al., 2022a). It is therefore plausible to assume that SES per se may not contribute substantially in a direct way, but rather indirectly by various mediating variables such as e.g. the psychosocial constitution (for a more detailed discussion see ☛section 4.4).

The prevalence of social media-related addictive behaviour is within, however at the upper limit of the range of data from the international *Health Behaviour in School-aged Children (HBSC)*-study from 2018, in which a range of 3 to 14% (on average 7.4%) of corresponding behaviour was shown (Boer et al, 2020) among students aged 11 to 17 years (Boer et al., 2020). By extracting the data for Austrian students from the HBSC-study, 9% were identified as showing strong indications of social media-related addictive behaviour in 2018 (Felder-Puig et al., 2020). Considering, smartphone-related addictive behaviour no current comparative data are available for Austrian populations. However, a meta-analysis of the corresponding prevalence among children and adolescents from 2019 yielded a range of 14 to 31% (with a median prevalence of 23%) (Sohn et al., 2019). Apart from all methodological issues that hinder comparability across studies (discussed in detail in ☛section 1.7), these previous findings may be considered reasonably in line with the current estimates, considering that the data of the referenced studies were collected before the pandemic and the current data of this thesis in 2022 during the pandemic, which was shown to foster problematic internet use among adolescents (Paulus et al., 2022, Werner et al., 2021, Neumann and Lindenberg, 2022, Fung et al., 2021, Meng et al., 2022). In line, the current 2021/2022 HBSC survey (Boniel-Nissim et al., 2024) also reports an increase of the prevalence of problematic social media use from around 7% in 2018 to the current 11% in 2021/2022. A similar increase was observed for problematic gaming. Another meta-analysis (Alimoradi et al., 2022), focussing exclusively on studies that were carried out during the COVID-19 pandemic, yielded pooled prevalence rates of 30.7%, 5.3% and 15.1% for smartphone-, gaming- and social media related addictive behaviour, respectively, which are remarkably close to the estimates of this thesis. Evidence for a COVID-19 driven increase was also provided for problematic gaming and gambling in a qualitative survey among international experts (Carragher et al., 2023) and also became apparent due to sharply rising numbers of people seeking treatment (Aragay et al., 2024). However, apart from the COVID-19 pandemic, in this context it is also essential to consider the inherent structural characteristics of the products themselves. The sophistication of reward (such as loot boxes in games (Rehbein et al., 2024)) and immersive mechanisms (such as infinite scrolling in social media (Montag et al., 2019)), both promoting addictive processes, is consistently increasing. Moreover, according to the products' business model to maximize the users' time spent using these products, the rapid advances in the field of artificial intelligence are also facilitating the tailoring of content to users (Perez-Lozano and Espinosa, 2024).

In addition, other impairments such as insomnia, anxiety and the overall psychosocial constitution are demonstrated to be present at high prevalences in the current thesis. This finding converges with recent reviews (Keyes and Platt, 2023, Odgers and Jensen, 2020) pointing to increasing problems with mental health among adolescents (especially females) in many countries. Also another study, based on the same dataset as this thesis, that focussed on insomnia and its relation to IRAB *"… found that female adolescents are more likely to be affected by insomnia symptoms as a potential indicator of mental health problems."* (Lederer-Hutsteiner et al., 2024, p. 9).

To summarize these findings, a high level of caution is required when deriving needs for addiction treatment policies. As mentioned above, despite a clear involvement of addiction symptoms the estimated prevalences do not provide an indication of their clinical relevance due to the absence of diagnostic interviews (Maraz et al., 2015). Abstaining from pathologization (Montag et al., 2024, Kardefelt-Winther et al., 2017) should therefore be imperative. However, extensive prevention and early intervention policies are clearly indicated and already summarized in a respective policy plan in Styria (Lederer-Hutsteiner and Koberg, 2024). The observed class-specificity as indicated by substantially varying ICCs of certain addictive online behaviours should be considered in the planning of respective preventive measures. While measures to prevent smartphone- and social media-related addictive behaviour, (both showing low ICCs) may be addressed universally with no particular focus on certain school classes, school types or grades, measures that aim to address gaming-related addictive behaviour (showing substantial heterogeneity across school classes) should be carried out with higher class-based specificity and take advantage of the homogeneity of certain student characteristics within schools classes. Based on the yielded correlates such classes may include grades 5 to 8 (since younger students show higher odds for gaming-related addictive behaviour).

4.4 Correlates of internet-related addictive behaviour

This subsection addresses the research questions 9 to 11 (see ☛section 1.9) and discusses the corresponding findings.

A central issue in epidemiological research is the identification of factors that promote (risk factor) and prevent (protective factor) the development of diseases or detrimental health conditions. Although both risk and protective factors are widely used terms associated with the reporting of pure cross-sectional correlational findings, they imply a certain degree of unjustified causality. Since the data the current thesis is based on is cross-sectional as well any suggestion of a causal relationship is unsubstantiated, even if it is merely implied by the terminology employed. Moreover, attempts to compensate for the data's lack to claim causality and directionality through conceptual rigour, is unwarranted due to the absence of consistent experimental and longitudinal evidence (see ☛section 1.8 for a detailed discussion). Consequently, the term correlate will be used in the following to describe relationships of unknown causal direction between IRAB and several associated characteristics.

Based on a robust body of existing correlational and bidirectional evidence including the I-PACE model introduced by Brand et al. (Brand et al., 2016) (see ☛Figure 3 in ☛section 1.8.1) associations of the extent of symptoms of IRAB with several intra- and interpersonal as well as family environmental characteristics are examined. Specifically, these characteristics encompass several DMD and internet use patterns, comorbid mental symptoms, sociodemographic characteristics, psychosocial characteristics and family environmental aspects. Personality factors are excluded from all analyses due to poor internal consistencies (see ☛Table 4 in ☛section 2.7.8). In this context, the dependent variable IRAB is differentiated into DRAB and ARAB to contribute to the question whether DRAB (e.g. related to smartphones commonly referred to as smartphone addiction) is a distinct phenomenon that has to be distinguished from ARAB, e.g. related to gaming referred to as gaming disorder in ICD-11. Some authors, such as Billieux (Billieux, 2012) and Liu et al. (Liu et al., 2022), argued against, while Davazdahemami et al. (Davazdahemami et al., 2016) argued in favour of a corresponding distinction. Moreover, associations of the above-mentioned characteristics with social media-related and gaming-related addictive behaviour as the two most prevalent phenomena among adolescents representing ARAB are contrasted. Although research showed that behavioural addictions generally interrelate and share some common correlates (Robbins and Clark, 2015, Király et al., 2014), another study points to small overlaps and distinct correlates of social media-related and gaming-related addictive behaviour (Andreassen Schou et al., 2016).

Referring to the question of overlaps between DRAB and ARAB, a comparison of the DRAB- and ARAB-models shows that both models converge in terms of a considerable proportion of 37% of variance explained by the included fixed-effect variables (see ☛Table 30 in ☛section 3.4). School classes as a random-effect variable only added a very small contribution in explaining additional variance as indicated by the low ICCs. This finding indicates that the extents of symptoms of DRAB and ARAB is highly homogeneous across school classes. In terms of prevention policies in school setting, together with the observed high prevalences this result indicates a broad mandate without any particular focus on certain school types. Both models also converge with regard to the associated correlates. With very few exceptions, most usage patterns, comorbid mental symptoms, sociodemographic, psychosocial and family environmental aspects are significantly linked to DRAB as well as to ARAB. However, anxiety (being positively related to ARAB) and the position of the smartphone during bedtime (more DRAB-symptoms if the smartphone is located in the bed) seem to represent distinct characteristics of ARAB and DRAB, respectively. The data also shows that DRAB and ARAB are highly correlated (r = 0.843; see ☛Table 9 in ☛section 3.1) and share 71% of common variance indicating that both represent closely related constructs. Substantial overlaps between DRAB and ARAB were also shown recently in studies among adolescents and university students and indicate DRAB to be just a manifestation of ARAB (Liu et al., 2022, Lee et al., 2020). However, apart from noise caused by potential inaccuracy of the involved self-report measurements, the remaining 29% indicate some unique variance that cannot be explained mutually. Some of the unexplained variance may be due to non-specification of DRAB and ARAB. It is reasonable to assume that e.g. gaming console-related addictive behaviour representing a specific DRAB is more closely linked to gaming-related addictive behaviour representing a specific ARAB than e.g. laptop-related to social media-related addictive behaviour. In conclusion, further research is needed to address this issue.

With respect to the associated usage characteristics, the DRAB-model shows that almost all considered DMD such as smartphones, tablet, gaming consoles and computers/laptops yield comparable extents of DRAB-symptoms. However TVs are linked with much lower extents of DRAB-symptoms. Referring to specific internet-related applications, the ARAB-model shows that predominately engaging in social media, gaming, watching films/series and porn content are linked to similar extents of ARAB-symptoms, whereas students, who are predominantly engaged in chatting show significantly lower extents of ARAB-symptoms. In line with a robust body of longitudinal evidence (Lemmens et al., 2011a, Mihara and Higuchi, 2017, Zhuang et al., 2023), the daily usage time is closely positively linked to the extent of DRAB- and ARAB-symptoms generally, as well as to the extent of symptoms that refer to social media- and gaming-related addictive behaviour. This result was to be strongly expected since increased usage is inherent to loss of control and tolerance, both of which are generally recognised criteria for addiction (American Psychiatric Association, 2022, World Health Organization, 2022). The usage of DMDs as part of bedtime routines such as pre-sleep activity and after-midnight usage is also positively associated with the extent of DRAB- and ARAB-symptoms, which is consistent with findings from previous research (Nalwa and Anand, 2003, Lederer-Hutsteiner et al., 2024). However, among ARAB only the symptom severity of social media-related addictive behaviour, but not gaming-related addictive behaviour, was linked with increased pre-sleep activity and after-midnight usage of DMD. In previous research both bedtime routines were found to be substantially linked to insomnia among adolescents since late-night use of DMD delays bedtimes (Hale and Guan, 2015, Lederer-Hutsteiner et al., 2024), reduces sleepiness and slow-wave activity measured with EEG (Grønli et al., 2016), suppresses melatonin by emitting short-wavelength light (Figueiro and Overington, 2016) and thus reduces sleep duration, but also enhances cognitive and physiological arousal and therefore reduces sleep quality (Brautsch et al., 2022, Hale and Guan, 2015, Lund et al., 2021). Moreover, the positive association of internet-related addictive behaviour and insomnia among adolescents was found to be partly mediated by after-midnight use of DMD (Lederer-Hutsteiner et al., 2024). As a consequence, bedtime routines involving DMD should be addressed in the context of awareness campaigns focussing on students and parents, since they occur to a very high extent. Also in line with previous studies (Beard et al., 2017, Charmaraman et al., 2022, Koyuncu et al., 2014, López-Bueno et al., 2023, Tsitsika et al., 2014, Kim et al., 2023) is the shown negative linkage between early exposure to regular internet use and symptom-severity of DRAB and ARAB, which is higher for students the earlier the onset was initiated.

Considering comorbid mental symptoms, insomnia, anxiety and a weaker overall psychosocial constitution are related to the extent of ARAB-symptoms. The same applies for DRAB-symptoms with the exception that anxiety is on the verge to significance. These results are highly in line with previous research, as mental health impairments and insomnia have been consistently shown to be closely linked to IRAB in many studies, reviews and meta-analyses (Ho et al., 2014, Carli et al., 2013, Zhuang et al., 2023, Busch and McCarthy, 2021, Alimoradi et al., 2019, Li et al., 2020, Zhang et al., 2022a). Moreover, delving into a differentiation of ARAB, this thesis also shows that symptom severity of social media-related addictive behaviour is the higher the more students are affected by insomnia, anxiety and a weaker overall psychosocial constitution. However, for gaming-related addictive behaviour, the same linkage is only shown for a weaker overall psychosocial constitution, but not for insomnia and anxiety, which may be due to limitations of sample power, since the gaming-model includes only around one third of the cases of the social media-model. Potential conceptual mechanisms underlying these differences may be issued in further research. In terms of causality and directionality of these relations, the current data of course do not provide any indication due to their cross-sectional nature. Findings from previous longitudinal studies do not support any indication on that issue either, since findings regarding the interplay of mental health and IRAB in terms of directionality are inconsistent and point to bidirectional relations, as concluded in a systematic review of longitudinal studies (Anderson et al., 2017b). Moreover, a bidirectional relation between mental health and IRAB is also indicated in the currently highly recognized I-PACE model (Brand et al., 2016), suggesting that psychopathologies predispose to IRAB, but are also exacerbated or triggered by IRAB.

Regarding sociodemographic characteristics as potential levels for target group-specific prevention and early intervention measures, two subgroups seem to stand out: female and younger students, both of whom show significantly higher levels of DRAB- and ARAB-symptoms. SES however, is in no relation. This is an interesting finding, which initially seems contradictory as it was mentioned above that the prevalence of IRAB in general and of smartphone-related addictive behaviour in particular is higher among low-SES students. Apart from applying different regression models (logistic regression for the relationship between the prevalence of IRAB and SES on the one hand and linear regression for the relationship between the extent of symptoms of IRAB and SES on the other), it should also be noted that in contrast to the logistic regression the linear regression model also adjusted for intra- and interpersonal characteristics such as mental comorbidities and psychosocial aspects. If the same limited set of predictors used in the logistic regression model that was restricted to sociodemographic characteristics only, had been applied in the context of linear regression, SES and IRAB would also be significantly linked. This finding suggests mediation mechanisms that foster the relation of SES and IRAB, which appears suitable for further research. Several mental health issues, such as depression, could act as potential mediators, since previous studies clearly showed lower SES to be linked to higher levels of mental health problems (Reiss et al., 2019, Quon and McGrath, 2014).

With respect to psychosocial characteristics, proneness to boredom was shown positively associated with the extent of DRAB- and ARAB-symptoms generally, which converges with a quite robust body of evidence carried out in reviews and meta-analyses (Camerini et al., 2023, Kuss et al., 2014). The same applies with regard to the extent of symptoms referring to social media- and gaming-related addictive behaviour. This should be considered in the context of environmental preventive measures aimed at focusing on socio-cultural aspects of young people’s daily environment to provide attractive offline offers, especially in decentralized regions as already emphasized in the current Styrian youth strategy (Amt der Steiermärkischen Landesregierung, 2024). The potential influence of socio-cultural and environmental aspects on the interplay of boredom and IRAB should also be subjected to further research by involving measures beyond the individual level, which are not covered in the data of this thesis. Moreover, the relation between mental health issues such as depression and anxiety and IRAB was shown to be mediated by boredom (Elhai et al., 2018), which affect IRAB through an increased attentional bias towards triggers of social media (Cannito et al., 2023). Self-reported concerns related to the students' extent of internet and DMD use are both positively associated with DRAB- and ARAB-symptoms. Apparently, students show a good sense of problem awareness. Since self-reported concerns linked to internet and DMD use have the strongest relation to IRAB among all correlates in the models, they may provide substantial predictive potential. This may be useful in the context of low-threshold screenings aimed at early detection. Given a trustworthy relation, students suspected of IRAB might be asked if they are concerned about their extent of internet usage or if they have ever considered seeking help. Another non-surprising finding refers to the linkage of DRAB- and ARAB-symptoms to self-efficacy as a potential protective personal resource, which is in line with a robust body of existing evidence from reviews and meta-analyses (Koo and Kwon, 2014, Kuss et al., 2014, Zhuang et al., 2023) that addressed the role of self-efficacy directly or through the closely related construct of self-esteem as an evidenced proxy-characteristic of self-efficacy (Lane et al., 2004, Stroiney, 2005). The same applies with regard to the extent of symptoms referring to social media- and gaming-related addictive behaviour. Life skills programmes, as a universal preventive measure, involve the promotion of self-efficacy and self-esteem and should therefore be extended or implemented where they are not yet in place.

Parental support is shown to be positively associated with the extent of DRAB- and ARAB-symptoms. However, generally perceived social support does not show any association. This finding indicates that students who perceive more support from their parents show higher symptom severity of IRAB and is in contrast to the results from a cross-sectional study that yielded a negative relation (Li et al., 2014). However, it is consistent with a recent large-scale 4-year longitudinal study (Donald et al., 2024) involving four survey waves that also showed a positive association of adolescents' perceived parental support and IRAB over time. The authors speculated that refrained regulative rules, which are also shown being absent to a high extent in this thesis, may contribute to this effect since they are likely to be popular and perceived as supportive among adolescents.

Feelings of well-being in school class are also positively linked to the extent of DRAB- and ARAB-symptoms (the more well-being in school class, the more symptoms). This is surprising since several previous studies showed negative relations (Hayixibayi et al., 2021, Wang, 2022, Zhang et al., 2022b). A potential explanation could be that students who do not participate in the mainstream of widespread intensive DMD use see themselves (or are seen) as some kind of outsiders to a certain extent and thus rate the class climate less favourably. The other way around, students who follow this mainstream may have better intraclass acceptance and relations, which positively affects well-being in school class. In line with this assumption, Boer et al. (Boer et al., 2020) showed that intense social media users indicated more peer support than less intense users in all 29 countries of the 2017/18 HBSC-survey wave. However, more research is necessary to better understand this interplay.

Prosocial behaviour does not show any association to the extent of DRAB- and ARAB-symptoms. Nor does it show any relation to more specific phenomena such as social media- or gaming-related addictive behaviour. This is inconsistent with prior findings from a recent meta-analyses that examined longitudinal linkages of prosocial behaviour and gaming-related addictive behaviour (Zhuang et al., 2023). However, there is also evidence that relations of IRAB with prosocial behaviour depend on the specific content of the preferred games and social media. While prosocial game content potentially increases prosocial behaviour, violent content increases the likelihood of aggressive behaviour as shown in a randomized control trial (Christakis et al., 2013) and meta-analysis (Greitemeyer and Mügge, 2014). As this thesis' dataset does not contain any information on the concrete preferred games or social media, this correlation could not be analysed to a degree of specificity that would presumably be required. Therefore, this may have led to a levelling of the issued relation.

Related to family environmental aspects, parental rules regulating their children's DMD usage were found to be positively associated with symptom severity of IRAB. Considering the coding, this means that symptom severity is higher in the presence of parental rules, suggesting that they are implemented for the purpose of an intervention in already existing patterns of excessive usage rather than as a preceding preventive measure. However, it should be noted that this finding should be treated cautiously and should not be overstrained since there is evidence to question the students' responses on parental rules, which were shown to highly differ from those of their parents if they were asked the same question (Wang et al., 2005) (for more details see ☛section 4.5). Moreover, the findings of previous studies are inconsistent, which is reflected by heavily varied correlations and heterogeneity across studies included in a recent meta-analysis that focussed on that particular relationship (Lukavska et al., 2022). While some studies showed that parental rules may prevent problematic internet use in general (Kalmus et al., 2015) and specifically problematic social media use (Koning et al., 2018), the meta-analysis by Lukavska et al. (Lukavska et al., 2022) mentioned above showed no overall relationship with IRAB (which was also confirmed in another meta-analysis (Zhuang et al., 2023) based on longitudinal studies). However, the meta-analysis by Lukavska et al. (Lukavska et al., 2022) showed this relation to be moderated by age. While no association was indicated for younger children/adolescents aged less than 14 years, a positive association was shown for older adolescents, which is in line with the findings of this thesis due to almost similar age groups. Despite all these reported inconsistencies, parent-educational measures have been suggested as a central aspect within a policy plan carried out in Styria by Gesundheitsfonds Steiermark and developed by an advisory board involving professionals from addiction and mental health care and prevention, addiction research, school social work, school administration and youth work (Lederer-Hutsteiner and Koberg, 2024).

Another finding of this thesis relates to the clear association of the parental extent of DMD use with the extent of their children's DRAB- and ARAB-symptoms, which are shown to be the more extensive the higher parental DMD usage is indicated. Although only limited research on that topic has been available up to now, this result converges with those of prior studies (Jago et al., 2012, Liu et al., 2024) and may be considered substantial in the context of parental education measures that address the parents' awareness of their role model function.

4.5 Strengths and limitations

Some of the strengths of this thesis have already been described in another publication of this thesis' author (Lederer-Hutsteiner et al., 2024). Since the same dataset was used, the same methodological strengths apply for this thesis. One of the methodological strengths of this study refers to the elaborated sampling strategy, carried out as a stratified one-stage cluster random sample, along with a very high participation rate and large sample size, all of which provide population-representative data that enhances generalizability of the yielded estimates. Moreover, the research employed several well-established instruments. CIUS as the outcome measure was chosen since it is theoretically well-founded (based on diagnostic DSM-IV-criteria for behavioural addictions and dependence), well-validated and psychometrically sound (Lopez-Fernandez et al., 2019, Laconi et al., 2019, Meerkerk et al., 2009) as highlighted in a review of assessment instruments of IRAB (Laconi et al., 2014), widely recognized (Király and Demetrovics, 2021) and offers a validated cut-off with high specificity of 97% (Besser et al., 2017). CUIS covers the diagnostic criteria disrupted control as well as functional impairment (interpersonal conflict, conflicts due to neglect of daily obligations), which are widely consented as being central in the context of IRAB (Billieux et al., 2015, Saunders et al., 2017, Rumpf et al., 2018a, Billieux et al., 2017) (see ☛section 1.6) as well as mental preoccupation and using the internet to cope with unpleasant moods. In order to estimate prevalences, a validated cut-off score showing good specificity and sensitivity is crucial in the course of classification, which was done by Besser et al. (Besser et al., 2017) by fully structured and standardized diagnostic interviews with 188 positively screened students of two German vocational schools according to the Munich-Composite International Diagnostic Interview, M-CIDI (Wittchen et al., 1995). This cut-off-validation was another important reason for which CIUS was chosen.

The conceptual strengths of this thesis employ the provision of an evidence-based foundation for policy planning in Austria, addressing a need that has been strongly demanded by various sectors (including health and education) but has previously been constrained by a lack of reliable data. Moreover, to the best of the authors' knowledge, this is the first study that provides extensive prevalence estimates for a number of potentially internet-related additive entities (including DMD such as smartphones, gaming consoles, PCs and laptops as well as internet-based applications such as social media, games and gambles, pornographic content and shopping facilities) that might be interesting for not only the scientific community of this research area, but also for regional policy planning. Accordingly, this thesis not only differentiates between addictive behaviour related to internet applications, but also employs corresponding behaviour related to DMD and thus, contributes to the highly debated question of whether these phenomena are to be considered as distinct phenomena or rather as overlapping and interrelated. Furthermore, the measurement involves specific applications, such as social media or gaming, as well as smartphones or gaming consoles as concrete entities of ARAB and DRAB, respectively. Normally, this approach is executed by applying specific scales (i.e. gaming disorder scales, social media use scales, problematic smartphone use scales), which rapidly devolves into a time-consuming and impossible to process scope of questions and severely limits data collection. This thesis provides a time-efficient approach that combines CIUS as a psychometrically sound generic measure of IRAB, which was presented twice, preceded by the question of which DMD and which internet application, respectively dominates active leisure time. Subsequently, the students were instructed to relate all questions of CIUS to this particular DMD and in the second round to this particular internet application. Another issue of scientific interest may be the provision of application-specific correlates for addictive gaming and social media use.

However, several methodological and conceptual limitations have to be considered as part of the interpretation and classification of the results of this thesis.

A first major limitation of this thesis is of course its study design and the use of a dataset that is cross-sectional in nature. Two of the three investigated superordinate research topics of this thesis are not affected by the study design and cross-sectional data may even be regarded as a gold standard in that context since the included research questions are all about accurately quantifying single variables, such as prevalences or usage times. However, the third superordinate topic aimed to examine associations between IRAB and potential correlates, which of course would have been more insightful if these associations could be based on cause-and-effect-relations. Simply put, the knowledge of an association e.g. between IRAB and insomnia is indeed useful and fosters hypothesis building for future studies to delve into the examination of this association, but with respect to the planning of prevention and treatment policies it would be crucial to know whether IRAB causes insomnia (this would imply to focus on IRAB in the course of preventive policies) or insomnia causes IRAB (implying to focus on insomnia). However, cross-sectional data does not at all justify any claims about causal relations, since all measures (dependent and independent) were observed at the same time and without any experimental manipulation that would justify a causal order of the observed relationships. Hayes, 2018 summarizes *"… three criteria often described as necessary conditions for establishing causation (covariation, temporal ordering, and the elimination of competing explanations) …"* (Hayes, 2022, p. 16). While the investigation of covariation can be addressed in the context of cross-sectional data, claims about the temporal order and the elimination of alternative explanations are out of reach from a methodological perspective. However, these fundamental restrictions could potentially be mitigated by a consistent body of unidirectional evidence yielded from previous experimental and longitudinal studies and corresponding reviews and meta-analyses based on them. Despite extensive literature research (summarized in ☛section 1.8) this conceptual claim could not be met within this thesis, since (1) the vast majority of the literature in that research field is cross-sectional as shown in two reviews (Duong et al., 2020, Fumero et al., 2018), (2) study designs suitable to claim causation are scarce and have repeatedly been demanded by many authors (Lam, 2014, Odgers and Jensen, 2020, Rumpf et al., 2019, Anderson et al., 2017b, Mihara and Higuchi, 2017, Zhuang et al., 2023) and (3) the evidence provided by the few experimental and longitudinal studies points to bidirectional relationships with only few exceptions (see ☛sections 1.8.2 to 1.8.7).

A second limitation of this study is the fact that all prevalence estimates of IRAB are solely based on a single self-reporting screening instrument without any kind of further professional diagnostic exploration. Thus, any prevalence rate has to be interpreted cautiously and without any claim of clinical relevance, although the used scale of CIUS is conceptually sound, considered as one of the best validated measures in the context of IRAB (Laconi et al., 2014) (see ☛section 2.7.1 for a more detailed discussion) and the applied cut-off showed high specificity in a validation study among adolescents (Besser et al., 2017). Consequently, any labels which refer to the clinically relevant classifications according to DSM-5 and ICD-11 (such as Gaming Disorder or Internet Use Disorder as the corresponding umbrella term) must not be assigned to the detected students showing IRAB, also because nothing is known about its temporal stability as a crucial dimension of addictive disorders (Billieux et al., 2015), which is due to the cross sectional study design. In summary, the results do not allow to derive any need for treatment capacities, however they may be considered robust to allow for deriving needs for prevention and early interventions. Another aspect related to CIUS is its use in the context of DMD-related addictive behaviour as applied within this thesis as another manifestation of IRAB. Although CIUS is well validated in the context of IRAB, validations regarding addictive behaviour related to DMD are still pending. However, the application of the same diagnostic criteria to screen for DMD-related addictive behaviour seems to conceptually justified, since it was argued that an addiction e.g. related to a mobile phone is just a manifestation of an underlying internet application-based addictive behaviour (e.g. gaming, social network use) (Billieux, 2012).

Third, another limiting issue in school-based surveys might be a potential absentee bias, as e.g. outlined by Smit et al. (Smit et al., 2002). Although this issue was addressed within this thesis by comparing the prevalence rates of the participating and screened students with those of absent students, it should be noted that the prevalence rates of absent students are based on a very rough estimation by teachers which did not incorporate any validated measure. However, based on this comparison the prevalence rates were shown not to differ significantly between participating and absent students. A substantial absentee bias may therefore be regarded as rather unlikely despite the above-mentioned limitation (see ☛section 2.8.2 for a detailed description).

Fourth, some scales show poor internal consistency. This refers to all subscales of BFI-10 to screen for personality traits and, less substantially but still enough that they warrant questioning, some subscales of SDQ to screen for psychosocial strengths and difficulties. Although BFI-10 was shown to be sufficiently reliable in the original validation study by Rammstedt et al. (Rammstedt, 2013), a lack of internal consistency was also shown in other recent studies (Park et al., 2022, Ludeke and Larsen, 2017), which also applies for subscales of SDQ (Koo et al., 2017). Apart from general psychometric problems that short scales such as BFI-10 face (Gosling et al., 2003), by looking at the overview of the internal consistencies of all measures of this thesis (see ☛Table 4 in ☛section 2.7.8) it is noticeable that internal consistencies also seem to be negatively associated with the presence of reversed items, which was also recommended to be avoided in the context of BFI-10 (Park et al., 2022). As a consequence, all BFI-10-related and thus personality traits-related data were ignored in course of the analyses. Likewise, the subscales of emotional problems, conduct problems, hyperactivity/inattention and peer problems of the SDQ-scale were ignored and the total difficulties index, which shows acceptable internal consistency, was used instead. Of course, this represents a conceptual limitation with respect to the regression models applied in course of the examination of associations between IRAB and potential correlates, given that personality issues have to be neglected and psychosocial difficulties could not be taken into account as differentiated as intended.

Fifth, another critical aspect relates to the fact that all measures were administered in self-reporting mode. Anderson et al. (Anderson et al., 2017b) summarize evidence for inaccurate answering due to lacks of judgement capabilities, self-insight and willingness to respond honestly. Moreover, Yook et al. (Yook et al., 2019) found that both female subjects and those experiencing psychosocial burden exhibited a tendency to overestimate their smartphone usage. Together, this may result in severe under- and over-reporting which has been shown in several studies that examined discrepancies of self-report and real smartphone use based on log data (Boase and Ling, 2013, Lee et al., 2017, Montag et al., 2015b) and also in a corresponding meta-analysis (Parry et al., 2021). In line, existing parental rules implemented to regulate the internet use of their children were reported to a much higher extent by parents (61%) than by their associated teenagers (38%) in a US-study involving 749 parent-children-dyads (Wang et al., 2005). Despite several procedures to examine data quality such as identification of speeders, straightliners, non-completes or students providing mischievous responses and a corresponding elimination of these cases from the dataset (see data cleaning procedures in ☛section 2.6), there is no guarantee that all individual cases will ultimately be detected. However, given the mentioned data cleaning procedures, this bias may be considered as limited. Future surveys may nevertheless benefit from the inclusion of real DMD-log data, which could be administered in the form of diaries distributed to students and completed on a daily basis based on log data. The information provided in the diaries is then used as the basis for processing some parts of the questionnaire. Despite substantially higher efforts, the feasibility of such an approach may be worth being examined.

Sixth, information on specific social media (e.g. TikTok, Instagram) and specific games (e.g. GTA, Minecraft) is generally missing in the dataset. Missing data on that issue may have levelled, inflated or supressed certain associations in the social media- and gaming-model. As already described above, the well evidenced and content specific association between prosocial behaviour and gaming-related addictive behaviour was not shown in this thesis. This may be a consequence of missing specificity of the analyses, since prior research showed that games potentially elicit pro- as well as antisocial behaviour, depending on their specific content to be violent or prosocial. A more specific data collection that takes into account the specific products of social media and games would likely provide some additional explanatory power of that relation, which was already mentioned in an article by Lederer-Hutsteiner et al. (Lederer-Hutsteiner et al., 2024) and in a meta-analysis from 2023 (Pagano et al., 2023).

Seventh, the set of correlates is exclusively limited to intra- and interpersonal characteristics. Structural features (addictive mechanisms of the applications per se) of certain games (such as loot boxes which shows similarities to gambling (Rehbein et al., 2024)) or social media (such as infinite scrolling mechanisms to prolong feelings of time distortion and immersion (Montag et al., 2019)) were not taken into account since information on the specific products used by the students was not included in the dataset. However, this knowledge would have enabled to assign each product a score of addictive structural aspects according to checklists of addictive risk characteristics provided by Rehbein et al. (Rehbein et al., 2024) and Griffiths and Nuyens (Griffiths and Nuyens, 2017) and thus, add some additional explanatory potential.

Finally eighth, any moderation and mediation mechanisms were not addressed in this thesis and should be investigated in further research. Previous studies have shown that, for example, the relationship between social media-related addictive behaviour and poor mental health is moderated by gender and is significantly stronger in female students than in male (Twenge et al., 2022, Kelly et al., 2018, Twenge and Farley, 2021).

5 Conclusions and implications

Based on increasing concerns about the detrimental health and educational effects of adolescents' excessive use of DMD, the objective of this thesis project was to extensively examine usage characteristics associated with DMD and internet-based applications, prevalences of addictive behaviour related to different internet-enabling DMD (DRAB) such as smartphones as well as to different internet-related applications (ARAB) such as social media or games and to investigate correlates linked to higher symptom severity of IRAB (used as an umbrella term for DRAB and ARAB) in a population of school students. Regarding the question of similarities of DRAB and ARAB, both models largely converge in terms of their associated correlates. Moreover, DRAB and ARAB are highly correlated (r = 0.843). Together these findings seem to warrant both phenomena to be summarized under the umbrella term IRAB. However, 29% of unexplained common variance indicates some distinct aspects, which should be addressed in subsequent research.

Most of the findings converge with existing evidence and provide insights into the digital media consumption patterns of adolescents, who

- are highly equipped with and own a plethora of DMD,
- use them to a large extent in their leisure time, in particular social media, games and video streaming,
- show bedtimes routines that are largely accompanied by DMD, which is highly evidenced to negatively affect sleep (Brautsch et al., 2022, de Sa et al., 2023, Hale and Guan, 2015, Lund et al., 2021, Lederer-Hutsteiner et al., 2024),
- show declining initial ages at which they commence to engage in internet use,
- exhibit remarkably high prevalences of IRAB, especially related to smartphones, social media (which is more prevalent among female students) and gaming (which is more prevalent among male students),
- show high rates of mental health problems and insomnia, which were shown to be related to IRAB generally, but to a higher degree to social media- than to gaming-related addictive behaviour,
- indicate boredom to be related to any kind of IRAB,
- show problem awareness, since their concerns related to their digital media use are linked to their symptom severity of any kind of IRAB,
- show self-efficacy as a potential protective factor to prevent IRAB,

- appear to be in line with their parents in terms of digital media use, since their parents' extent of digital media use was found to be related to their symptom severity of IRAB
- and whose digital media use appears to be restricted by parental regulative rules not as a preventive, but rather as an interventional measure

Consequently, the thesis' findings support decision-making in the context of policy planning and provides some substantial implications for the following actions both on a preventive and treatment level (partly taken from a governmental action plan that has been elaborated in Styria with central involvement of this thesis' author (Lederer-Hutsteiner and Koberg, 2024)):

- **Measures to strengthen parental awareness:** The thesis shows that addiction-related DMD and internet use patterns of adolescents are robustly linked to their parents' level of use and also indicates a rather low extent to which adolescent's digital screen time is subject to parental rules, which appear to come into effect only late as an intervention rather than as a preventive measure. The delineation of rules may represent a delicate equilibrium between the principles of autonomy and guidance. Nevertheless, parents are responsible for providing role models and structure with regard to their children's use of digital devices, since the adolescent brain's network for impulse control is not yet fully developed and therefore adolescents may show reduced resistance to the multiple temptations they may encounter on the internet (Hartley and Somerville, 2015). Moreover, it is also important for parents to be aware that the current trend of purchasing DMD for younger and younger children is potentially causing harm, since this thesis showed that early onset of engaging with the internet is linked to symptom severity of IRAB. In Germany, the miniKIM-study wave from 2023 among parents of 2 to 5 year old children indicated that the proportion of children in that age spectrum who own a smartphone increased from 4% in 2020 to 10% in 2023 (Medienpädagogischer Forschungsverbund, 2023b). This approach strongly contradicts recommendations of a consensus-based guideline registered by the "Arbeitsgemeinschaft der Wissenschaftlichen Medizinischen Fachgesellschaften (AWMF)" and carried out in 2022 by the German Society for Paediatrics and Adolescent Medicine (Deutsche Gesellschaft für Kinder- und Jugendmedizin e.V., 2022), according to which children under the age of nine, or even more appropriately, under the age of 12, should not have their own mobile phone. Moreover, the recommendations set forth in this guideline with regard to usage times of approximately two hours also diverge substantially from the observed five hours on average of this thesis project. The same applies to the strongly DMD-dominated bedtime rituals.

- **Measures to strengthen awareness among health and school professionals:** Since the thesis indicate high prevalences of IRAB that are also robustly related to mental health problems and insomnia, professionals in health care should be addressed in order to strengthen awareness that IRAB could be covertly involved in the complex etiological interplay of more recognised mental health problems such as depression, anxiety or insomnia. This measure is supported by a German study according to which a large proportion of people suffering from IRAB remain undetected in the psychotherapeutic care system (Scherer et al., 2021). Furthermore, teachers may play an important role in the context of early detection as they could recognise a potential IRAB among their students at early stages. In order to exploit this potential, teachers should have at least basic information about IRAB (especially diagnostic criteria and risk factors) and its various manifestations such as social networks and gaming and be aware of existing counselling and advice services.
- **Measures to foster non-digital reward mechanisms:** Boredom was shown as one of the strongest correlates of IRAB among the entire subset of all associated individual characteristics. Although it remains unclear which uncovered environmental aspects mediate this relation, it should be considered that the absence of offline leisure activities that are appealing to adolescents may be a contributing factor. In Styria this assumption may be indicated by the fact that a corresponding focus has recently been incorporated into the current youth strategy (Amt der Steiermärkischen Landesregierung, 2024). Furthermore, future studies should examine the nature of adolescents’ boredom and its interplay in the context of IRAB.
- **Measures to generally strengthen mental health among adolescents with a special focus on the role of social media:** Given the evidence presented in the thesis, which demonstrates not only high proportions of IRAB but also high proportions of other mental health impairments such as anxiety and insomnia, it is recommended to comprehensively address the topic of adolescent mental health. Increasing mental health problems, especially among female adolescents, have consistently been reported for some time now in previous research and have been summarized in a current review (Keyes and Platt, 2023). Although the cross-sectional findings of this thesis do not allow for the indication of causality and directionality, the role of social media has been spotlighted in the context of poor female mental health,

based on longitudinal and experimental evidence (Hunt et al., 2018, Engeln et al., 2020). In this thesis too, compared to other applications, among female students social media is by far the most common form to which addictive processes are related to and which is, compared to addictive gaming, generally associated with a more extensive variety of mental health impairments. As a consequence, life skills programs as an ongoing and well-established school-based measure on individual level may consider this. They might be augmented with supplementary training elements to enhance self-efficacy (which was indicated in this thesis to potentially act as a protective factor) and self-regulation in the context of DMD use generally as a universal preventive measure and with a special focus on female social media use as a selective preventive measure. In order to move beyond measures on individual level and to address higher-order meso-, exo- and macrosystemic aspects, which are evidenced to affect adolescent mental health according to Bronfenbrenner's ecological system theory (Bronfenbrenner, 2000) or Dahlgren and Whitehead's model of health determinants (Dahlgren and Whitehead, 1991), it is additionally recommended to constitute a trans-sectoral task force as a first step towards transforming the topic of IRAB into a public health issue.

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A. Appendix A: Approval for data use

GESUNDHEITSFONDS
STEIERMARK

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Bei Antwortschreiben bitte
Geschäftszeichen (GZ) anführen

GZ: GFSTMK 29.00-00/2020-6
Datennutzung im Rahmen einer Dissertation - Genehmigung

Graz, am 28.6.2021

Sehr geehrter Herr Mag. Lederer-Hutsteiner,

Hinsichtlich Ihrer Anfrage zur Datennutzung im Rahmen einer Dissertation darf unter Bezugnahme auf den zugrundeliegenden Vertrag über „ Studie und Strategieentwicklung zum Thema Internetsucht" vom 21.12.2020 auf die AVB (Allgemeine Vertragsbedingungen) des Gesundheitsfonds hingewiesen werden.

Gemäß Punkt VIII. „Nutzungsrechte" wird in Ziffer 3 hinsichtlich der Nutzung des vereinbarten Werkes die ausdrückliche Zustimmung des Auftraggebers verlangt, welche wir Ihnen hiermit für die beiden Befragungen unter SchülerInnen bzw. Erwachsenen erteilen.

Wir wünschen Ihnen viel Erfolg und verbleiben

mit freundlichen Grüßen

Mag. Michael Koren
Geschäftsführer

Dr. Bernd Leinich
Geschäftsführer

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B. Appendix B: Ethics approval

Medizinische Universität Graz
Ethikkommission

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Tel.: +43 / 316 / 385-13928, Fax: -14348

FOLGEVOTUM
gültig bis 08.10.2022

EK-Nummer:	33-600 ex 20/21 1391-2021
Studientitel:	Prevalence and correlates of internet-related addictive behaviour among Styrian pupils.
Prüfer:	Univ.-Prof. Dr. Wolfgang Freidl Institut für Sozialmedizin und Epidemiologie
Sponsor:	Medizinische Universität Graz, Institut für Sozialmedizin und Epidemiologie
Ansprechpartner:	Univ.-Prof. Dr. Wolfgang Freidl, 8010 Graz, Universitätsstraße 6/I
CRO:	-
Antragsteller:	Medizinischen Universität Graz, Institut für Sozialmedizin und Epidemiologie
Ansprechpartner:	Mag. Thomas Lederer-Hutsteiner

Die o.a. Studie wurde von der Ethikkommission erstmals im 'expedited Review' am 26.07.2021 behandelt. Die Ethikkommission ist zu folgendem Schluss gekommen:

Es besteht kein Einwand gegen die Durchführung der Studie in der vorliegenden Form.

Kommissionsmitglieder, die für diesen Tagesordnungspunkt als befangen anzusehen waren und daher gemäß Geschäftsordnung an der Entscheidungsfindung und Abstimmung nicht teilgenommen haben: keine

Zur Beurteilung vorliegende Dokumente:

Dokumente eingegangen am 16.07.2021, begutachtet im 'expedited Review' am 26.07.2021

✓	Cover Letter Anschreiben Ethikkommission Version 1	16.07.2021
✓	Antragsformular ECS	16.07.2021
✓	Originalprotokoll Beilage 1_EK-Antrag_Studienprotokoll Version 1	16.07.2021
	Sonstiges: Beilage 6_EK-Antrag_Fragebogen Version 1	16.07.2021
	Sonstiges: Beilage 5_EK-Antrag_Elternbrief Version 1	16.07.2021
✓	Sonstiges: Beilage 2_EK-Antrag_Genehmigung Datennutzung Gesundheitsfonds Steiermark Version 1	16.07.2021
✓	Sonstiges: Beilage 3_EK-Antrag_Antrag Gebührenbefreiung EK Version 1	16.07.2021
✓	Sonstiges: Beilage 4_EK-Antrag_Unterlagen für Schulen Version 1	16.07.2021

Dokumente eingegangen am 16.09.2021 (in der nächsten Begutachtung mitbegutachtet)

✓	Antragsformular ECS Unterschriftenseiten	04.08.2021

Dokumente eingegangen am 22.09.2021 (in der nächsten Begutachtung mitbegutachtet)

	Fragebögen mit Informationsschreiben für SchülerInnen 2, September 2021	
	Sonstiges: Informationsschreiben für Eltern 2, undatiert	

Dokumente eingegangen am 30.09.2021, begutachtet im 'expedited Review' am 08.10.2021

✓	Fragebögen mit Informationsschreiben für SchülerInnen 3, undatiert	
✓	Sonstiges: Informationsschreiben für Eltern 3, undatiert	
✓	Letter of Authorization Med. Uni Graz ohne Auflage	30.09.2021

EK-Nummer: **33-600 ex 20/21** Votum (31.03.2022) Seite 1 von 2

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- ✓ Originalprotokoll 2, März 2022
- ✓ Fragebögen mit Informationsschreiben für SchülerInnen 4, März 2022
- ✓ Sonstiges: Unterlagen zur Befragung 2, März 2022
- ✓ Sonstiges: Informationsschreiben für Eltern 4, März 2022

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Die Ethikkommission geht - rechtlich unverbindlich - davon aus, dass es sich um keine klinische Prüfung nach AMG bzw. MPG handelt.

Es handelt sich um eine Studie im Rahmen einer Dissertation.

Das Votum der Ethikkommission berührt in keiner Weise die alleinige Verantwortung der Prüferin / des Prüfers / der Prüfer für die ordnungsgemäße Durchführung der Studie unter Einhaltung aller einschlägiger gesetzlicher Bestimmungen und Richtlinien.

Weiters machen wir darauf aufmerksam, dass der Kommission unverzüglich zu melden sind:

- Abweichungen vom Protokoll aus Sicherheitsgründen oder Protokolländerungen

- Änderungen, die das Risiko der Teilnehmer/-innen erhöhen oder die Durchführung der Studie wesentlich beeinflussen

- Mutmaßliche unerwartete schwerwiegende Nebenwirkungen - SUSARs (AMG-Studien ab 1.5.2004) oder schwerwiegende unerwünschte Ereignisse - SAEs (andere Studien)

- Jegliche Information über sonstige Umstände, die die Sicherheit der Teilnehmer/-innen oder die Durchführung der Studie beeinträchtigen können

zusätzliche Auflagen: Die behördlich vorgeschriebenen Maßnahmen hinsichtlich der COVID-19 Pandemie müssen beachtet werden. Der Prüfer und der Sponsor müssen in ihrem jeweiligen Wirkungskreis unter allfälliger Beachtung von Leitlinien gewährleisten, dass keine zur Bekämpfung der Pandemie benötigten Ressourcen gebunden werden bzw. ausreichend Personal vorhanden ist und die TeilnehmerInnen durch ihre Studienteilnahme keiner zusätzlichen Infektionsgefahr ausgesetzt werden.

Graz, 31. März 2022

Univ.Prof.DI Dr.Josef Haas
Vorsitzender

Univ.Prof.Dr.Hans Peter Dimai
Stv. Vorsitzender

Achtung: Bitte bei allen das Projekt betreffende Schreiben oder telefonischen Anfragen die EK-Nummer angeben!

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Instructor Name	Prof. Wolfgang Freidl	Expected Presentation Date	2024-12-02

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Integrating psychological and neurobiological considerations regarding the development and maintenance of specific Internet-use disorders: An Interaction of Person-Affect-Cognition-Execution (I-PACE) model

Matthias Brand,Kimberly S. Young,Christian Laier,Klaus Wölfling,Marc N. Potenza

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