University of Bremen
Faculty 3: Mathematics and Computer Science
May 2023

Growing up in a digital environment:

The role of digital media use in European children's and adolescents' health and health behaviours

Elida Sina

Doctoral dissertation submitted to fulfill the requirements for the degree of
"Doctor of Natural Sciences (Dr. rer. nat.)"

Advisor: Prof. Dr. Wolfgang Ahrens
Faculty of Mathematics and Computer Science, University of Bremen
Leibniz Institute for Prevention Research and Epidemiology – BIPS

Co-advisor: Dr. Antje Hebestreit
Leibniz Institute for Prevention Research and Epidemiology – BIPS

Date of the defence:	17th of July 2023
Reviewer 1:	Prof. Dr. Wolfgang Ahrens (University of Bremen)
Reviewer 2:	Prof. Dr. Jess Haines (University of Guelph)

Hiermit erkläre ich, Elida Sina, geboren am 15.08.1993, dass für das Verfassen der vorliegenden Dissertation “ Growing up in a digital environment: The role of digital media use in European children’s and adolescents’ health and health behaviours ” folgende drei Aussagen zutreffen:

1. Ich habe die Arbeit ohne unerlaubte fremde Hilfe angefertigt.
2. Ich habe keinen anderen als die von mir angegebenen Quellen und Hilfsmittel benutzt.
3. Ich habe die den benutzten Werken wörtlich oder inhaltlich entnommenen Stellen als solche kenntlich gemacht.

Bremen, May 2023

Elida Sina

Acknowledgments

I would like to express my gratitude to those who supported me during the my doctoral studies and on the process of writing this thesis. First, I would like to thank my mentors: Prof. Dr. Wolfgang Ahrens and Dr. Antje Hebestreit. I am grateful for your ever-lasting support and the knowledge gained during the fruitful discussions over the last few years. Thank you for believing in me, for the constructive feedback on manuscripts, proposals, and presentation drafts, and for giving me the freedom to explore my research ideas, which I never take for granted.

I want to thank the Leibniz Institute for Prevention Research and Epidemiology-BIPS for the opportunity to conduct the research on which this thesis is based. Many thanks go to Dr. Christoph Buck for his support and for answering my questions on statistical methods. Thank you to Stefanie, Daniel, Maike, Lara, Rajini and Chen-Chia for the helpful discussions on manuscripts, presentations, and life. Thank you to Nele, Eva, Ina, and Moritz for the support and patience every time I needed to deal with visa and administrative issues. Special thanks go to all student assistants for their support, and especially Gows for translating the abstract of this thesis into German. Thank you to the IDEFICS/I.Family consortia, the data management team behind, and all the children, adolescents and parents participating in the IDEFICS/I.Family cohort, without whom this research wouldn't have come to life. I would like to thank the Leibniz Science Campus - Digital Public Health Bremen (LSC-DiPH) for supporting my work and ECRA for the great collaborations.

And, of course, thank you to my wonderful family. My parents, Naxhi and Nurie, who with their selfless attitudes, supported me in keeping my nose under the book for 20 years already. My sisters, Jeta and Vaku, thank you for always holding my hand and supporting me along the way. I owe this achievement to you. Also, thank you to my brother Judi for always having my back! My nieces and nephews (from Oriana to Seidi), who are also the true motivation behind my Ph.D topic and from whom I learned a lot. Stefanie, I am grateful we were on this journey together. Thank you for being that close friend I needed in Bremen and the beautiful memories we created together.

Last but not least, thank you to my goodhearted husband, Gezim, for supporting me, motivating me, making me laugh, wiping my tears, and cooking me dinner when I worked long hours. Thank you for taking care of me, helping me to overcome the struggles of the Ph.D. and long Covid. I wouldn't be able to finish this project without you being there. You are my safe place and joy.

Contents

Summary

Background

Children's and adolescents' health state suffers from the double burden of metabolic and mental health disorders, representing a critical public health matter. As never before, today's children are growing up in a saturated digital media (DM) environment. Despite the immense opportunities for learning and self-development, little is known about the role of DM exposure on children's health.

Aim

This doctoral dissertation aims to provide evidence on the potential association of DM exposure with health outcomes, including metabolic syndrome and cognitive functioning, as well as health behaviours, namely dietary intake, eating habits, and sensory taste preferences in children and adolescents.

Methods

The present cumulative thesis is constituted of four papers: one systematic literature review (SLR, *paper 1*) and three original investigations (*papers 2, 3,* and *4*). In *paper 1*, a total of 35 studies conducted worldwide were reviewed, critically appraised, and synthesized. These studies examined the association of social media (SM) exposure with the dietary intake, breakfast skipping, and nutrition literacy of healthy children and adolescents. The SLR was based on the Preferred Reporting Items for Systematic Reviews and Meta-analysis (PRISMA) guidelines. The empirical research conducted in *papers 2* to *4* used data provided by children aged 2-18 years of IDEFICS/I.Family cohort. The cohort was carried out in three waves across nine European countries. The first examination wave (i.e., baseline, W1) was conducted during 2007-2008, and 16,229 children participated. The second examination wave (i.e., first follow-up, W2) was conducted during 2009-2010 and included 13,596 children. The third examination wave (i.e., second follow-up, W3) was conducted during 2013-2014 and included 9,617 children and adolescents. The overarching aim of the cohort was to identify dietary- and lifestyle-induced health effects in children and adolescents, considering sensitive developmental periods, and to develop a community-based intervention on childhood obesity. Across *paper 2* to *paper 4*, the analysis group varied from 3,261 to 10,359 participants after respective inclusion/exclusion criteria were met.

DM exposure (hours/day) was self-reported, including: i) television viewing (TV), ii) computer/game console (PC), iii) smartphone, and iv) internet exposure. The related behaviour of media multitasking, defined as the simultaneous use of several media, was also reported. In *paper 2*, sensory taste preferences for sweet, fatty, salty, and bitter taste were evaluated via a Food and Beverage Preference Questionnaire. In *paper 3*, measures of cognitive functioning, namely cognitive inflexibility and decision-making ability were assessed via computerized tests, while emotion-driven impulsiveness was self-reported. In *paper 4*, metabolic syndrome (MetS) and its components: abdominal obesity (via waist circumference), blood pressure (systolic and diastolic), insulin resistance (homeostasis model assessment for insulin resistance (HOMA-IR) or fasting glucose), and dyslipidaemia (HDL-cholesterol and triglycerides), were objectively measured. Age and sex-specific z-scores and monitoring levels ($\geq 90^{th}$ percentile, as defined by Ahrens et al. 2014) were considered for each metabolic outcome.

The statistical approach used to investigate the associations of interest varied depending on the research questions. Logistic regression models were used to examine associations between exposures and dichotomized outcomes (*papers 2* and *3*). Latent class analyses were performed to identify underlying patterns of DM exposure (*paper 3*), based on a combination of using the individual media (in categories). In *paper 4*, to examine the longitudinal association of DM exposure with MetS and its components, a two-step trajectory approach was used: first, the age-dependent trajectories of DM exposure were calculated using linear mixed models; second, to estimate the association between childhood DM trajectory and MetS at follow-up, generalized linear mixed models were used. Across papers, analyses were stratified by sex, age, country of residence, parental educational status, and family structure, to characterize children and adolescents that are most vulnerable to the potential negative impact of DM exposure.

Results

The SLR revealed a dose-dependent relationship between SM exposure and daily intake of sugar and caffeine and the consumption frequency of sugar-sweetened beverages in both children and adolescents. SM exposure was also associated with low frequency intake of fruits and vegetables and less frequent breakfast consumption. No association between SM exposure and nutrition literacy was observed. SM exposure, measured either as WhatsApp use, watching YouTube videos, or exposure to SM influencer’s advertising on Instagram, led to an increased intake of unhealthy food and beverages at ad-libitum and after two years. A neuro-physiological mechanism was identified: exposure to digital food images increased the neural activation of brain areas related to reward and attention. Peers' presence on SM but not of SM influencers, showed a potential to improve adolescents' vegetable intake.

In IDEFICS/I.Family children exposure to DM increased over age, from 2.4 h/day at the age of two years to 5.5 h/day at the age of 16 years. This increase was steeper among boys compared to girls. Country differences were also observed, where Estonian, Cypriot, and Swedish children had the highest DM increase, while Spanish children showed the lowest DM increase. The observational research conducted in *paper 2* showed that prolonged DM exposure (>2 h/day) was associated with a high preference score for sweet, fatty, and salty-tasting foods among adolescents, especially females. An inverse association between prolonged DM exposure and bitter taste preference was observed among males. In *paper 3*, it was observed that one additional hour of exposure to smartphones and the internet, and higher media multitasking was positively associated with children's emotion-driven impulsiveness and cognitive inflexibility and negatively associated with decision-making ability. Compared to participants with low exposure to all media, participants with "high smartphone and internet, in combination with medium TV and low PC exposure", showed higher scores for emotion-driven impulsiveness and cognitive inflexibility and a lower score for decision-making ability. In paper 4, it was found that increasing DM exposure during childhood was positively associated with the z-scores of MetS, waist-circumference, HOMA-IR, HDL-c^{-1}, and triglycerides after two or six years. The stratified analyses revealed that associations were independent of moderate to vigorous physical activity. Children with an above-average DM increase over age (DM slope> 0 h/day/year) showed a 22% higher risk for later incident MetS. This risk was higher among boys compared to girls (41% and 10%, respectively).

Conclusion

The findings of this thesis suggest that DM exposure is associated with unfavorable dietary intake and poor eating behaviors. A neuro-physiological mechanism and a clear impact of peers and SM influencers on the SM environment explain these findings. The results also showed that DM exposure is positively associated with a preference for sweet, fatty, and salty-tasting foods and negatively associated with a preference for bitter-tasting foods. This suggests that DM exposure may lead to obesity by favoring the taste preference of unhealthy foods over healthy ones.

Moreover, exposure to modern DM was positively associated with children's emotion-driven impulsiveness and cognitive inflexibility and inversely associated with decision-making ability. This sheds light on a new potential mechanism by which DM exposure leads to poor mental health in children and adolescents. Finally, the findings support the hypothesis that increasing DM exposure during childhood may be an independent risk factor for metabolic syndrome later in life, with boys being at higher risk. These long-term associations need to be confirmed in other populations of children and adolescents, considering not only duration but also patterns of DM exposure, as well as children with an unfavorable background regarding socio-economic status, learning difficulties, or predisposing mental disorders. Further interdisciplinary, longitudinal studies may consider the interplay between health determinants in the physical and digital environment to identify potential intervening factors to promote children's health in a hybrid world. Future health interventions may consider a precautionary approach and use the identified mechanisms to increase children's and adolescents' resilience against the potential adverse health effects of the digital environment at an early stage of their development.

Zusammenfassung

Hintergrund

Der Gesundheitszustand von Kindern und Jugendlichen leidet unter der Doppelbelastung von Stoffwechsel- und psychischen Erkrankungen, welches ein kritisches Problem für Public Health darstellt. Wie nie zuvor wachsen die Kinder heutzutage in einer gesättigten Umgebung von digitalen Medien (DM) auf. Trotz der enormen Möglichkeiten zum Lernen und zur Selbstentwicklung ist nur wenig über die Rolle der DM-Exposition auf die Gesundheit von Kindern bekannt.

Ziel

Ziel dieser Dissertation ist es, den potentiellen Zusammenhang zwischen der DM-Exposition und den gesundheitlichen Outcomes, einschließlich des metabolischen Syndroms und der kognitiven Funktionen, sowie dem Gesundheitsverhalten, d.h. die Nahrungsaufnahme, Ernährungsgewohnheiten und Geschmackspräferenzen bei Kindern und Jugendlichen, zu untersuchen.

Methoden

Die vorliegende kumulative Thesis besteht aus vier Artikeln: eine systematische Übersichtsarbeit (SLR, Artikel 1) und drei eigenen Studien (*Artikel 2, 3 und 4*). In *Artikel 1* wurden insgesamt 35 weltweit durchgeführte Studien überprüft, kritisch bewertet und zusammenfassend dargestellt. Diese Studien untersuchten den Zusammenhang zwischen der Exposition von sozialen Medien (SM) und der Nahrungsaufnahme, dem Auslassen des Frühstücks und der Ernährungskompetenz von gesunden Kindern und Jugendlichen. Die SLR basierte auf den „Preferred Reporting Items for Systematic Reviews and Meta-analysis“ (PRISMA) Richtlinien. Für die empirischen Untersuchungen in den *Artikeln 2* bis *4* wurden Daten von Kindern im Alter von 2-18 Jahren aus der IDEFICS/I.Family-Kohorte verwendet. Die Kohorte wurde in drei Wellen in neun europäischen Ländern durchgeführt. Die erste Untersuchungswelle (d.h. Baseline, W1) wurde im Zeitraum 2007-2008 durchgeführt und es nahmen 16.229 Kinder daran teil. Die zweite Untersuchungswelle (d.h. erstes Follow-Up, W2) wurde im Zeitraum 2009-2010 durchgeführt und umfasste 13.596 Kinder. Die dritte Untersuchungswelle (d.h. zweites Follow-Up, W3) wurde im

Zeitraum 2013-2014 durchgeführt und umfasste 9.617 Kinder und Jugendliche. Das übergreifende Ziel der Kohorte bestand darin, ernährungs- und lebensstilbedingte gesundheitliche Auswirkungen in Kindern und Jugendlichen unter Berücksichtigung sensibler Entwicklungsphasen zu untersuchen und eine gemeindebasierte Intervention gegen Adipositas bei Kindern zu entwickeln. Zwischen *Artikel 2* und *Artikel 4* variierte die Analysegruppe zwischen 3.261 und 10.359 Teilnehmern, je nach Erfüllung der jeweiligen Ein-/Ausschlusskriterien.

Die DM-Exposition (Stunden/Tag) war selbstberichtet, einschließlich: i) Fernsehen (TV), ii) Computer/Spielekonsole (PC), iii) Smartphone und iv) Internet-Exposition. Das damit in Zusammenhang stehende Verhalten des Medien-Multitasking, d.h. der gleichzeitigen Nutzung mehrerer Medien, wurde ebenfalls berichtet. In Artikel 2 wurden die sensorischen Geschmackspräferenzen für süßen, fettigen, salzigen und bitteren Geschmack anhand eines Fragebogens zur Lebensmittel- und Getränkepräferenz bewertet. In Artikel 3 wurden die kognitiven Fähigkeiten, d. h. die kognitive Inflexibilität und Entscheidungsfähigkeit, mit Hilfe von computergestützten Tests gemessen, während die emotionsgesteuerte Impulsivität selbstberichtet wurde. In Artikel 4 wurde das Metabolische Syndrom (MetS) und seine Komponenten: abdominale Adipositas (über den Taillenumfang), Blutdruck (systolisch und diastolisch), Insulinresistenz (Homeostasis Model Assessment for Insulin Resistance (HOMA-IR) oder Nüchternglukose) und Dyslipidämie (HDL-Cholesterin und Triglyceride), objektiv gemessen. Alters- und geschlechtsspezifische z-Scores und Überwachungswerte (≥90. Perzentil, wie von Ahrens et al. 2014 definiert) wurden für jedes metabolische Outcome berücksichtigt.
Der statistische Ansatz, der zur Untersuchung der interessierenden Assoziationen verwendet wurde, variierte in Abhängigkeit von den Forschungsfragen. Logistische Regressionsmodelle wurden verwendet, um Zusammenhänge zwischen Expositionen und dichotomisierten Outcomes zu untersuchen (*Artikel 2* und *3*). Es wurden latente Klassenanalysen durchgeführt, um zugrundeliegende Muster der DM-Exposition zu identifizieren (*Artikel 3*), die auf einer Kombination der Nutzung der einzelnen Medien (in Kategorien) basieren. In der *Artikel 4* wurde zur Untersuchung des longitudinalen Zusammenhangs zwischen DM-Exposition und MetS und seinen Komponenten ein zweistufiger Trajektorien-Ansatz verwendet: Zunächst wurden die altersabhängigen Trajektorien der DM-Exposition mit Hilfe linearer gemischter Modelle berechnet; anschließend wurden zur Schätzung des Zusammenhangs zwischen dem DM-Verlauf in der Kindheit und MetS bei der Nachuntersuchung verallgemeinerte lineare gemischte Modelle

verwendet. Die Analysen wurden nach Geschlecht, Alter, Wohnsitzland, Bildungsstand der Eltern und Familienstruktur stratifiziert, um die Kinder und Jugendlichen zu charakterisieren, die für die potenziellen negativen Auswirkungen der DM-Exposition am anfälligsten sind.

Ergebnisse

Die SLR zeigte eine dosisabhängige Beziehung zwischen der SM-Exposition und der täglichen Aufnahme von Zucker und Koffein sowie der Häufigkeit des Konsums von zuckergesüßten Getränken bei Kindern und Jugendlichen. Die SM-Belastung wurde auch mit einem niedrigen Verzehr von Obst und Gemüse und einem weniger häufigen Frühstücksverzehr assoziiert. Es wurde keine Assoziation zwischen der SM-Exposition und Ernährungskompetenz festgestellt. Die SM-Exposition, die entweder als WhatsApp-Nutzung, Anschauen von YouTube-Videos oder als Exposition gegenüber Werbung von SM-Influencern auf Instagram gemessen wurde, führte zu einem erhöhten Konsum von ungesunden Lebensmitteln und Getränken ad-libitum und nach zwei Jahren. Ein neuro-physiologischer Mechanismus wurde identifiziert: Die Exposition gegenüber digitalen Bildern von Lebensmitteln erhöhte die neuronale Aktivierung von Hirnregionen, die mit Belohnung und Aufmerksamkeit in Verbindung stehen. Die Präsenz von Gleichaltrigen auf SM, aber nicht die Präsenz von SM-InfluencerInnen, zeigte ein Potential den Gemüseverzehr von Jugendlichen zu verbessern. Die Präsenz von Gleichaltrigen auf SM, aber nicht die Präsenz von SM-InfluencerInnen, zeigte ein Potenzial zur Verbesserung des Gemüsekonsums von Jugendlichen.

Bei IDEFICS/I.Family-Kindern nahm die Exposition gegenüber DM mit dem Alter zu, von 2,4 Stunden/Tag im Alter von zwei Jahren auf 5,5 Stunden/Tag im Alter von 16 Jahren. Dieser Anstieg war bei den Jungen stärker als bei den Mädchen. Länderunterschiede wurden auch beobachtet, wobei Kinder aus Estland, Zypern und Schweden den höchsten DM-Anstieg verzeichneten, während Kinder aus Spanien den geringsten Anstieg aufwiesen. Die in *Artikel 2* durchgeführte Beobachtungsstudie zeigte, dass eine längere DM-Exposition (>2 Stunden/Tag) mit einem höheren Präferenzscore für süße, fettige und salzige Lebensmittel bei Jugendlichen, insbesondere bei Mädchen, verbunden war. Ein umgekehrter Zusammenhang zwischen längerer DM-Exposition und bitterer Geschmackspräferenz wurde bei den Jungen beobachtet. In *Artikel 3* wurde festgestellt, dass eine zusätzliche Stunde Smartphone- und Internetexposition sowie ein höheres Medien-Multitasking positiv mit der emotionsgesteuerten Impulsivität und kognitiven Inflexibilität der

Kinder und negativ mit der Entscheidungsfähigkeit verbunden war. Im Vergleich zu TeilnehmerInnen mit geringer Exposition gegenüber alle Medien zeigten TeilnehmerInnen mit „hohem Smartphone- und Internetkonsum in Kombination mit mittlerem TV- und geringem PC-Konsum" höhere Scores für emotionsgesteuerte Impulsivität und kognitive Inflexibilität und einen niedrigeren Score für die Entscheidungsfähigkeit. In *Artikel 4* wurde festgestellt, dass eine zunehmende DM-Exposition in der Kindheit positiv mit den z-Scores von MetS, Taillenumfang, HOMA-IR, HDL-c-1 und Triglyceriden nach zwei oder sechs Jahren verbunden war. Stratifizierte Analysen zeigten, dass die Assoziationen unabhängig von moderater bis intensiver körperlicher Aktivität waren. Kinder mit einer überdurchschnittlichen Zunahme der DM im Laufe des Lebens (DM-Steigung > 0 h/Tag/Jahr) wiesen ein 22 % höheres Risiko für ein späteres MetS auf. Dieses Risiko war bei Jungen höher als bei Mädchen (41 % bzw. 10 %).

Fazit

Die Ergebnisse dieser Thesis deuten darauf hin, dass die DM-Exposition mit einer ungünstigen Nahrungsaufnahme und einem schlechten Essverhalten verbunden ist. Ein neuro-physiologischer Mechanismus und ein deutlicher Einfluss von Gleichaltrigen und SM-InfluencerInnen auf das SM-Umfeld erklären diese Ergebnisse. Die Ergebnisse zeigten auch, dass die DM-Exposition positiv mit einer Präferenz für süß, fett und salzig schmeckende Lebensmittel und negativ mit einer Präferenz für bitter schmeckende Lebensmittel assoziiert. Dies deutet darauf hin, dass die DM-Exposition zu Fettleibigkeit führen kann, indem ungesunde Lebensmittel gegenüber gesunden bevorzugt werden. Darüber hinaus wurde die Exposition gegenüber modernen DM positiv mit der emotionsgesteuerten Impulsivität und kognitiven Inflexibilität der Kinder in Verbindung gebracht und umgekehrt mit der Entscheidungsfähigkeit. Dies wirft ein Licht auf einen neuen möglichen Mechanismus, durch den die DM-Exposition zu einer schlechten psychischen Gesundheit bei Kindern und Jugendlichen führt. Schließlich unterstützen die Ergebnisse die Hypothese, dass eine erhöhte DM-Exposition in der Kindheit ein unabhängiger Risikofaktor für das metabolische Syndrom im späteren Leben sein kann, wobei Jungen einem höheren Risiko ausgesetzt sind. Diese langfristigen Zusammenhänge müssen in anderen Populationen von Kindern und Jugendlichen bestätigt werden, wobei nicht nur die Dauer, sondern auch die Muster der DM-Exposition sowie Kinder mit einem ungünstigen Hintergrund in Bezug auf sozioökonomischen Status, Lernschwierigkeiten oder prädisponierende psychische Störungen zu berücksichtigen sind. Weitere interdisziplinäre Längsschnittstudien können das Zusammenspiel zwischen

Gesundheitsdeterminanten in der physischen und digitalen Umgebung berücksichtigen, um potenzielle Interventionsfaktoren zur Förderung der Gesundheit von Kindern in einer hybriden Welt zu identifizieren. Künftige Gesundheitsmaßnahmen könnten einen vorsorgenden Ansatz verfolgen und die ermittelten Mechanismen nutzen, um die Widerstandsfähigkeit von Kindern und Jugendlichen gegenüber den potenziellen negativen gesundheitlichen Auswirkungen des digitalen Umfelds in einem frühen Stadium ihrer Entwicklung zu stärken.

Abbreviations

ADHD	attention deficit hyperactivity disorder
BMI	body mass index
dmPFC	dorsomedial prefrontal cortex
dlPFC	dorsolateral prefrontal cortex
ED foods	energy dense foods
EI	energy intake
ED	energy density
DM	digital media
fMRI	functional magnetic resonance imaging
FBPQ	food and beverage preference questionnaire
FFQ	food frequency questionnaire
FOMO	fear of missing out
IDEFICS	Identification and Prevention of Dietary- and lifestyle-induced health EFfects In Children and infantS
HDAS	healthy diet adherence score
HDL-c	High density lipoprotein cholesterol
HOMA-IR	homeostasis model assessment for insulin resistance
HFSS foods	foods high in fat, sugar, and salt content
mPFC	medial prefrontal cortex
MVPA	moderate to vigorous physical activity
NCDs	non-communicable diseases
IFG	inferior frontal gyrus
ISCED	International Standard Classification of Education
MetS	metabolic syndrome
OFC	orbitofrontal cortex
PA	physical activity
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-analyses
PS	portion size
PC	computer use
PPHG	parahippocampal gyri
RCT	randomized controlled trials
SSB	sugar-sweetened beverages
SDGs	sustainable development goals
SES	socio-economic status
SM	social media
SLR	systematic literature review
vmPFC	ventromedial prefrontal cortex
UPPS-P	urgency, premeditation, perseverance, sensation seeking, and positive urgency
UN	United Nations
USA	United States of America
WHO	World Health Organization

A reference guide to the brain regions described in this thesis and their respective functions

Brain region	Specialization
Regions related with attention and memory	
Amygdala	Attention; Memory; Processing food stimuli; Reward learning
Fusiform gyrus	Attention; Processing food stimuli;
Hippocampus	Memory functions; Control of food intake; Processing food stimuli; Food craving
Left and right posterior PPHG	Declarative memory functions
Visual cortex	Processing emotional and visual cues; Processing food (marketing) stimuli
Regions related with reward and gustation	
Caudate	Reward
Nucleus accumbens	Reward processing; Behaviour reinforcement; Motivated behaviour
Orbitofrontal cortex	Evaluating food-related reward; Processing food stimuli Taste and smell processing; Sensory specific satiety Goal-directed behaviour
Insula	Gustation
Operculum	Reward
Ventrial stratium	Motivation; Reward; Cravings
Regions related with cognitive functioning	
Anterior cingulate	Cognitive flexibility; Reward based decisions Conflict monitoring and resolution
Dorsomedial prefrontal cortex	Decision-making; Information processing;
Dorsolateral prefrontal cortex	Language production
Inferior frontal gyrus	Inhibitory control; Cognitive control of emotion Attentional control; Processing food stimuli
Prefrontal cortex	Cognitive/Inhibition control; Goal-directed behaviour Processing food stimuli

Outline

This cumulative dissertation consists of three published papers in peer-reviewed international journals (two original investigations and one systematic review) and one submitted original manuscript. The thesis is elaborated in six chapters. Chapter 1 provides the scientific background and the rationale for examining the impact of the digital environment on children's and adolescents' health and related behaviors. *Chapter 2* presents the overarching aim and the main objectives of the thesis. Moreover, the underlying conceptual framework is described. *Chapter 3* describes the study population and the measurement methods for the exposures, outcomes, and confounders of interest. In addition, the statistical approach used for each paper is described. *Chapter 4* presents the main results yielded by this thesis. In *Chapter 5*, findings are discussed in light of excisting literature, while the strengths and limitations of the overall research are elaborated. In *Chapter 6*, the main conclusions and public health implications of the findings are described. Finally, an outlook and a number of recommendations for future research are also provided.

Note: For the research conducted within this thesis, I received guidance, advice, support and suggestions by all my co-authors. Hence, the pronoun "we" instead of "I" will be used where appropriate in the following chapters**.**

List of funding sources supporting the research in this thesis

1. The research conducted in *paper 1* was supported by the Leibniz ScienceCampus Bremen Digital Public Health (lsc-diph.de), jointly funded by the Leibniz Association (W4/2018), the Federal State of Bremen and the Leibniz Institute for Prevention Research and Epidemiology – BIPS.
2. The research conducted in *paper 2, paper 3,* and *paper 4* was funded by the European Community within the Sixth RTD Framework Programme Contract No. 016181 (FOOD) and Seventh RTD Framework Programme Contract No. 266044.
3. For *paper 2*, open access funding was enabled by the Open Access Fund of the Leibniz Association.
4. For *paper 3 and 4*, open access funding was enabled and organized by Projekt DEAL.

Publications constituting this thesis

1. **Elida Sina**, Daniel Boakye, Lara Christianson, Wolfgang Ahrens, Antje Hebestreit, Social Media and Children's and Adolescents' Diets: A Systematic Review of the Underlying Social and Physiological Mechanisms, *Advances in Nutrition*, Volume 13, Issue 3, May 2022, Pages 913–937, https://doi.org/10.1093/advances/nmac018
2. **Sina, Elida**; Buck, Christoph; Ahrens, Wolfgang; De Henauw, Stefaan; Jilani, Hannah; Lissner, Lauren; Molnár, Dénes; Moreno, Luis A.; Pala, Valeria; Reisch, Lucia; Siani, Alfonso; Solea, Antonia; Veidebaum, Toomas; Hebestreit, Antje; on behalf of the I.Family Consortium. 2021. "Digital Media Use in Association with Sensory Taste Preferences in European Children and Adolescents—Results from the I.Family Study" *Foods* 10, no. 2: 377. https://doi.org/10.3390/foods10020377
3. **Sina, Elida**, Buck, Christoph, Ahrens, Wolfgang, Coumans, Juul, Eiben, Gabriele, Formisano, Annarita, Krogh, Vittorio, Lissner, Lauren, Mazur, Artur, Michels, Nathalie, Molnar, Dénes, Moreno, Luis, Pohlabeln, Hermann, Reisch, Lucia, Tornaritis, Michael, Veidebaum, Toomas, Hebestreit, Antje, & on behalf of the I.Family consortium. Digital media exposure and cognitive functioning in European children and adolescents of the I.Family study. Sci Rep 13, 18855 (2023). https://doi.org/10.1038/s41598-023-45944-0
4. **Sina, Elida**, Buck, Christoph, Veidebaum, Thomas, Siani, Alfonso, Reisch, Lucia, Pohlabeln, Hermann, Pala, Valeria, Moreno, Luis A., Molnar, Dénes, Lissner, Lauren, Kourides, Yannis, De Henauw, Stefaan, Eiben, Gabriele, Ahrens, Wolfgang, Hebestreit, Antje, & IDEFICS, I.Family consortia (2021). Media use trajectories and risk of metabolic syndrome in European children and adolescents: the IDEFICS/I.Family cohort. *The international journal of behavioral nutrition and physical activity*, *18*(1), 134. https://doi.org/10.1186/s12966-021-01186-9

Presentations at scientific conferences

1. **Sina, Elida**, Buck Christoph, Ahrens Wolfgang, Coumans M.J. Juul, Eiben Gabriele, Formisano Annarita, Lissner Lauren, Mazur Artur, Michels Nathalie, Molnar Dénes, Moreno Luis, Pala Valeria, Pohlabeln Hermann, Reisch Lucia, Tornaritis Michael, Veidebaum Toomas & Hebestreit Antje. Exposure to the digital environment and cognitive functioning in children and adolescents – findings from the I.Family study. *Abstract book for the ISBNPA 2023 Annual Meeting*. International Society of Behavioral Nutrition and Physical Activity.
2. **Sina, Elida**, Boakye Daniel, Christianson Lara, Ahrens Wolfgang., Hebestreit Antje, Social media and children's diet - a systematic review of the underlying mechanisms, *Abstract book for the ISBNPA 2022 Annual Meeting*. International Society of Behavioral Nutrition and Physical Activity.
3. **Sina, Elida**, Buck, Christoph, Eiben, Gabriele, De Henauw, Stefaan, Lissner, Lauren, Molnar, Dénes, Moreno, A. Luis, Reisch, Lucia, Siani, Alfonso, Kourides, Yannis, Veidebaum, Toomas, Ahrens, Wolfgang, & Hebestreit, Antje (2020). Media Use and Metabolic Syndrome and its Components in European Children and Adolescents: Results from the I.Family Study. In W. V. Lippevelde, & E. Hinckson (Eds.), *Abstract book for the ISBNPA 2020 Annual Meeting* (pp. 206-207). International Society of Behavioral Nutrition and Physical Activity.

1. Introduction

In 2015, the United Nations promulgated 17 Sustainable Development Goals (SDGs), with 169 targets to be achieved by 2030 [1] . The main aims were twofold: first, to protect the planet from hazardous factors and processes, and second, to ensure safe, fair, and healthy lives for the generations to come. Notably, at the centre of these goals are children and adolescents. They are the future of human existence, hence protecting and ensuring them a healthy and prosperous life should be the vision of the current and future policymaking. Nevertheless, improvements in the indicators of children's health and well-being are currently at halt across the SDGs [2].

Today, the state of children's and adolescents' health suffers from the double burden of cardio-metabolic and mental health disorders, and two main factors currently undermine it:

1) Cardio-metabolic risk factors, including obesity, insulin resistance, dyslipidaemia, and hypertension,
2) Environmental and lifestyle-related risk factors, including sedentary behaviours, predatory commercial activities and obesogenic environments.

The increasing levels of childhood obesity are considered a growing pandemic and one of the most critical public health crises of the 21st century [3]. Obesity represents the health consequence of the energy imbalance between calorie expenditure and intake, resulting from greater consumption of energy-dense foods and increased sedentary lifestyle. The number of overweight and obese children rose from 11 million in 1975 to 124 million in 2016, a more than 10-fold increase [2,4]. Obese children have a higher risk for obesity, disability, and premature death in adulthood, as well as for type 2 diabetes, hypertension, and cardio-vascular diseases [5], especially boys and young males [6]. The prevalence of cardio-metabolic risk factors, namely hyperglycemia/insulin resistance, hypertension, abdominal obesity and dyslipidaemia, the clustering of which is known as metabolic syndrome (MetS) [7], has also increased during the last decades among children and adolescents. Childhood MetS prevalence has increased in both wealthy and developing countries. A recent meta-analysis of 169 studies, including more than 550.000 children and adolescents from 44 countries and across 13 worldwide regions, showed that MetS is not only a first-world health issue and that the country's development stage does not necessarily drive the prevalence of MetS [8]. The prevalence of MetS varied from 2.8% in children to 4.8% in adolescents, equating to 25.8 million children and 35.5 million adolescents living with MetS around the globe.

In fact, the pathogenesis of MetS is complex; to date, many processes are still poorly understood. At the heart of the pathophysiological causes of MetS lies abdominal obesity and/or insulin resistance [9]. The risk for MetS increases with the accumulation of visceral fat, as a result of energy and nutrient imbalance from the consumption of energy-dense foods high in sugar and fat and high levels of sedentary time. Insulin, the glucose-suppressing hormone released by the pancreatic ß-cells, also plays a role in the origins of MetS. In an insulin-resistant state, although insulin travels from the pancreas to the liver through the pancreatic and portal veins, the suppression of production of hepatic glucose is impaired, leading to abnormal glucose regulation [9]. Moreover, although in an insulin-resistant state, insulin may still stimulate hepatic lipogenesis, leading to the release of free fatty acids and triglycerides into the blood circulation. This leads to dyslipidaemia, characterized by low levels of high-density lipoprotein cholesterol (HDL-c), combined with increased levels of triglycerides and low-density lipoproteins, which increase the risk for atherosclerosis and other cardiovascular diseases [10]. Several factors have been suggested as determinants of MetS in children and adolescents. Besides genetic factors and inherited family influences, several environmental and lifestyle-related factors can also predict the clustering of metabolic risk factors.

At the heart of the cardio-metabolic health emergence in children and adolescents lies the current obesogenic environment, which drives the intake of foods low in fibre and protein, but high in fat, sugar, and salt content (HFSS foods). Among children and adolescents aged 2-18 years, circa 40% of the daily energy intake (800 kcal) comes from empty calories in solid fats and added sugars [11]. Only the consumption of sugar-sweetened beverages (SSBs) makes up 7% of daily calories consumed by children and 10% of calories consumed by adolescents. Dietary patterns characterised by high intake of sodium, saturated fat, red meat, and fast food [12,13], and increased intake of SSBs (>1.3 cups/day) [14], have been positively associated with unfavourable markers of cardiometabolic health in children and adolescents. Other lifestyle-related behaviours like sleep and sedentary behaviors are also associated with metabolic risk. Both short (<7.5-8 hours/day) and long (>8.5-9 hours/day) sleep duration were associated with increased metabolic risk in adolescents [15,16]. Sedentary behaviors and lack of physical activity (PA) are two other crucial elements of the obesogenic environment and contributors of the current health crisis in children and adolescents [17]. Moreover, the prolific use of digital technologies contributes to excessive sedentary time in youth. A dose-response relationship between increasing screen-time duration and decreasing physical activity levels with cardio-metabolic risk has been reported in children and adolescents [18].

Closely associated with cardio-metabolic health are the brain and mental health [19]. Childhood and adolescence are critical stages for the development of cognitive, psycho-emotional, and social skills, including critical thinking and control of emotions, which shape mental health at later stages of life. According to World Health Organization (WHO), 1 in 10 children and adolescents suffer from a mental disorder, with 50% of these disorders starting at the age of 14 years [20]. Anxiety and depression, characterised by rapid mood changes and prolonged worry, are the most common mental health problems among children aged 10-18 years [20]. Several factors affect children's mental health, including peer pressure and relationships, family environment, gender norms, and digital media use. The latter can exacerbate the disparities between children's and adolescents' lived reality, facilitating upward appearance-based comparisons and affecting perceptions of body image, social withdrawal, and loneliness [20]. The role of digital media may go beyond the aforementioned aspects of mental health by also influencing children's cognitive development [21]. Non-educational television viewing (TV), for instance, is associated with reduced executive functioning in pre-schoolers [22] and poor academic performance in children aged 4-18 years [23].

1.1. Growing up in a digital world – the current digital media landscape in children and adolescents

As never before, today's children and adolescents are growing up in a digital media (DM) saturated environment. The DM landscape has changed during the last two decades, where the use of internet-connected digital devices has replaced TV viewing. This change has led to an emerging concept: the digital environment, which encompasses the increasing number and types of digital technologies used, and the related content children are exposed to daily. These include mainly handled devices like smartphones, computers, and tablets, but also (virtual) game worlds, internet-based platforms, and social media (***Figure 1***). The digital environment comprises two main underlying definitions. First, the traditional "screen-time" definition, which refers to the time spent with screen devices, like television, computers, or smartphones. Second, the "digital media" definition, which goes beyond the duration of using screens and considers also the content transmitted by the internet-connected devices. A growing literature suggests that besides duration, the content children are exposed to should also be considered an important determinant for health [24]. Hence, the digital media definition will be used throughout this thesis, referring to the type, content and duration of using digital devices.

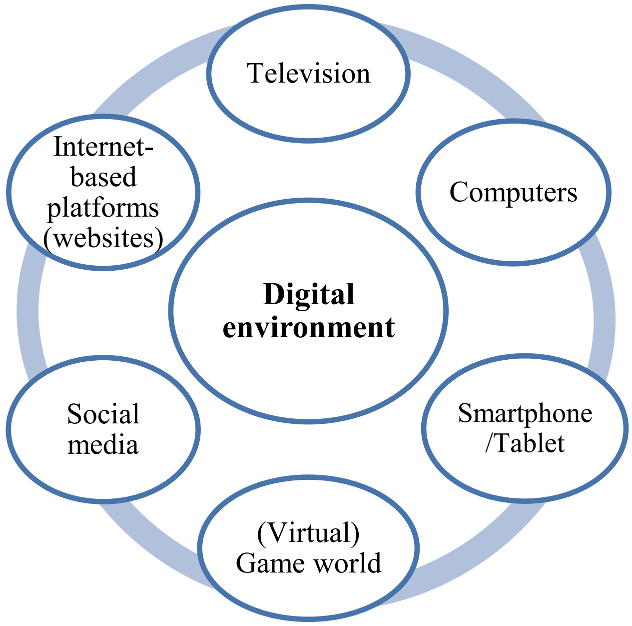

Figure 1. An overview of the digital media that today's children and adolescents are exposed to[1].

[1] Although internet-based platforms and social media are overlapping entities, they are considered separately in this thesis, given the complex nature of social media platforms, in terms of design and purpose of use.

Children and adolescents, who are often named "digital natives", use DM for various purposes, including education, communication with peers and family, watching online videos, and sharing or receiving content via social media platforms. Social media (SM) represents an essential part of the digital environment in which today's youth live. SM encompasses the social networking sites like Facebook, Instagram, Snapchat, and TikTok, messaging applications like WhatsApp, web blogs, and content communities like YouTube [25]. Facebook is the most used social network (2.7 billion monthly active users), and 6.3 % of its users are adolescents (13-17 years old) [26]. Remarkably, today's children face an entirely new cognitive challenge never met by humans: To divide and maintain their attention between multiple media devices, leading to the contemporary media multi-tasking behavior. The latter refers to using multiple media devices simultaneously (e.g., computer used during TV) or using DM while engaging in non-media activities.

Thanks to the use of handled devices, SM, and related media multitasking, the digital environment now allows children of all ages to access information, entertainment, and social contact ubiquitously [27]. Hence, durations of DM use have increased across age groups. The latest data from the US show that children younger than two years use digital screens for almost one hour/daily. This duration increases to 2.5 h/day among 2- to 4-year-olds and more than three h/day in 5- to 8-year-olds [28]. For entertainment only, children aged 6-12 years spend, on average, five hours with

DM daily, while adolescents aged 12-18 years spend eight hours with digital screens every day [29]. These durations are higher than any other waking activity and exceed the international recommendations for DM use in these population groups. The American Academy of Pediatrics [30] and the WHO [31] recommend no media exposure for children younger than two years; less than one h/day of DM use for children aged 2-5 years, and for older children and adolescents to limit recreational DM use.

The data presented above clearly indicate that these recommendations are not being followed. The duration of DM exposure differs by media type. In Europen, children younger than eight years spend 75% of their digital screen time watching television and videos online, while older children and adolescents (9-16 years) spend most of their DM time with smartphones [32]. Concerning SM, adolescents (and young adults) have the highest duration of SM use globally, with an average of 3.34 hours/day. They also have the highest number of SM accounts (9.1 accounts per person, as of 2022) [26]. Young children aged 9-11 years also use SM, mostly to watch YouTube videos [32]. The patterns of DM use have also changed between boys and girls. Boys use DM mainly to play video-games on game consoles/computers or smartphones, while girls use DM for listening to music and navigating SM. The average SM use duration in adolescent girls stands at 1.5 h/day while in boys, at 51 min/day [29]. Besides age and sex, several factors have been identified as determinants of DM use in children and adolescents. Those living in one-parent families were shown to have higher DM use and fewer media rules at home compared to children living in two-parent families [33]. Correlates of prolonged DM use in children include low paternal and maternal education (i.e., less than high school) compared with college [34], less living space per person, excessive TV viewing in the household [35], prolonged parental screen time (>2 h/day), lack of family media rules [36], having a television on child's bedroom [37] and having an older sibling [35]. As children grow older, their media use is related to their peers' DM use, while the sibling's influence diminishes [38].

1.2. The digital environment - a space to connect and belong: Benefits of using digital media for children and adolescents

The digital environment provides children and adolescents rich opportunities for learning, self-development, and entertainment. However, these benefits depend on the child's age, context (with or without parental supervision), media type, and the content children are exposed to. The evidence on the positive effects of DM exposure for infants and toddlers is limited. Therefore, no DM exposure is recommended for this age group. For older children and adolescents, the DM environment provides a space to connect with family and friends, learn new ideas, and work on school-related projects [27]. Among adolescents, DM and SM, in particular, may be beneficial for identity development, peer engagement, social support, self-presentation, and self-disclosure, all crucial elements for healthy development during adolescence [39]. Besides using DM as a platform to create and maintain social contacts, adolescents exploit DM to express their views and opinions in matters that interest them (e.g., climate change), engage in community service, or stay updated with current news, trends, and developments [39]. DM is also useful for adolescents to access information on sensitive topics they find difficult to discuss with their parents or teachers, like sexual health or sexual identity [40]. From a public health perspective, DM are powerful tools to promote healthy behaviors among youth, given their high accessibility and acceptability within this age group. Evidence shows that SM, particularly, is useful for delivering interventions targeting nutritional behaviors in youth, with improvements in fruit and vegetable intake reported in adolescents and young adults [41,42]. In addition, interventions via DM showed small but promising results in promoting well-being and relieving anxiety in adolescents [43].

1.3. The relevance of considering the digital environment as a third risk factor undermining children's health

Along with the benefits of DM use also come risks, such as prolonged sedentary time, exposure to unhealthy products and behaviors, advertising, exploitation of personal data, loneliness, or bullying, to name a few, all of which can affect children's and adolescents' health and wellbeing [44]. These potential effects may exacerbate due to children's and adolescents' limited defense mechanisms against harmful factors in the DM environment. Specific malicious technological designs, often called "dark patterns", implemented in modern DM like video-games or SM platforms, aim to impact users' decision-making, such as prolonging the time spent with these media [45]. Dark patterns include features that require and remind users to interrupt their daily activities to return to the game or SM (e.g., notifications), advertisements that pop up unprompted on websites, YouTube video characters, or advertisements on Instagram that encourage purchases of branded products, or the auto-play feature that prolongs the time spent on TikTok or YouTube, with no physical end of the content [45]. As these design patterns impact children's and adolescents' DM use, it may be inferred that children's "choice" to use DM does not entirely reflect their free will, given that their media literacy and the cognitive "defense" mechanisms are not yet developed. Although SM platforms have age limit restrictions whereby users need to be at least 13 years old, younger children can register using fake birth dates or by asking their parents or siblings to set up an account for them. In Europe, one-third of children aged 9-10 years and 60% of 11-12-year-olds have an SM profile [32], which indicates that the age restrictions on SM do not work. This threatens children's security and safety in the digital environment considering their limited ability to manage privacy, and the potential exploitation of their data by third parties. For instance, children's online data may be unappropriately used for targeted advertising activities [44], which in turn may exploit children's vulnerability towards advertising. Children cannot distinguish between entertainment and advertising content due to their limited cognitive competence to recognize the selling intent of advertisements [46,47]. Hence, in this thesis, I will refer to the term DM exposure instead of DM use.

The data presented above clearly indicate that DM has penetrated children's and adolescents' lives and thus represent a fundamental part of the context in which they develop. The digital environment provides children and adolescents a new world of learning and self-presentation. On the other end of the spectrum, the ubiquitous exposure to DM, in addition to the predatory design patterns, puts children and adolescents in a new digital ecosystem and exposes them to a new set of health determinants. Hence, it is crucial to examine the role of DM as a third group of determinants of children's health, including cardio-metabolic health, cognitive functioning, and mental health.

1.4. Digital media exposure and cardio-metabolic health in children and adolescents

The current research examining the role of DM exposure on children's cardio-metabolic health has focused on TV viewing and video-gaming. Prolonged TV exposure is associated with poor eating habits, overweight, and obesity in children and adolescents [48,49]. Findings from the pan-European IDEFICS study [50] showed that children aged 2-9 years with high-risk TV patterns, i.e., prolonged duration of TV exposure, TV viewing during meals, and having televisions in their bedrooms, were more often overweight and had higher propensities to consume high-fat and high-sugar foods. In the two-year follow-up of the IDEFICS study, Olafsdottir et al. observed that high-risk TV patterns influenced children's consumption of sugar-sweetened beverages (SSBs) and increased the risk for abdominal obesity after two years [51]. Other studies show that prolonged video-game playing is associated with childhood obesity [52], also in the long-term [53]. Only a few cross-sectional studies have investigated the association of DM exposure with metabolic disorders in children and adolescents. In these studies, DM exposure - measured as TV and computer use - was associated in a positive dose-dependent manner with MetS [54,55]. Another study observed that children with excessive DM exposure (>5 h/day) had higher levels of triglycerides and a higher risk for insulin resistance [56]. Yet, these studies did not account for emerging DM, such as internet exposure. As the data presented at the beginning of this chapter suggest, while growing up, children have adopted new digital technologies in their daily routines, with the internet being a considerable contributor to their daily total DM exposure. Moreover, studies evaluating the long-term impact of DM exposure on MetS in children and adolescents are lacking. DM exposure may impact children's and adolescents' metabolic health through a number of potential underlying mechanisms, which will be elaborated on in the following section.

1.4.1. Digital media exposure impacts food and energy intake

The most prominent mechanism via which DM exposure may affect metabolic health is by increasing the dietary energy intake. A majority of the literature has reported adverse dietary outcomes among children with as little as one hour of TV exposure per day [57]. Children with increasing DM exposure, measured as TV and computer use, have a higher intake of foods high in sugar and fat [50], higher consumption frequency of SSBs [51], low intake of fruits and vegetables [58] and higher total energy intake [57]. Interventional studies have reported that DM exposure, measured as video-game playing, leads to increased energy intake, even in the absence of hunger [59]. One underlying pathway via which DM exposure leads to increased food intake is by acting as a trigger or prompt to eating [49]. Mindless eating in front of screens is a well-documented factor associated with increased food intake, especially energy-dense snack foods rich in sugar and fat [50], with media obscuring or distracting from feelings of satiety [49]. Prolonged DM use is also associated with increased exposure to advertising for unhealthy food and beverages, like energy-dense foods and SSBs. Child-directed food advertising, often embedded in animated television programs, is shown to increase the intake of foods being advertised [60]. While an energy surplus of 69-77 kcal/day over a few years is sufficient to make a child overweight [61], meta-analytic evidence shows that exposure to food advertising on television and the internet increases children's ad-libitum energy intake by 30-50 kcal [62]. This effect could be much larger in real life for two reasons: first, due to the prolific and repeated exposure to food advertising, often across multiple DM simultaniously and second, due to the priming effects of food advertising, which can increase the intake of foods not being advertised as well [63]. Food advertising also leads to heightened brand preference, even in food commercials as short as 30 seconds [64].

With newer DM, such as smartphones and SM, which children and adolescents ubiquitously access, food companies have adapted their advertising strategies by employing new product advertising forms. These include advergames, where advertising content is embedded in the videogame, or paid partnerships with (video) bloggers or SM influencers, which mix advertising, cultural and personal messages in the same post. Other strategies include giveaways, competitions based on user-generated content in SM, and many more. Several studies have examined the extent to which children and adolescents are exposed to advertisements in the digital environment. One study conducted in Canadian children aged 7-16 years, found that they watch almost 200 food and beverage advertisements on SM every week, predominantly promoting unhealthy foods and beverages [65]. Similar findings were observed in Australian and Belgian children and adolescents [66,67]. These new (digital) forms of food advertising may also affect children's food and energy intake. In a randomized-controlled trial (RCT), children who played an advergame had higher ad-libidum energy intake, regardless of the advertised food (i.e., energy-dense snack or fruit). Remarkably, advergame playing increased the intake of energy-dense foods, but not that of fruits [68]. Another RCT showed that exposure to SM influencers' advertising for unhealthy foods increased children's energy intake from those foods [69]. In contrast, advertising of healthy foods did not affect the actual healthy food intake [69]. The mechanisms behind these effects remain unknown.

1.4.2. Digital media exposure may impact taste preferences

One of the main drivers of food choice and intake are the taste preferences, which in turn, are affected by various factors, including genetic and environmental factors. Exposure to a highly rewarding digital environment may also influence taste preferences. The hypothesis lies in the ubiquitous exposure to highly appetizing food images and videos, which may stimulate a plethora of neural, physiological, and behavioral responses [70]. Eye-tracking research shows that children allocate more visual attention to food images than non-food images [71]. The mere viewing of food compared to non-food cues is associated with increased levels of ghrelin - the orexigenic hormone - hence increasing the appetite and caloric intake [72]. Moreover, the branding of foods and beverages impacted children's taste perceptions in side-by-side taste tests, especially among those with longer TV [73]. Watching food compared to non-food advertisements on television influenced children's taste preferences and was associated with increased neural activation in brain areas specialized in reward response [74]. Using electroencephalography, Ohla and colleagues showed how mere exposure to unhealthy compared to healthy food images may enhance the taste evaluation of a neutral taste stimulus [75]. Using a small current, they sent a hedonically neutral electric taste signal to the participant's tongue and observed that participants evaluated the neutral taste stimuli as more pleasant after viewing unhealthy, high-calorie food images compared to low-calorie food images. Participants also showed higher activation in the insula and orbitofrontal cortex, brain areas specialized in reward and decision-making, after exposure to high-calorie food images compared to low-calorie ones [75]. The association of DM exposure and taste preferences in free-living children and adolescents (i.e., outside of laboratory conditions) is lacking.

1.4.3. Digital media exposure displaces the time spent doing physical activity

Physical activity (PA) is beneficial for weight loss and maintenance, and has been negatively associated with MetS and related factors in children and adolescents, independent of their weight status [9]. Evidence on the long-term health effects of PA in children is inconsistent, also due to different measurement methods and follow-up periods. Findings from the IDEFICS/I.Family cohort showed bi-directional associations between moderate to vigorous physical activity (MVPA) durations and weight status in children and adolescents [76]. Children engaged in MVPA for 45 or 60 min/day at baseline had lower odds of becoming overweight after two or six years, while children who became overweight over the time span had lower odds of achieving 45 or 60 min of MVPA daily [76]. Findings from the EarlyBird cohort in the UK showed that higher PA levels at the age of five or seven years did not predict less body fat percentage nor lower BMI after three years, suggesting that interventions tackling PA might not be successful in children [77,78].

Besides technology development and urbanization, the excessive time spent with DM has contributed to the displacement of PA in favor of sedentary time among children and adolescents. Sedentary time is characterized by activities that require low energy expenditure performed in a lying or reclining position, like watching TV or sitting in front of a computer. Previous studies showed that screen-based sedentary time measured as watching TV and videos was positively associated with cardio-metabolic risk factors, including systolic blood pressure, body fat percentage, and waist circumference [79]. Sedentary time was also inversely associated with HDL-cholesterol levels in obese children, independent of MPVA[80]. Interventional studies aiming to reduce recreational DM exposure have shown only minor if any, improvement in PA levels [9], but with important reductions in obesity prevalence [81], suggesting that displacement of PA may not be the most robust pathway via which DM exposure leads to obesity and detrimental metabolic health.

1.4.5. Digital media exposure displaces sleep duration

In children and adolescents, increased time spent in front of digital screens has been associated with adverse sleep outcomes, including shorter sleep duration, later mid-point sleep timing, and reduced sleep quality [82]. The main reason is that children who spend more time with media, particularly before and during bedtime, get shorter total sleep duration. Using portable devices such as smartphones and tablets enable children and adolescents to use these screens in their bedroom, before going to sleep, or right after waking up, making it more difficult for a parent to control their child's DM exposure. The blue and bright light emitted by digital devices, especially smartphones, impacts the circadian rhythm and has been suggested as a suppressor of melatonin secretion, the sleep-inducing hormone, leading to delayed sleep timing [83]. The use of smartphones has been associated with sleep disturbances, also due to the content of messages received before bedtime [84].

These data indicate a great public health challenge as sleep deprivation has been associated with overweight and obesity in the long-term [85]. The underpinning mechanisms are three-fold: first, shorter sleep duration affects the secretion of ghrelin and leptin, hormones responsible for appetite regulation, leading to increased hunger and reduced satiety [86]. Second, shorter sleep duration leads children to consume foods higher in energy density, particularly high sugar content [87], and less nutritionally-dense foods like fruits and vegetables [88]. Third, the displacement of sleep with DM use may lead to unhealthy eating behaviors, such as eating outside regular mealtimes and night-snacking [89]. Although associations between short sleep duration and adiposity are well-established, the current evidence shows inconsistent results for the longitudinal association between sleep duration and cardio-metabolic disorders in children and adolescents. Findings from the IDEFICS/I.Family cohort showed that sleep duration was not directly associated with insulin resistance but indirectly through abdominal obesity [90]. Other studies have found U-shaped associations between sleep and cardiometabolic risk factors, with positive associations reported for both short and long sleep duration, independent of obesity [15].

1.5. Digital media exposure and mental health of children and adolescents

Mental health in early childhood is associated with cardio-metabolic markers in adolescence [19,91], mediated through lifestyle factors, including exposure to digital screens [19]. Early childhood DM exposure is a predictor of poor well-being in both children [92] and adolescents [93]. Research suggests that compulsive and excessive DM use leads to addiction and psychosocial distress in children and adolescents [94]. Internet gaming disorder is included in the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) [95], and WHO has included digital gaming disorder in the International Classification of Diseases since 2018. Prolonged smartphone exposure is associated with poor mental health, suicidal feelings, and self-injury in adolescents [84]. Excessive SM exposure has also raised concerns among the research community, parents, and adolescents [96]. The main drivers of excessive SM exposure are the “fear of missing out” (FOMO), which is related to the fear that others might be having rewarding experiences that one is missing from [97], and the “no mobile phone phobia” [25]. The dark patterns implemented on SM platforms also contribute to the excessive and addictive SM use [45]. Exessive SM exposure is associated with depression in children and adolescents [98,99], even in the long-term [100]. SM exposure is also linked with low self-esteem through upward-social comparisons [101] to idealized lives and body shapes, especially in adolescent girls [102]. A content analysis of “fitspiration” images on Instagram, which intend to motivate viewers to achieve their fitness goals by exercising, showed that most images contained a thinned and toned body type [103]. Exposure to these images did not affect exercise behaviour, but was related to adverse effects on body image in adolescents and young women [104].

1.6. Digital media exposure and cognitive health in children and adolescents

Another potential mechanism via which DM exposure might impact children’s mental and cardio-metabolic health is by affecting their cognitive functioning. Cognitive functioning begins to develop early in life and continues through adolescence to adulthood in terms of functional and structural changes in the brain, known as neuroplasticity. The latter signifies that children’s brain and neural structure and functioning are shaped through interactions with the external environment [105]. Studies conducted in healthy children and adolescents have shown that poor cognitive functioning is associated with a risk for type 2 diabetes [106], independent of BMI [107], as well as with metabolic syndrome [108], cardiovascular disease [109], and mortality later in adulthood [110]. The underpinning pathway lies in the importance of cognitive functioning for healthy lifestyle choices, known as neuro-selection. Children with lower cognitive functioning are likelier to engage in unhealthy behaviors, including smoking, alcohol drinking [111], physical inactivity, and consumption of unhealthy foods later in adulthood [112]. Measures of cognitive functioning, including emotional regulation, decision-making ability, and cognitive flexibility are related to eating behaviors [113], psychosocial well-being [114], and weight status in children and adolescents [115].

The prolific presence of DM in children's lives represents an utterly new context in which their development occurs. Children's and adolescents' development is now intertwined with smartphones, computers, tablets, and SM feeds. Prolonged exposure to DM during childhood, when the brain is highly plastic, might deteriorate the development of the brain structure. Studies based on functional magnetic resonance imaging (fMRI) have shown that prolonged exposure to DM is associated with reduced microstructural integrity of the brain white matter in areas related to language, attention, and executive functioning in children [116] and adolescents [117]. The urge to constantly check online content and the notifications received on a smartphone can distract children during tasks, impact their emotion regulation, and limit their cognitive processing capacities [118,119]. Adolescents with frequent and excessive smartphone exposure have shown lower connectivity in brain areas specialized in inhibition control (i.e., impulsivity- prefrontal cortex) and decision-making ability (orbitofrontal cortex), especially in reward-seeking behaviors [120]. Media multitasking has also been associated with long-term attention problems [121], poor memory, and reduced volume in the anterior cingulate cortex, a region involved in cognitive flexibility and socio-emotional control [122].

The data presented in this chapter suggest that exposure to the digital environment may influence children's and adolescents' cognitive functioning, including impulsivity, decision-making ability, and cognitive flexibility, constructs which were previously associated with unhealthy snack intake [113] and weight status in adolescents [115]. Yet, the association of DM exposure and media multitasking with measures of cognitive functioning have not been investigated in free-living participants.

2. Aim and objectives of the thesis

Based on the existing evidence on the association of DM exposure with children's and adolescents' health outcomes, and the potential underlying mechanisms described, I identified research gaps that need to be addressed to holistically understand the impact of the contemporary digital environment on children's and adolescents' health. Notably, evidence is lacking for:

i) The impact of SM exposure on children's and adolescents' diets and the potential underlying mechanisms,
ii) The potential influence of DM exposure on the sensory taste preferences of free-living children and adolescents,
iii) The potential impact of DM exposure on children's and adolescents' cognitive functioning, including cognitive inflexibility, impulsivity, and decision-making ability,
iv) The potential long-term effect of DM exposure during childhood on the risk of metabolic syndrome later in life.

To close these knowledge gaps, in the framework of this thesis, I aim to provide evidence regarding the impact of DM exposure on children's and adolescents' health outcomes, including metabolic syndrome and cognitive functioning, as well as health-related behaviors, such as food intake, eating habits, and sensory taste preferences. This thesis used information collected between 2007 and 2014 from children and adolescents aged 2-18 years, from nine European countries and of diverse socio-economic and migration backgrounds.

To tackle the overarching research aim, I addressed four main specific objectives:

1) To understand the mechanisms underlying the association between social media exposure and dietary outcomes in healthy children and adolescents, using a systematic review approach (Paper 1)
2) To examine the association between digital media exposure and sensory taste preferences in free-living children and adolescents (Paper 2)
3) To determine the impact of digital media exposure on children's and adolescents' cognitive functioning (Paper 3)
4) To investigate the long-term association between digital media use and incident metabolic syndrome in children and adolescents (Paper 4)

2.1. Potential associations investigated in the present doctoral thesis

The hypothesized associations are illustrated in ***Figure 2***. First, I conducted a systematic review of worldwide studies examining the association of SM exposure with food intake and dietary behaviours in healthy children and adolescents, to understand the potential underlying mechanisms (*paper 1*). Second, exposure to DM was hypothesized to be associated with increased sweet, fat and salty taste preference but with decreased bitter taste preference. These associations were examined in *paper 2*. Third, prolonged use of DM, particularly smartphone, internet, and media multi-tasking, were hypothesised to negatively impact cognitive functioning, by increasing the emotion-driven impulsiveness and the cognitive inflexibility, and decreasing the decision-making ability, independently of psychosocial well-being. These associations were examined in *paper 3*. Lastly, prolonged DM use over time was hypothesized to increase the risk for incident metabolic syndrome and its components, independent of physical activity and food intake. These longitudinal associations were investigated in *paper 4*.

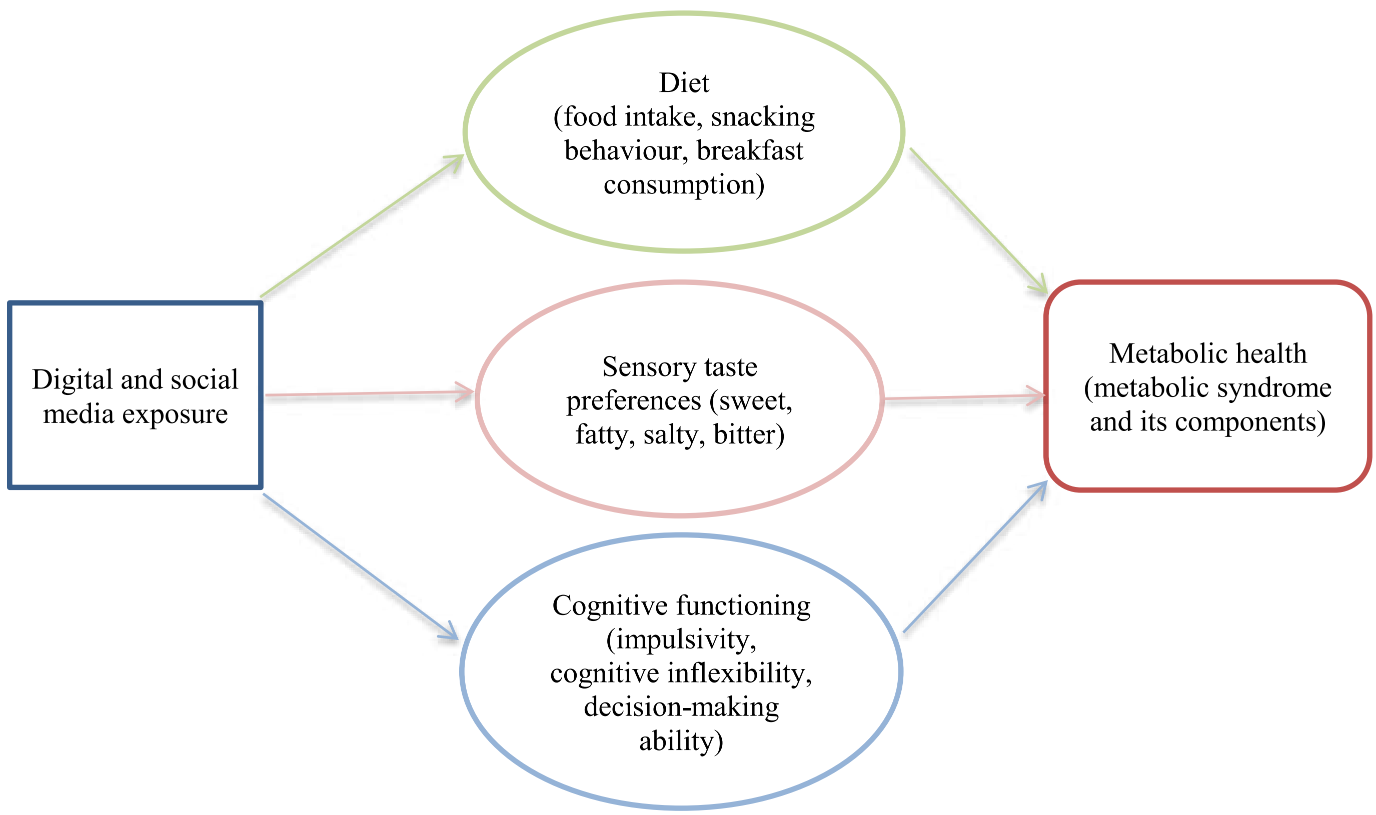

Figure 2. Illustration of associations investigated in the present doctoral thesis.

3. The methodology used in the framework of this thesis

In this chapter, the methodology used in each paper constituting the thesis will be elaborated. First, I present the method used in the systematic literature review (SLR) of *paper 1,* and then, the methods used in the empirical research conducted in *paper 2* to *paper 4*.

3.1. Methodology used in the systematic literature review

The body of research described in the introduction of this thesis suggests that SM exposure may influence children's and adolescents' diets and related behaviors. No previous systematic review has synthetized the literature on the role of SM on children's and adolescents' diets, considering developmental differences in age and brain maturation. Hence, paper 1 – a SLR - aimed to identify, appraise, and synthesize the body of research and to tackle two main research gaps:

i) To examine how exposure to SM impacts children's and adolescents' diets, including food intake (frequency and quantity of consuming unhealthy, high-calorie vs. healthy, low-calorie foods), food preference of healthy vs. unhealthy foods, related behaviors (breakfast consumption or night snacking), and nutrition literacy,
ii) To identify the potential mechanisms underlying the aforementioned assoctions.

3.1.1. Search strategy

The literature search was systematically conducted in three databases: MEDLINE (via PubMed), Scopus, and CINAHL (via EBSCO), from 2008 to December 2021. The beginning year in the search strategy was 2008 because Facebook launched in 2006, and the first iPhone entered the market in 2008. Different combinations of search terms were used to identify articles targeting:

i) SM exposure ((or social networking sites or Facebook, Instagram, YouTube, TikTok, Snapchat), or influencers' marketing, or online SM food marketing/advertisement)); or proxies such as internet or smartphone use, or exposure to digital food images/videos.
ii) In association with food intake (fruit/vegetable intake, unhealthy vs. healthy food intake, junk food intake, SSB intake), food preference/liking, nutrition or diet literacy, and related behaviors (night snacking, breakfast skipping, or breakfast consumption);
iii) Conducted in healthy children and adolescents aged 2-18 years.

Exclusion criteria were: i) lack of an SM component or not measuring dietary outcomes, ii) diseased children (e.g., having obesity, diabetes, eating or neurological disorders); iii) children aged <2 years or >18 years. Studies that targeted parents and/or families and where the primary exposure was TV, computer use, advergames, or mobile applications (except SM applications) were also excluded. No restrictions on language, publication type or study design were imposed. The review was conducted based on the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) [123]. The protocol was registered in the International Prospective Register of Systematic Review (PROSPERO) with registration number: CRD42020213977.

3.1.2. Study selection and synthesis of the results

The identified articles across all databases were screened using the online Rayyan QCRI app [124]. First, I blind-screened the articles based on title/abstract in collaboration with three independent reviewers (with a Public Health background) and then, based on full-texts. Disagreements were resolved by consensus or adjudicated by two additional reviewers. References of included studies and relevant review articles were manually searched for citations. The four reviewers (in pairs) independently extracted relevant data from the eligible articles. A predefined and piloted data extraction template was used to record the extracted data, including 1) study details: e.g., year, country, study design, and SM exposure (type of platform and/or food image/video, frequency/duration of use), 2) demographic information of the study sample: age, sex, sample size, SES, ethnicity/migration background; 3) outcomes investigated, main primary and secondary findings. The results were synthesized narratively. Findings were clustered by the outcomes investigated (healthy vs. unhealthy food intake) and by age group (children: <12 years; adolescents ≥ 12 years) to account for developmental differences.

3.1.3. Risk of bias and assessment of study quality

Two independent reviewers assessed the quality and risk of bias of the selected studies. For cohort studies, the Newcastle-Ottawa Scale was applied [125]. For cross-sectional studies and randomized controlled trials (RCTs), the Joanna Briggs Institute appraisal tool [126] and the revised Cochrane risk of bias (RoB 2.0) tool were applied, respectively [127]. An aggregate quality rating was given to each study, and for all discrepancies, consensus was achieved via discussions among all initial reviewers or by consulting an additional reviewer. No study was excluded based on its quality.

The systematic literature search identified 5518 articles; four additional articles were manually identified. After inclusion and exclusion criteria were applied, 35 studies were included in the final review (*paper 1*, Appendix, page XX). These studies were conducted in North America [128-139], Europe [69,140-152], Australia [67,153,154], Brazil [155], and Asia [156-160]. The sample size ranged from 11 to 54,603 children and adolescents. More than half of the included studies were interventional studies (i.e., RCTs: n=23) [69,129-137,139-145,147,149-151,153,158] while 12 studies were observational, of which one and 11 studies were respectively longitudinal [146] and cross-sectional [67,128,138,148,152,154-157,159,160]. Various SM platforms were examined, including Instagram [69,141,142,147,150], YouTube [67,146], Facebook [138,149], and WhatsApp [158]. Four studies examined smartphone or internet use as proxies for SM exposure [148,153,155,156,159,160]. The exposure to digital food images was measured in 12 RCTs using fMRI methods, while food video advertisements were considered in one RCT only [134]. The only longitudinal study included was rated as low quality (i.e., high risk of bias) [146]. Seven cross-sectional studies were rated high quality [128,148,152,154,155,159,160], while four were rated medium quality [67,138,156,157]. Among RCTs, one was rated high quality (i.e., low risk of bias) [153], three medium quality [69,141,150], and nineteen low quality [129-137,139,140,142-145,147,149,151,158].

3.2. Methodology used in the observational studies conducted in this thesis

3.2.1. Study design and population

The observational research constituting this doctoral thesis (*paper 2* to *paper 4*) is based on data provided by children and adolescents participating in the IDEFICS/I.Family cohort. Participants resided in 9 European countries, including Belgium, Cyprus, Estonia, Germany, Hungary, Italy, Poland, Sweden, and Spain. The IDEFICS (Identification and prevention of dietary- and lifestyle-induced health effects in children and infants) study represents the baseline examination wave ((hereinafter first wave (W1)) and was conducted during 2007–2008. A total of 16,229 children aged 2–9 years who met the primary inclusion criteria of full information on age, sex, height and weight; attending kindergartens or grades 1 and 2 of primary schools, and residing in the respective regions (except Poland), participated in W1 [161]. The first follow-up of the IDEFICS study was carried out from 2009 to 2010, where 13,596 children were re-examined. In this examination wave (hereinafter second wave (W2)), 68% of children (11,041) had participated in W1, and 2,555 children were recruited from new families. The second follow-up (i.e., I.Family study, hereinafter third examination wave (W3)) was conducted during 2013–2014 and aimed to investigate the determinants of eating behaviors of European children and adolescents and their parents. Here 10,676 children and (meanwhile) adolescents aged 2–18 years were re-examined, where 73.8% of them already participated in W2 (7,105) and 3,571 were new children (i.e., siblings from the same families). In W3, children and adolescents residing in Poland were also recruited.

During 2019-2022, the fourth examination wave (W4) of the cohort was carried out, with the participation of adolescents and young adults, which facilitated the examination of health and behaviour factors during the transition from adolescence to young adulthood. As data collection was still ongoing by the time of writing this thesis, the information from this wave was not available to answer research questions of the present thesis. Across all study waves, adolescents (≥ 12 years) provided the informed consent, and the assent was orally given from younger children in addition to written parental informed consent. Ethical approval was obtained from the local ethic committees of each study center. An overview of the study waves of the IDEFICS/I.Family cohort is illustrated in ***Figure 3***.

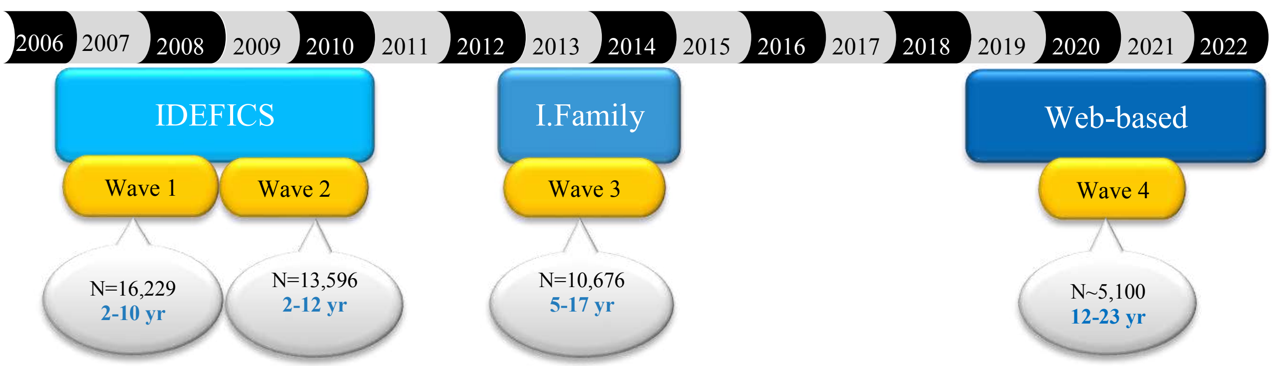

Figure 3. Timeline of examination waves of the IDFICS/I.Family cohort

Participation in the single modules at each examination wave was voluntary, which allowed children and their parents to consent to single components of the study while abstaining from others. Consequently, the size of the analysis group included in the observational research conducted in the single papers of this thesis varied from 3261 to 10,359 children and adolescents. The age range of the included participants also varied, from 6-17 years in *paper 2*, 8-18 years in the *paper 3*, to 2-16 years in the *paper 4*. An overview of the age range and size of the analysis groups of single papers is provided in **Table 1**.

Table 1. The size of the analysis groups included in the four papers of this doctoral thesis

	Examination wave	Analysis group size	Age range (in years)
Paper 1	SLR[1]	11 - 54,603	2-18
Paper 2	W3	7094	6-17
Paper 3	W3	3261 - 4046	8-18
Paper 4	W1, W2, W3	10,359	2-16

[1] SLR- systematic literature review, W1- 1st examination wave; W2- 2nd examination wave; W3- 3rd examination wave

3.2.2. Data collection and examination procedures

Children and adolescents who participated in the IDEFICS/I.Family cohort provided data on metabolic and mental health, their determinants and lifestyle behaviors via physical examinations, blood, saliva, and urine samples, accelerometers, diaries, questionnaires, and computerized cognitive tests. All instruments and procedures were standardized across all participating study centers and have been described in detail elsewhere [162]. In the following, the collection of information on outcomes, exposures and confounders considered in the single papers is provided.

3.2.3. Measurement of outcomes of interest

3.2.3.1. Assessment of sensory taste preferences

At W3, a Food and Beverage Preference Questionnaire (FBPQ) was administered to children aged 6–17 years, to assess preferences for sweet, fatty, salty, and bitter taste. The FBPQ was based on a list of selected food and beverage items and was evaluated for its relative validity to characterize taste phenotypes in children and adolescents [163]. The ultimate aim of FBPQ was to examine sensory taste preferences that are linked to the current obesogenic diets, characterized by foods low in fiber but high in fat, sugar, and salt content [164,165]. As such, sensory preferences for sweet, fatty, and salty-tasting foods were measured as a proxy for preferences for unhealthy foods [166] and bitter preference as a proxy for preferences for healthy foods (e.g., vegetables) [167]. A pre-test was conducted across all study centers to ensure the availability of food items in all countries except Belgium, as the FBPQ was not administered to Belgian children [168]. A list of 63 food items was considered appropriate for all age groups. Pictures of these foods were depicted in the final questionnaire, including i) single foods (e.g., spinach, banana); ii) condiments (e.g., mayonnaise, nougat spread); iii) mixed foods (e.g., sausage, kebab) and iv) drinks (e.g., lemonade).

Using a five point-Likert scale, children and adolescents indicated how much they liked the taste of the foods/drinks in the photographs. The scale ranged from 1, meaning “I do not like at all,” to 5, meaning “I like very much.” Children who had never tried (or did not know) a specific type of food indicated the respective option. A-priori, an age- and sex-specific factor analysis, was conducted to assign particular foods and beverages to taste modalities: sweet, fatty, salty, and bitter, to account for the factorial structure of food preferences [168]. The taste preference scores were calculated as the sum of the rating for foods/beverages assigned to each taste category, and divided by the total number of food/beverage items included in that category, separately for males and females of two age groups (<12 years vs. ≥ 12 years), to control for age and sex discrepancies in food preferences. The cut-off age of 12 years was chosen as the median age of puberty onset, which is associated with anatomical and psychological changes, including in the gustatory and olfactory systems [169]. The taste preference scores for female children, female adolescents, male children, and male adolescents were then merged into one unified score for each taste modality to create a non-stratified taste preference score. The score was then used as the dependent variable in the analyses of *paper 2*. Based on within-sample median values (sweet, fatty, and salty preference: median=4; bitter taste preference: median=3), the scores were categorized as “high” vs. “low” taste preference.

3.2.3.2. Measures of cognitive functioning

Children and adolescents aged 8-18 years participating in W3 completed two computerized cognitive tests to assess cognitive inflexibility and decision-making ability. The emotion-driven impulsiveness was measured via a self-reported questionnaire. Additionally, information on attention deficit hyperactivity disorder (ADHD) diagnosis was provided via the health and medical history questionnaire for all participating children and adolescents (aged 2-18 years).

Cognitive inflexibility

To measure cognitive inflexibility, children and adolescents performed a computerized version of the Berg Card Sorting test [170,171]. Participants were shown four cards of different colors and shapes (1=one red dot, 2=two green stars, 3=three blue squares, 4=four yellow crosses) and a deck of 64 stimulus cards. Participants had to sort all cards from the deck according to a particular rule (by number, symbol, or color) that was not known to them by choosing one of the key cards (for instance, if ‘by color’ is the correct rule, the color of symbols on the stimulus card should match the color of symbols on the key card). Feedback (‘correct’ or ‘incorrect’) was provided to the participants after sorting each card, and they had to discover the sorting rule accordingly. Without notice, the rule was changed after ten consecutive correct trials, and the participant had to find the new rule. The number of perseverative errors after the rule changed (or the number of cards sorted according to the previous rule, was used to measure cognitive inflexibility. Subsequently, the cognitive inflexibility score ranged from 0 to 39, with a higher number of perseverative errors indicating higher cognitive inflexibility.

Decision-making ability

Decision-making ability was measured using a computerized version of the Hungry Donkey Test [172], a child-friendly version of the Iowa Gambling Task [173], consisting of 100 trials. In each trial, participants should help a hungry donkey to collect as many apples as possible by choosing one of the four doors shown on the screen. Each choice resulted in a reward (gaining apples); on some trials, it also resulted in punishment (losing apples). Doors 1 and 2 were the disadvantageous doors because they yielded a larger immediate reward but led to losing more apples in the long-term, resulting in a net loss. Doors 3 and 4 were considered as advantageous doors because they yielded smaller immediate rewards compared to doors 1 and 2 but led to winning more apples in the long term, resulting in a net gain. Participants had to learn which doors were advantageous and which were disadvantageous [172]. Decision-making ability was calculated as the difference between the number of advantageous choices (doors 3 and 4) and the number of disadvantageous choices (doors 1 and 2), resulting in a score ranging from −100 to +100. Decision-making ability (hereinafter, decision-making) was characterized by more advantageous choices than disadvantageous ones.

Emotion-driven impulsiveness

Emotion-driven impulsiveness, which refers to an impulsive response or action to negative emotions, was measured using the 12-item negative urgency subscale from the UPPS-P (Urgency, Premeditation, Perseverance, Sensation seeking, and Positive urgency) questionnaire [174]. Adolescents self-completed the questionnaire, while parents proxy-reported for younger children. An item example includes: “Sometimes when I feel bad, I can't seem to stop what I'm doing even though it is making me feel worse”. Each item was rated on a 4-point Likert scale ranging from 1, meaning “agree strongly” to 4, meaning “disagree strongly”. All items were recoded, except for one item, to make sure that all items ran in the same direction. For participants who completed ≥ 8 items of the scale, a sum score for emotion-driven impulsiveness was calculated ranging from 12 to 48 [174], with a higher score indicating higher impulsivity.

Attention Deficit Hyperactivity Disorder

In W3, parents (or caregivers) proxy-reported whether the participating child/adolescent was diagnosed with ADHD using the Health and Medical History Questionnaire. Parents answered the questions “Has the child ever been diagnosed with any of the following diseases?” and by ticking the answer “Attention-deficit/hyperactivity disorder (ADHD)”. Among 9,382 children and adolescents, 118 were reported as diagnosed with ADHD (1.26%). Despite the low number of cases, in a sensitivity analysis, I examined the potential cross-sectional association of DM exposure with clinical ADHD diagnosis (unpublished data).

3.2.3.3. Physical, clinical, and laboratory measurements

Each participant was measured for weight and height in light clothing and in fasting status. Weight was measured to the nearest 0.1 kg using a Tanita scale (TANITA Europe GmbH, Sindelfingen, Germany). Height was measured using a portable stadiometer (Seca GmbH & Co. KG., Hamburg, Germany) to the nearest 0.1 cm. Body Mass Index (BMI) was calculated for all children and adolescents as weight divided by squared height and transformed into age- and sex-specific z-scores. Participants’ weight status was categorized according to the cut-offs of Cole et al. (2012) as thin/normal weight vs. overweight/obese [175]. Waist circumference was measured based on the international standards of kinanthropometry [176], in an upright standing position, midway between the lowest rib margin and the iliac crest, to the nearest 0.1cm.

Using an automated oscillometric device (Welch Allyn 4200B-E2, Welch Allyn Inc., New York, NY, USA) [177], systolic and diastolic blood pressure (BP) of each child was measured after resting for 5 min in a sitting position. The measurement was carried out in the child’s arm twice with a 2-minute interval in between, or three times if the first two measurements differed by more than 5% [178]. The average of two measurements was calculated for systolic and diastolic BP, respectively. To calculate total BP, the average of systolic and diastolic BP values was calculated [178]. Additionally, fasting blood samples were collected, and levels of blood lipids, including high-density lipoprotein cholesterol (HDL-c) and triglycerides, as well as fasting glucose and insulin, were measured [179-181]. The Homeostasis Model Assessment for Insulin Resistance (HOMA-IR) was calculated as (fasting insulin*fasting glucose)/405 [181]. For children and adolescents aged 2–16 years, age and sex-specific z-scores were derived for waist circumference [182], HDL-c, triglycerides [179], diastolic and systolic BP (also height-specific) [178], and HOMA-IR [181]. According to the definition of metabolic disorders in children and adolescents proposed by Ahrens et al. [180], children exceeding the 90th percentile of the age- and sex-specific (and height-specific in the case of BP) score were classified as being at the monitoring level for each metabolic component. Specifically, children were identified with unfavorable monitoring levels for: i) abdominal obesity if waist circumference was ≥ 90th percentile; ii) insulin resistance if HOMA-IR or fasting insulin were ≥ 90th percentile; iii) hypertension if diastolic or systolic BP were ≥ 90th percentile; and iv) dyslipidemia if triglyceride score was ≥ 90th percentile or HDL-c score was ≤10th percentile.

Metabolic syndrome

Metabolic syndrome in children and adolescents was defined using the continuous metabolic syndrome score (MetS) that combines four single components, suggested by Ahrens et al. [180]. The MetS score was calculated as the sum of z-scores of waist circumference, BP (mean of age-, sex- and height-specific z-scores of diastolic and systolic BP), HOMA-IR, and dyslipidemia (mean of z-scores of triglycerides and HDL-c, the latter multiplied with -1 due to its negative relationship with the metabolic risk). The equation below depicts the calculation of the MetS z-score.

$$\text{MetS z-score} = Z_{WC} + Z_{HOMA\text{-}IR} + (Z_{SBP} + Z_{DBP})/2 + (Z_{TRG} - Z_{HDL})/2$$

The monitoring level for MetS was defined if at least three out of four components of MetS exceeded the 90th percentile of the respective age- and sex-specific distributions. Children who were at the monitoring level for MetS were considered as requiring a close monitoring by a clinician. For clarity, the terms MetS, abdominal obesity, elevated BP, dyslipidaemia and insulin resistance will be respectively used to refer to the monitoring level for each metabolic outcome.

3.3. Measurement of digital media exposure

Digital media exposure was measured in W1, W2, and W3 based on self-reported data by adolescents (≥ 12 years) and proxy-reported by parents of younger children (<12 years) using the teen and the parental version of the core questionnaire, which were previously tested for validity and reproducibility [183]. Participants reported the time spent with different DM types, including TV/DVD/video, computer/game consoles (PC), and internet during weekdays and weekend days as: not at all, less than 30 min/day, 30 min to 1 h/day, about 1–2 h/day, about 2–3 h/day and >3 h/day" - a methodology similarly used in previous studies [184]. For internet use – assessed in W3 only – participants could also choose the option of "I'm online more or less all day/night". For PC use, we explicitly asked, "How long do you usually sit at a computer/game console per day? (Please disregard the time spent on internet use.)", to obtain precise information regarding the passive use of PC/game consoles and to prevent potential overlap with internet use. Then, a combined duration of DM use (total hours/week) was calculated as the weighted average of the durations reported for weekdays and weekend days and converted into total hours/day. In W3, a more detailed assessment of DM exposure enabled to measure smartphone exposure and media multitasking behavior. The daily duration of smartphone exposure was assessed using the question: "Thinking only about yesterday, about how much time did you spend watching television shows, movies or music videos on a cellphone?". Based on a 5-point Likert-scale, answers ranged from 0, meaning "not at all" to 5, meaning "more than 3 h/day". A definite attributed time was assigned to each category to calculate the duration (hours/day) of smartphone exposure. Due to the different assessment methods, smartphone exposure was not added to combined DM exposure. To assess media multitasking, participants were asked whether they were engaging in other activities while using PCs, including TV, sending text messages, playing video-games, listening to music, and reading. Participants answered either "Yes" or No." Subsequently, a sum score of media multitasking behavior ranging from 0 to 5 was calculated.

3.4. Measurement of potential confounders

Data on various potential confounders of the associations of interest investigated in this thesis were assessed using questionnaires and accelerometers. Participants' age was measured as the difference between the examination date and birth date. Information on sex, country of residence, and migration background was also collected. Parents reported their highest educational attainment, which was then classified according to the International Standard Classification of Education (ISCED) [185] as high, medium, and low education status. As puberty impacts physiological (e.g., hormonal changes), behavioral (e.g., food intake, sedentary patterns) [186] and psychosocial processes, at W3 children aged ≥ 8 years provided information on puberty status as changes in voice (boys) and the onset of menarche (girls) [187]. Information on the pubertal Tanner stage, i.e., the development of pubic hair in boys and breast development in girls, was collected in all study centers but Italy, to complement the information on puberty [188].

Dietary patterns

Food intake and eating habits of participants in the IDEFICS/I.Family cohort were measured using the Children's Eating Habits Questionnaire (CEHQ), previously tested for relative validity and reproducibility [189,190]. Using the food frequency questionnaire (FFQ) section from the CEHQ, participants self-reported (by adolescents) or proxy reported (by parents of younger children) the consumption frequency of 59 different foods, beverages, and mixed dishes in a typical week during the preceding four weeks. Answers varied from 'never/less than once a week', '1–3 times/week', '4–6 times/week', '1 time/day', '2 times/day', '3 times/day' to '4 or more times/day'. The description of food items was standardized across countries, and examples of country-specific foods were included for certain food items to account for cultural differences in food intake. A healthy diet adherence score (HDAS) was calculated for children with ≥ 50% of non-missing food items to assess the overall diet quality. The composite diet quality score was developed to reflect the adherence to healthy dietary guidelines common across all participating countries, as established by Waijers et al. [191], including:

i) High consumption of fruits and vegetables (at least 400-500 grams/day),
ii) Limited intake of refined sugars and fat (especially saturated fats),
iii) Consumption of whole meals, and
iv) Consumption of fish 2-3 times per week [192].

The score ranged from 0 to 50 and was dichotomized based on the median value (median HDAS=20) as "high" vs. "low".

Additionally, sweet and fat intake propensity scores were calculated to reflect the proportion of sweet and fatty foods in children's and adolescents' diets [50]. The sweet intake propensity was calculated as the proportion of consumed foods/drinks with high sugar content by dividing the sum of the weekly frequency intake of corresponding foods (e.g., chocolate, fruit juice, nut-based spreads, and items with added sugar: drinks, milk, cereal products etc.) by the total frequency of all food/beverage items included in the FFQ, and multiplied by 100. This prevented a potential classification bias by misclassifying children in the high-sugar or high-fat groups only because they have a high-frequency consumption of all types of food [50]. The score ranged from 0%-100%. A value of 50% for the sweet propensity intake indicates that half of the reported food consumption frequencies included foods rich in sugar content. Similarly, the fat propensity intake score was calculated, considering the consumption of foods high in fat, including cheese, mayonnaise, meat products, savory snacks, etc. The scores were dichotomized as “high” vs. “low” propensity intake at the median value (22.5 for sweet propensity intake and 25.7 for fat intake propensity).

Using the FFQ, participants also reported the consumption frequency of unhealthy snacks (times/week) during the preceding four weeks, including sugar-sweetened drinks, chocolate/candy bars, chocolate/nut-based spread, candies, marshmallows, loose candies, crisps, corn crisps, and popcorn. The sum score of the daily consumption frequency of unhealthy snacks was calculated and categorized as high vs. low snack intake (median=1.4). These variables were considered because they are closely related to metabolic health [193], screen-time, and mental health in children.

Objectively-measured physical activity and sedentary time using accelerometers

The daily duration of moderate-to-vigorous physical activity (MVPA) and sedentary time was measured for children with available accelerometer data using Actigraph accelerometers (Actigraph, LLC, Pensacola, FL, USA). In W1 and W2 of the cohort, either ActiTrainer or GT1M devices were used, as both models have identical sensor units. In W3, either GT3X+ or GT1M devices were used. In W1 and W2, children were asked to wear the accelerometer for at least three days (two weekdays and one weekend day) [194], while in W3, for seven consecutive days [195]. During waking hours, children wore accelerometers on the right hip (attached with an elastic belt). They removed them only when taking a shower or engaging in water-based activities such as swimming [196]. Accelerometer data were included when physical activity was recorded for at least two valid weekdays and one valid weekend day, and for a minimum valid wear-time of 6 hours/day [195], after exclusion of non-wear time as defined by Choi et al. (2011) [197]. Then, the total time spent in ≥ 10 min MVPA-bouts and in ≥ 30 min sedentary-bouts (derived allowing two minutes of accumulated activities within 30 min. of sedentary time according to Evenson et al. cut-point [198]), as well as the valid accelerometer wear-time (≥ 6 h/day) were calculated, in line with the methodology of previous studies [80,199,200]. The duration of sedentary time in bouts was categorized as high vs. low sedentary time at median = 798 min/day. The MVPA-time in bouts (median of any MVPA = 34 min/day) was categorized as: no MVPA (MVPA=0 min/day), low MVPA ($0 < \text{MVPA} \leq 34$ min/day), and high MVPA (> 34 min/day) duration.

Family environment and structure

Parents provided information on family structure via a kinship and household interview [201]. Based on the number of children (< 18 years) and adults (≥ 18 years) in the household, in addition to the relation of household members with the participating child, I calculated whether the participating child was an only child in that household. Being an only child may impact children's cognitive development and was hence used as a confounding variable. Only children tend to pursue more solitary activities, such as solo play with media and are deprived of sibling interactions, which in turn facilitates emotional regulation and learning opportunities that enhance psychosocial skills [202,203]. For the reported relationship status of each household member to the participating child, codes were assigned that corresponded to: 'biological mother', 'biological father', 'biologically unrelated female adult', 'biologically unrelated male adult', 'any other adult', 'biological sibling', 'half-sibling' or 'non-biological sibling'. The number of parents in the household (biological or non-biological parent) was calculated. I then derived whether the participating child/adolescent lived in a one-parent vs. two-parent family.

Using the family questionnaire, parents also reported the number of media rules at home [33]. They responded to a 9-item question on family rules for TV, video-games, smartphone use, etc. Item examples include: "Do you have any rules about: i) what your child/children is/are allowed to watch on TV; ii) if your child/your children is/are allowed to have a profile on a social networking site like Facebook and how much time they can spend on it?". Based on dichotomized answers ("yes" vs. "no"), a sum score on family media rules was calculated, ranging from 0 to 9.

Sleep duration and psycho-social well-being

Total daily sleep duration (hours/day) was calculated as the sum of the duration reported for nocturnal sleep and daytime napping during weekend days, and weekdays. Psychosocial well-being was measured based on the 16 items of the KINDL^R Questionnaire for Measuring Health-Related Quality of Life in children and adolescents. The validity and reliability of the KINDL^R have been previously reported [204]. The questionnaire was structured in four subscales measuring emotional well-being, self-esteem, family life, and relations to friends [204]. A psychosocial well-being score was calculated by summing up the 16 items scored on a 5-point Likert scale ranging from "0" meaning "never" to "4," meaning "all the time." Six items of the original scale were inversely coded to allow all items to run in the same direction. Consequently, the well-being score ranged from 0 to 48, with a higher score indicating higher psychosocial well-being.

3.5. Statistical Analyses

Throughout the empirical research conducted in *papers 2, 3*, and *4*, descriptive analyses were performed to explore differences in the characteristics of the respective analysis groups. Continuous variables were presented as mean/SD or median/interquartile range depending on their distribution. Categorical variables were depicted as frequencies and percentages. To answer each research question, different statistical approaches were used.

In *paper 2*, the cross-sectional association of DM exposure (smartphone, internet, television, PC) with sensory taste preferences (sweet, fatty, salty and bitter taste, dichotomized as high vs. low) at W3 was examined using logistic regression analyses, adjusting for potential confounders. These models allow the investigation of the relationship between discrete responses and explanatory variables while adjusting for covariates. Sensitivity analyses were stratified by sex and age group (children vs. adolescents), parental education status (high, medium, low), as well as sweet and fat propensity intake (high vs. low) to explore differences in the respective associations.

In *paper 3,* the associations between the duration of exposure to single DM and cognitive outcomes at W3 were separately examined using generalized linear mixed regressions, adjusting for confounders. In all models, a random effect for family ID was added to consider family influences given that siblings were also included (not independent observations) and to partially account for genetic factors influencing cognitive functioning. To correct for missing values, multiple imputation based on standard fully conditional specification was performed with ten replications. This procedure has demonstrated unbiased handling of missing values and enables the inclusion of continuous and categorical variables in the same imputation model [205]. To correct for multiple testing, the statistical significance level was set at $\alpha = 0.0021$, and 99.9 confidence intervals (CI) were calculated based on the Sidak correction method [206]. Furthermore, latent class analyses (LCA) clustered by country were used to identify underlying (latent) patterns of DM exposure from a combination of the single media examined. In a second step, the impact of the latent DM patterns on children's cognitive functioning was investigated. LCA is a powerful analytical strategy used in child developmental research [207]. Using a probabilistic approach, it categorizes latent sub-groups (or "classes" or "profiles") within a heterogeneous population on a set of behaviors or characteristics, as opposed to describing the variability of a single variable. The underlying assumption of LCA is that membership in unobserved latent classes can explain patterns of scores across survey questions, assessment indicators, or scales [208].

The cross-sectional association (unpublished) between DM exposure and reported clinical ADHD diagnosis was examined using data from W3 of the IDEFICS/I.Family cohort. Associations were adjusted for various confounders like sex, age, mother's age at child's birth, mother's smoking frequency during pregnancy, child delivery via Cesarian section, child's well-being score, parental education status, and country. The associations were also examined in stratified analyses by sex, age group (children: <12 years vs. adolescents: ≥ 12 years), and the age of the mother at her child's birth (<25 years vs. ≥ 25 years). The latter was previously observed to be a risk factor for ADHD in children [209]. The stratified analyses were controlled for the same confounders as the analyses of the overall group. To account for residual confounding, the stratified analyses by child's age group were additionally adjusted for the continuous child's age. Similarly, the analyses stratified by mother's age at the child's delivery were adjusted for the continuous mother's age at the child's birth. All models included a random effect for family ID, to partially account for family influences.

In *paper 4*, the aim was to investigate the longitudinal effect of changes in DM exposure over time on the risk for MetS at latest examination wave (either W2 or W3). Here, children participating in ≥ 2 examination waves (W1&W2; W1&W3; W2&W3; W1&W2&W3) were included. Children could enter the cohort at W1 or at W2 (baseline age: mean= 6 years, SD=1.8), and were then followed up until W3. Children who at baseline were clinically diagnosed with chronic diseases (e.g. MetS, Type 2 Diabetes) or were taking related medications were excluded, to examine the role of DM exposure on incident metabolic outcomes. The mean age at last follow-up was 10 years (SD=2.4). To account for unbalanced data with a different number of observations (i.e., repeated measures) per each child, the assessment of DM at different time points, and subjects measured at different ages [195,210,211], a two-step trajectory approach was used. This approach enables the evaluation of changes in DM duration (hours/day) with increasing age and allows participants to have different intercepts and age-effects, such that each child has their individual DM trajectory.

1) *First step: Linear age-dependent trajectories of DM exposure*

The trajectories of DM exposure over age (2 to 16 years, centered at age 8) were estimated using linear mixed models by regressing continuous age to continuous DM exposure (h/day). To reduce data dimensionality and derive comparable exposure measures between children, the linear mixed models considered a two-level hierarchical cluster structure (1. repeated measurements, 2. nested within individuals). Models considered a random intercept and random linear slope over age for each child. The subject-specific DM intercepts and slopes were estimated from fixed and random effects in order to account for repeated measurements. To consider sex- and country-specific habits of DM exposure, the age-dependent trajectories were additionally calculated by sex and country of residence, considering sex- and country-specific population intercepts and slopes, respectively.

2) *Second step: age-dependent trajectories of DM exposure in association with incident MetS*

In longitudinal analyses, the estimated individual DM intercepts (i.e, baseline DM in h/day) and slopes (i.e., change of DM exposure over age in h/day/year) were used as independent (i.e., exposure) variables in association with z-scores of MetS, waist circumference, blood pressure, HOMA-IR, triglycerides and HDL-c at the most recent examination (W2 or W3, meaning, the highest age of each individual within the cohort). Generalized linear mixed regressions were used to calculate regression coefficients (β) and 95%CI, adjusting for confounders. Generalized linear mixed regression models are an extension of linear mixed models and are useful in longitudinal analyses. They allow response variables from different distributions and inclusion of both fixed and random effects. The association between DM trajectories and z-score of metabolic outcomes was investigated in stratified analyses by levels of MVPA (no MVPA at all, low MVPA, high MVPA) to identify a potential modifying effect of MVPA.

The impact of DM exposure during childhood on the risk of developing MetS <u>at a monitoring level</u> was further investigated. The slopes of the age-dependent DM trajectories were dichotomized at the population mean (random slope= 0 h/day/year) to identify children with increasing DM trajectories above or below the average. Logistic regressions were used to calculate odds ratios (OR) and 95%CI, adjusting for continuous individual DM intercept and potential confounders. Here, based on the rare disease assumption (MetS prevalence was 5.5%), the ORs instead of relative risks were used as association measures. Children who at baseline were at the monitoring level ($\geq 90^{th}$ percentile) for MetS, abdominal obesity, dyslipidemia, elevated BP and insulin resistance were excluded from the respective analyses, in order to examine the long-term effect of DM exposure on <u>incident</u> MetS and its components. The association of the dichotomized DM trajectories with MetS and its components was further investigated in stratified analyses by sex, country, and parental educational status, to explore underlying differences and characterize children that are most vulnerable to the potential adverse effect of DM.

4. Results

In this chapter, the main findings of the thesis are presented. First, the results of the systematic review are described, and then, the results of the observational research are provided. The findings are presented by type of DM investigated in association with the outcomes of interest, starting with the single DM exposures, namely SM, internet, smartphone, TV, and PC exposure. The role of duration of total DM exposure in association with the outcomes of interest is described last.

4.1. Social media exposure, dietary intake, and related behaviors

4.1.1. Social media exposure, unhealthy food intake, and dietary behaviors

The SLR (*paper 1, Appendix, page 90*) confirmed that SM exposure is associated in a dose-response manner with daily intake of sugar and caffeine [128], and with consumption frequency of SSBs, sweets, and fried foods, in both children and adolescents [152]. Moreover, SM exposure is associated with a higher likelihood of skipping breakfast in adolescents [138]. One RCT found that adolescents using WhatsApp consumed 58% more snacks (corn puffs) than the control group who read an offline article [158]. Exposure to culinary videos on SM influenced the food choice of Flemish adolescents [151]. Watching the cooking video of a sweet snack reduced the liking of fruits and vegetables, and the likelihood of choosing a fruit over a cookie. In contrast, watching a fruit and vegetable video did not influence adolescents' food choices [151]. Among Chinese adolescents, watching videos online was associated with higher fast food preference, with those living in rural areas reporting a higher frequency of eating at fast food restaurants [156]. A similar association was observed in Indonesian children [157]. In Dutch children, the frequency of watching YouTube video blogs was associated with increased unhealthy beverage consumption two years later [146].

4.1.2. Social media exposure, nutrition literacy, and healthy food intake

In children, exposure to SM was not associated with higher nutrition literacy [157]. Two interventional studies found that SM influencers' advertising of healthy snacks (banana or strawberry) on Instagram did not influence children's ad-libitum intake of these foods [69], independently of the influencer's lifestyle (athletic or sedentary) [150]. However, when the sedentary SM influencer promoted unhealthy foods (donuts), this led to increased choice for healthy snacks (strawberries) [150]. Among adolescents, exposure to healthy foods (fruits and vegetables) posted on SM either by peers, celebrities, or influencers, was positively associated with the intake of healthy foods, mediated through higher food literacy [152]. Nevertheless, food literacy did not mediate the association between exposure to unhealthy food posts (soft drinks, fried food, chips, and candy) on SM and reported frequency intake of those foods [152]. The associations between SM exposure and the dietary intake of children and adolescents may be explained by a neuro-physiological mechanism, where exposure to digital food images affects children's brain activation in areas related to reward, attention, and decision-making. The impact of social influencers, including the role of peers and SM influencers provides further information on the observed associations.

4.1.3. The neuro-physiological mechanism: impact on attention, memory, and reward response

Exposure to food images (unhealthy vs. healthy) compared to non-food images impacted the neural activation of different brain areas in children and adolescents. In children, exposure to food vs. non-food digital images led to increased activation in brain areas related to attention and visual processing (visual cortex) [135], memory functions (left and right posterior para-hippocampal gyri (PPHG)), information processing and decision-making (dorsomedial prefrontal cortex) [135]. Activation in similar areas was observed after exposure to unhealthy compared to healthy food images, including regions specialized in visual attention (right temporal/occipital gyri), reward (left precentral gyrus), and memory-related processes (left hippocampus) [145]. Masterson et al. [134] compared children's neural response to high vs. low-calorie food images following exposure to either food or toy advertisements. Compared to viewing toy advertisements, children who viewed food advertisements and were then exposed to high-calorie food images showed reduced neural activation in regions related to cognitive control, including the left fusiform gyrus, left supra-marginal gyrus, and left orbitofrontal cortex. This suggests an interaction between advertisement type and the calorie content of food images on children's cognitive control.

In adolescents, exposure to food vs. non-food images also led to increased activation in areas related to gustation and reward (insula and operculum) [140]. Adolescents with an implicit incentive salience (i.e., wanting, motivation) for palatable foods like fried potatoes or sweets showed a reduced response in regions associated with inhibitory control (dlPFC, medial prefrontal cortex (mPFC), and the right inferior parietal lobule) after exposure to unhealthy vs. healthy food images [133], indicating difficulties to inhibit consumption impulses. Adolescents at high vs. low risk for obesity (given parental obesity), who were repeatedly exposed to milkshake images, showed a higher neural response in brain areas related to reward (the caudate and posterior cingulate cortex) both without tasting [139], and after tasting the milkshake [136]. A significant effect of paternal but not maternal obesity was observed in caudate response after repeated exposure to milkshake cues [139].

The role of children's and adolescents' appetitive state when exposed to food images

The appetitive state (hungry vs. satiated) seemed to play a role in the neural processing of unhealthy vs. healthy food images. Children and adolescents in a hungry compared to a satiated state showed increased response in areas related to reward (dorsomedial and medial prefrontal cortex (dmPFC)) and self-control during food choices (dlPFC) [144] after exposure to high vs. low-calorie food images. Further activation in brain areas related to sensory perception and processing (left thalamus) was observed in children only [132]. When children were exposed to food images of high dietary ED, they showed lower activation in areas specialized in appetite regulation (left hypothalamus), independent of the satiety status prior to the exposure [130]. Increased activation in regions involved in reward and taste processing (caudate, cingulate, and precentral gyrus) was also observed [131].

The role of dietary energy density and portion size of foods depicted in digital images

The dietary ED and portion size of foods depicted in digital images also affected children's neural response in brain areas related to reward, inhibitory control, and decision-making, which in turn impacted food intake. Exposure to food images of large vs. small portion sizes led to increased activation in brain areas specialized in information processing and inhibition control (the right inferior frontal gyrus (IFG)) [130], decision-making (left vmPFC), salience, and associative learning (left OFC)[137]. Children who showed heightened activation in the vmPFC after exposure to food images in varying portion sizes, increased their food intake from baseline by 32% more than children with low activation [137]. Children exposed to images of high ED foods in large vs. small portion sizes showed increased activation in areas associated with reward (right caudate) and inhibitory control (right IFG). Children with increased activation in the IFG consumed 87% less dietary energy from baseline compared to children with low activity in this region, indicating an increased conflict. Exposure to images of low ED foods in large vs. small portions did not show a brain response-food intake interaction for low ED foods [137], suggesting that exposure to images of healthy foods in higher portion sizes does not affect the actual healthy food intake. Of note, these associations were not investigated in adolescents.

4.1.4. The social influencers: the role of peers and SM influencers

The social influencers, namely peers and SM influencers differently impacted the association between SM exposure and food intake in children and adolescents. First, peers who shared food pictures on SM impacted adolescents' food intake, depending on the type of food depicted (healthy or unhealthy). Although adolescents gazed at unhealthy food pictures for longer when posted by peers compared to celebrities or companies [149], exposure to images of unhealthy snacks and SSB posted by adolescent peers did not affect the subsequent intake of these foods and beverages [142]. Another interventional study compared the effect of exposure to videos of peers addressing barriers to healthy eating (i.e., peers acting as role models) on adolescents' vegetable intake compared to the control group. At post-intervention (after eight weeks), significantly more adolescents in the treatment group ate ≥3 servings of vegetables/day in the preceding week compared to the control condition [129]. These results suggest that peers may be a potential source within the SM environment for promoting healthy food intake in adolescents.

Second, the SM influencer also played a role on the impact of SM exposure on children's and adolescents' dietary intake. The SLR (*paper 1*) showed that SM influencer advertising of unhealthy foods led to higher intake of these foods in both children and adolescents. Coates and colleagues [69] found that children exposed to unhealthy food pictures advertised by an Instagram influencer consumed more energy in total, and more energy from unhealthy snacks compared to children exposed to healthy food and non-food images. Moreover, exposure to SM influencers' marketing of a branded unhealthy snack with or without advertisement disclosure (using precise wording: "This is an advert"), led to higher consumption of the advertised branded snack compared to the alternative brand, indicating no interaction with the usage of advertising disclosure [141]. Additionally, watching branded food videos on SM (e.g., YouTube) increased the preference for unhealthy foods (sweets and fried foods) [152], and the consumption of unhealthy beverages (fruit juice, sports, and soft drinks), independent of age [67,154]. While exposure to unhealthy food/beverage advertisements on SM was associated with a high beverage but not food intake, engagement with advertising posts on SM by liking or sharing them, was associated with a high intake of both unhealthy foods and beverages [154]. This suggests that engagement with food/beverage advertising might have a higher impact on adolescents' diets than exposure per se. Remarkably, adolescents exposed to unhealthy vs. healthy food advertisements could recall and recognize unhealthy food brands more than healthy ones when coming from celebrities and companies, but not peers [149]. This indicates that unhealthy foods are memorized better than healthy ones, and the effect of the advertised unhealthy food on the memory depends on the source of advertising.

4.2. Internet exposure in association with sensory taste preferences and cognitive functioning

The SLR confirmed that prolonged internet use was associated with poor nutritional behaviors, including low consumption frequency of fruits and vegetables, but high frequency intake of SSBs, fast food and unhealthy snacks, and more frequent breakfast skipping [159], especially in girls using multiple devices [148]. ***The purpose of using the internet seemed to play an underlying role***. Prolonged internet use for entertainment was associated with unfavorable nutritional behaviors like high consumption frequency of fried foods, sweets, and snacks [159]. Internet use for educational purposes (searching for education-related information or studying) was positively associated with a high intake of unhealthy snacks and of fruits and vegetables [159].

The cross-sectional association of internet exposure with sensory taste preferences (*paper 2*, Appendix, page 116), and cognitive functioning (*paper 3*, Appendix, page 135) was investigated in children and adolescents participating in W3 of the IDEFICS/I.Family cohort. Prolonged internet exposure (>2 h/day) was associated with higher odds for fatty taste preference in adolescents only, especially girls. Moreover, prolonged internet exposure was negatively associated with bitter taste preference and positively related to salty taste preference, particularly in adolescent boys. No association between internet exposure and sweet taste preference was observed. Remarkably, one additional hour of daily internet exposure was associated with a 0.57-unit increase in the emotion-driven impulsiveness score, independent of confounders. No association was observed between internet exposure and cognitive inflexibility or decision-making ability.

4.3. Smartphone exposure in association with sensory taste preferences and cognitive functioning

The SLR showed that prolonged smartphone exposure was associated with unfavorable nutritional behaviors among adolescents, including a high-frequency intake of sweets [155] and a low frequency of eating breakfast [160]. ***Besides duration, the purpose of using smartphones also seemed to play an important role.*** Adolescents who used smartphones most frequently for communication (chatting, using SM) had a higher likelihood of consuming fast food than those who used smartphones mainly for educational purposes [160].

Findings of paper 2 showed that increasing duration of smartphone exposure was associated with higher odds for fatty taste preference independently of diet quality and weight status. Smartphone exposure for a prolonged (>2 h/day) compared to short duration (≤ 2 h/day) was positively associated with fatty taste preference in all participants and in stratified analyses by sex and age group. Additionally, prolonged smartphone exposure was positively related to sweet taste preference, especially among children. An inverse association was found between prolonged smartphone exposure and bitter taste preference, particularly in adolescent boys. Prolonged smartphone exposure was positively associated with salty taste preference among young girls only. Cross-sectionally, one additional hour of daily smartphone exposure was associated with a 0.74-unit increase in emotion-driven impulsiveness score of all children and adolescents, independently of confounders (*paper 3*, Appendix, page 135). In addition, smartphone exposure was positively associated with cognitive inflexibility and negatively associated with the decision-making ability score of all children and adolescents.

4.4. TV viewing in association with sensory taste preferences and cognitive functioning

The cross-sectional association of TV viewing with sensory taste preferences was also investigated (paper 2, Appendix, page 116). TV viewing for longer than 2 h/day compared to ≤2 h/day was positively associated with sweet taste preference in all children and adolescents, with more robust associations in young girls. Prolonged TV viewing (>2 h/day) was positively associated with fatty taste preference in girls only, with stronger associations among adolescent girls. Additionally, increasing durations of TV viewing were associated with lower odds for bitter taste preference. The stratified analyses by sex showed that boys but not girls with prolonged TV viewing (>2 h/day) reported lower bitter taste preference. No associations with salty taste preference were observed. One additional hour of daily TV viewing was positively associated with emotion-driven impulsiveness among children and adolescents (*paper 3*, Appendix, page 135). However, TV exposure was not associated with cognitive inflexibility or decision-making ability.

4.5. Computer exposure in association with sensory taste preferences and cognitive functioning

Increasing durations of PC exposure was positively associated with fatty taste preference in European children and adolescents (*paper 2*, Appendix, page 115). Prolonged (>2 h/day) compared to short duration (≤ 2 h/day) of PC exposure was cross-sectionally associated with higher odds for fatty taste preference among adolescents, especially adolescent girls. In contrast, a negative association with bitter taste preference among adolescent boys was observed. Prolonged PC exposure was positively associated with salty taste preference in young girls only. Nevertheless, large 95%CIs were obtained, requiring cautious interpretation. Among ADHD-free children and adolescents, one additional hour of daily PC exposure was associated with a higher score for emotion-driven impulsiveness and decision-making ability. No associations with cognitive inflexibility were observed (*paper 3*, Appendix, page 135).

4.6. Media multitasking in association with food intake and cognitive functioning

The SLR provided evidence of the role of engagement with media multitasking on the food intake of children and adolescents. One RCT showed that media multitasking - measured as simultaneous use of smartphone, iPad, and TV - did not affect dietary energy intake compared to single-screen use (TV only) [153]. Another cross-sectional study found that using multiple devices for a prolonged duration (TV, computer, videogames, and smartphone, each used for >2 h/day) was associated with increased consumption frequency of fried foods, sweets, and snacks, compared to using multiple devices for a short duration [155].

The cross-sectional association between media multitasking and measures of cognitive functioning in children and adolescents was investigated using data from W3 of the IDEFICS/I.Family cohort (*paper 3*, Appendix, page 135). Media multitasking was positively associated with emotion-driven impulsiveness and cognitive inflexibility score of all children and adolescents (a 0.73-unit and 0.39-unit increase, respectively), independent of their weight status, family structure, and psycho-social well-being. Moreover, media multitasking was negatively associated with the decision-making ability score of all participants. Engagement in high media multitasking (more than two activities simultaneously) compared to low media multitasking (1-2 activities simultaneously) was associated with a 1.6-unit increase in the emotion-driven impulsiveness score. This association was more pronounced in girls, adolescents, and participants living in one-parent families. Higher media multitasking was negatively associated with decision-making ability across all strata, with stronger associations in boys and participants living in one-parent families.

4.7. Underlying patterns of digital media exposure in association with cognitive functioning

To identify underlying patterns of DM exposure in children and adolescents participating in W3 of the cohort, a latent class analysis was conducted based on four single DM variables: TV, PC, internet, and smartphone exposure (*paper 3*, Appendix, page 135). Four latent profiles (i.e., patterns) of DM exposure were identified: i) low exposure to all media types (57% of children); ii) high DM exposure except smartphone (13%); iii) high smartphone and internet exposure, combined with medium TV and low PC exposure (10%); iv) medium TV and internet exposure, combined with a low smartphone and PC exposure (20%). The four DM patterns were cross-sectionally investigated in association with measures of cognitive functioning. Participants with "high DM exposure, except smartphone" showed almost 2-point higher impulsivity score (β, 1.81; 99.9%CI, 0.67-2.96) compared to those with "low exposure to all media", after adjusting for media multitasking behavior and other covariates. This association was more prominent in girls, adolescents, participants living in two-parent families, and who had parents with medium and high educational backgrounds. A positive association was also found between "high DM exposure, except smartphone" patterns and decision-making ability. Participants with "high smartphone and internet, combined with medium TV and low PC exposure" showed higher scores for impulsivity and cognitive inflexibility, and lower score for decision-making ability compared to those with "low exposure to all media". Higher association estimates for impulsivity were found among girls, adolescents, and participants in two-parent families.

4.8. Digital media exposure in association with reported clinical ADHD diagnosis

The potential cross-sectional association of DM exposure with clinical ADHD diagnosis was examined in W3 (unpublished data) and results are shown in ***Table 2*.** The combined DM exposure (TV, PC, and internet use in h/day) was similar in children diagnosed with ADHD (median/IQR)= 2.75/1.46,4.75) and ADHD-free participants (median/IQR= 2.75/1.71,4.50), respectively. However, one additional hour of combined DM exposure and exposure to single media (TV, PC, internet, smartphone) was associated with lower odds for clinical ADHD diagnosis. These associations were more pronounced in boys and children. Remarkably, media multitasking was the only media variable associated with higher odds of a clinical ADHD diagnosis. Particularly, engagement in media multitasking was associated with approximately 30% higher odds for ADHD diagnosis in boys and adolescents.

Table 2. Odds ratios for reporting a clinical ADHD diagnosis in children and adolescents by type of digital media exposure

ADHD diagnosis (Ref. No) [a]	DM exposure	TV viewing	Computer exposure	Internet exposure	Smartphone exposure	Media multitasking
	Adjusted OR (95% CI)	Adjusted OR (95% CI)	Adjusted OR (95% CI)	Adjusted OR (95% CI)	Adjusted OR (95% CI)	Adjusted OR (95% CI)
Analysis group [b]	0.92 (0.83, 1.02)	0.87 (0.68, 1.11)	0.80 (0.60, 1.07)	0.94 (0.78,1.14)	0.80 (0.60, 1.05)	1.16 (0.93, 1.43)
Boys	0.89 (0.78, 1.01)	0.78 (0.57 1.06)	0.83 (0.61, 1.14)	0.87 (0.67, 1.12)	0.83 (0.58, 1.20)	**1.32 (1.02, 1.70)**
Girls	1.00 (0.84, 1.20)	1.08 (0.72 1.60)	0.62 (0.29, 1.30)	1.06 (0.79, 1.42)	0.77 (0.50, 1.21)	0.90 (0.60, 1.35)
Children	0.82 (0.66, 1.03)	0.68 (0.45, 1.03)	0.68 (0.39, 1.21)	1.03 (0.68, 1.55)	0.69 (0.25, 1.92)	1.02 (0.69, 1.50)
Adolescents [c]	0.95 (0.85, 1.07)	0.99 (0.72, 1.36)	0.84 (0.60, 1.18)	0.93 (0.74, 1.15)	0.82 (0.61, 1.11)	1.26 (0.96, 1.65)
Low mother's age at birth (<25 years)	0.85 (0.67 1.08)	0.99 (0.56, 1.75)	**0.31 (0.10, 0.90)**	0.89 (0.59, 1.34)	0.72 (0.39 1.34)	1.17 (0.71, 1.91)
High mother's age at birth (≥25 years) [c]	0.94 (0.84, 1.05)	0.85 (0.64 1.12)	0.93 (0.69, 1.25)	0.94 (0.76 1.17)	0.79 (0.58, 1.09)	1.14 (0.90 1.45)

[a] ADHD- Attention Deficit Hyperactivity Disorder, DM- digital media; [b] Models are adjusted for age (continuous), sex (not in stratified analysis by sex), pubertal status, diet quality, unhealthy snack consumption frequency, parental education attainment, mother's age at child's birth (not in the respective stratified analyses), country, mother's smoking frequency during pregnancy, child delivery via Caesarean-section, child's well-being score. Bold significance is provided via CIs. [c] The stratified analyses by age group are further adjusted for continuous age to account for residual confounding.

4.9. Combined digital media exposure in association with sensory taste preferences

The cross-sectional association between combined DM exposure (measured as TV, PC, and internet exposure) and sensory taste preferences, adjusting for weight status and other covariates, was examined in *paper 2* (Appendix, page 116). Prolonged (>2 h/day) compared to short DM exposure (≤2 h/day)was associated with higher odds for sweet taste preference in adolescents (≥ 12 years). This association was similar in boys and girls, and independent of the sweet propensity intake. Prolonged duration of DM exposure (>2 h/day) was associated with higher odds for fatty taste preference, independent of the propensity intake of fatty foods, particularly among adolescents. Increasing durations of DM exposure was negatively associated with bitter taste preference in all children and adolescents. No association was observed for salty taste preference.

4.10. Long-term association between digital media exposure and metabolic syndrome

The longitudinal association between DM exposure (measured as TV, PC and internet exposure) and risk of incident MetS over a follow-up of two to six years was examined in children and adolescents of the IDEFICS/I.Family cohort (*paper 4*, Appendix, page 164). DM exposure increased as children grew up: from 2.4 h/day at the age of 2 years to 5.5 h/day at 16 years. Boys had a steeper DM increase over age compared to girls (boys: 2.6 h/day at 2 years to 5.9 h/day at 16 years; girls: 2.2 h/day at 2 years to 5 h/day at 16 years, **Figure 4**). Estonian children showed the steepest DM increase: from 3 h/day at the age of 2 years to 6.6 h/day at 16 years, while Spanish children showed the lowest DM trajectory (**Figure 4**).

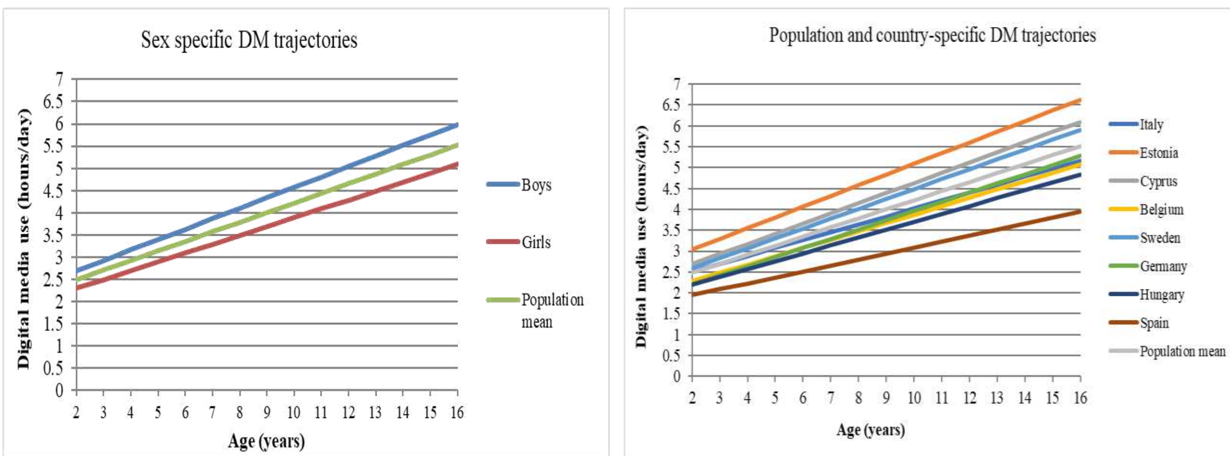

Figure 4. Age-dependent DM exposure in children and adolescents - by sex and country [1].

[1]After publication of paper 4, a programming error was found in the calculation of DM trajectories. Thus, the DM trajectories shown here are slightly higher than the published version. All subsequent analyses were corrected, and remained similar to the published ones. An erratum was submitted to the editor (Erratum, Appendix, page 178).

The increasing duration of DM exposure at baseline (DM intercept, in W1 or W2) and with increasing age (DM slope) was positively associated with the z-score of MetS after two to six years (W2 or W3 of the cohort). Remarkably, one additional hour of DM exposure over time (DM slope, h/day/year) was associated with a 0.26-unit increase in MetS z-score at follow-up, independent of baseline MetS z-score and current abdominal obesity status. One additional hour in baseline DM and DM slope were positively associated with the z-score of HOMA-IR and inversely associated with the z-score of HDL-c at follow-up. Also, baseline DM exposure, but not DM slope, was positively associated with the z-scores of waist circumference and triglycerides after two or six years. In the sub-group of children with accelerometer data, analyses were further adjusted for objectively-measured MVPA and sedentary time, and results remained similar. However, larger

95%CIs were observed (including the null) due to the smaller sample size. The associations between age-dependent DM trajectories and z-scores of metabolic outcomes were stratified by levels of MVPA duration (no MVPA at all, low MVPA, and high MVPA at latest examination wave), to test for a moderating effect of MVPA (unpublished data, **Table 3**). Across all categories of MVPA, baseline DM was positively associated with the z-scores of waist circumference and HOMA-IR, and inversely associated with the HDL-c z-score after two to six years. DM slope was positively associated with z-scores of MetS and its components, both in the high and low MVPA groups. In children with no MVPA at all, DM slope was not associated with the MetS z-score, but was inversely associated with the z-scores of single components, with more robust associations observed for waist circumference.

Children who increased their DM trajectory above the population average showed 22% higher risk for incident MetS (at monitoring level) compared to children with below-average DM trajectory. This risk was higher in boys (41%) than in girls (10%). Baseline DM exposure remained associated with higher risk for abdominal obesity, dyslipidemia, and insulin resistance. Boys were at higher risk for developing dyslipidemia than girls, but at lower risk for abdominal obesity. In countries with steepest DM trajectories - Cyprus and Sweden - an above-average increase in DM exposure was associated with a higher risk for incident MetS. This association was observed in northern countries (Sweden, Germany) but not in southern countries (Spain, Italy), suggesting regional differences in the associations between age-dependent DM exposure and MetS.

Table 3. Odds ratios for metabolic syndrome and its components in children and adolescents, by DM intercept and DM slope, and stratified by levels of MVPA at the latest examination wave.

Z-score of metabolic outcomes	DM exposure	Children with accelerometer data	No MVPA at all [a]		Low MVPA		High MVPA	
		Adjusted β (95% CI) [b]	**N**	**Adjusted β (95%CI) [c]**	**N**	**Adjusted β (95%CI)**	**N**	**Adjusted β (95% CI)**
Waist circumference	**Intercept**	**0.17 (0.10, 0.24)**	2152	**0.18 (0.09, 0.29)**	1028	**0.18 (0.05, 0.32)**	1031	0.09 (-0.04, 0.23)
	Slope	0.04 (-0.24, 0.32)		**-0.46 (-0.88, -0.04)**		**0.72 (0.14, 1.29)**		0.39 (-0.16, 0.95)
Blood pressure [d]	**Intercept**	0.004 (-0.05, 0.06)	2043	0.02 (-0.06, 0.10)	995	-0.007 (-0.12, 0.10)	987	-0.02 (-0.14, 0.09)
	Slope	0.08 (-0.15, 0.32)		-0.09 (-0.43, 0.24)		0.35 (-0.14, 0.83)		0.18 (-0.31, 0.67)
Triglycerides	**Intercept**	0.05 (-0.02, 0.12)	1376	0.07 (-0.03, 0.17)	645	-0.06 (-0.22, 0.08)	657	0.10 (-0.05, 0.27)
	Slope	0.04 (-0.27, 0.35)		-0.16 (-0.59, 0.27)		**0.66 (0.02, 1.30)**		-0.09 (-0.74, 0.55)
HDL-c	**Intercept**	-0.06 (-0.13, 0.008)	1147	-0.08 (-0.19, 0.01)	686	-0.004 (-0.15, 0.14)	719	-0.07 (-0.21, 0.07)
	Slope	**-0.36 (-0.67, -0.06)**		-0.37 (-0.81, 0.06)		-0.57 (-1.19, 0.05)		-0.13 (-0.72, 0.45)
HOMA	**Intercept**	**0.12 (0.01, 0.23)**	807	0.05 (-0.11, 0.22)	415	0.17 (-0.03, 0.38)	456	0.15 (-0.06, 0.36)
	Slope	0.19 (-0.26, 0.65)		-0.12 (-0.82, 0.57)		0.90 (-0.008, 1.80)		0.15 (-0.67, 0.99)
MetS	**Intercept**	0.04 (-0.04, 0.12)	721	0.03 (-0.08, 0.16)	361	0.002 (-0.18, 0.18)	386	0.01 (-0.17, 0.19)
	Slope	0.28 (-0.07, 0.63)		0.006 (-0.49, 0.50)		0.80 (-0.001, 1.61)		0.42 (-0.24, 1.09)

[a] MetS- metabolic syndrome, MVPA – moderate to vigorous physical activity, DM- digital media, HDL-c – high-density lipoprotein cholesterol, HOMA- homeostasis model assessment for insulin resistance; [b] Models are based on the accelerometer sample and are adjusted for age (continuous), sex, pubertal status, HDAS, snack consumption, parental educational attainment, country, observation period (age at follow-up – age at baseline) and baseline z-scores of the respective outcome, as well as MVPA, sedentary time and valid accelerometer wear time. Bold significance is provided via confidence limits. N varied due to missing values for each outcome; [c] The stratified models are adjusted for the same confounders as the overall models, expect for MVPA time; Further adjustment for duration of light PA did not attenuate the results. [d] Models for the z-scores of BP, HDL-c, TRG, and HOMA-IR are additionally adjusted for the z-score of waist circumference at the last examination wave. The number of participants varied for metabolic outcomes due to missing values.

5. Discussion

The findings of this doctoral dissertation suggest that DM exposure, measured as exposure to single media types (TV, PC, smartphone, internet, and SM) or as combined DM duration, is associated with unfavorable health outcomes and dietary behaviors in children and adolescents. First, the results suggest that SM exposure leads to unhealthy food intake and poor eating habits in children and adolescents, independent of age. Second, prolonged exposure to single DM is positively associated with sweet, salty, and fatty taste preference and negatively associated with bitter taste preference, independent of the actual dietary intake. Third, exposure to modern DM, like smartphones and internet, and the related media multitasking is positively associated with the emotion-driven impulsiveness and cognitive inflexibility, and negatively associated with the decision-making ability of children and adolescents. Fourth, high DM exposure during childhood is associated with a higher risk for metabolic syndrome and its components in the long term. ***Figure 5*** illustrates the observed associations. In the following, these results are discussed in the context of the latest knowledge in the field. Additionally, the strengths and limitations of the research conducted are acknowledged.

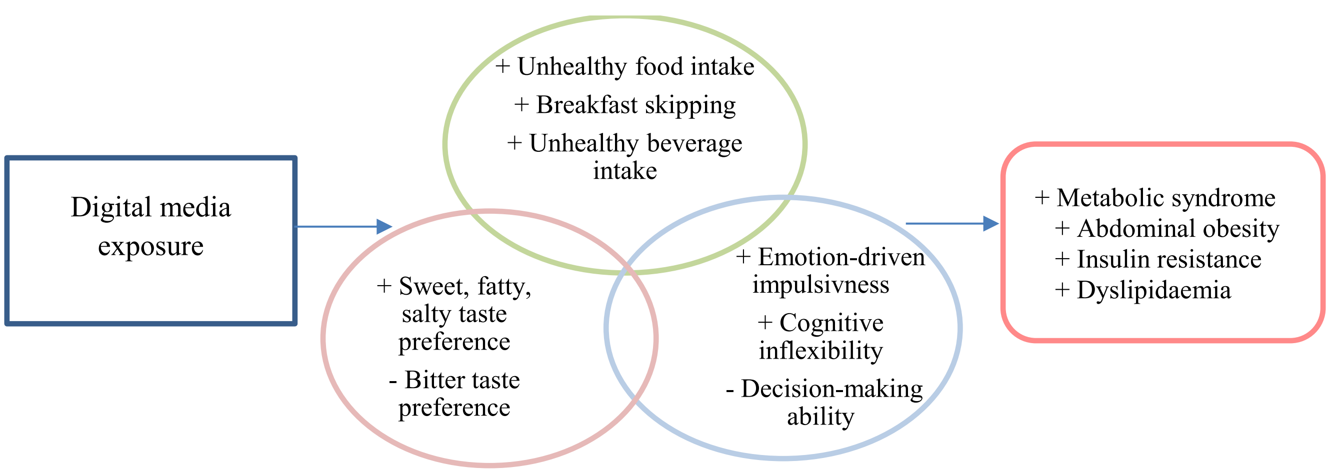

Figure 5. Illustration of associations found in the present doctoral dissertation[1].

[1]The overlap between the dietary outcomes, sensory taste preferences, and cognitive functioning was not directly examined in the present thesis, but was instead inferred from the data.

5.1. Social media exposure impacts the dietary intake and eating behaviors of children and adolescents

Exposure to SM was found to negatively impact the dietary intake and eating behaviors of healthy children and adolescents in developing and developed countries. A dose-response relationship was observed between exposure to SM and daily sugar and caffeine intake, the consumption frequency of SSB, sweets, and fried foods, and more frequent breakfast skipping. Exposure to a range of SM activities, from using messaging applications like WhatsApp to watching videos on YouTube or to food advertising by SM influencers on Instagram - either with or without advertising disclosures, negatively impacted food choice and intake, independent of age. Unfavorable dietary outcomes included unhealthy snack consumption at ad-libitum, higher consumption frequency at fast food restaurants, and unhealthy beverage intake after two years. These findings align with previous systematic reviews on digital advertising [212] and suggest that SM exposure has short-term and long-term adverse effects on children's and adolescents' dietary intake and eating behaviors. Findings support the need to limit SM exposure and regulate the digital advertising of unhealthy food and beverage products targeting children and adolescents. ***Figure 6*** presents a conceptual model in which the link between SM exposure and dietary intake is grounded.

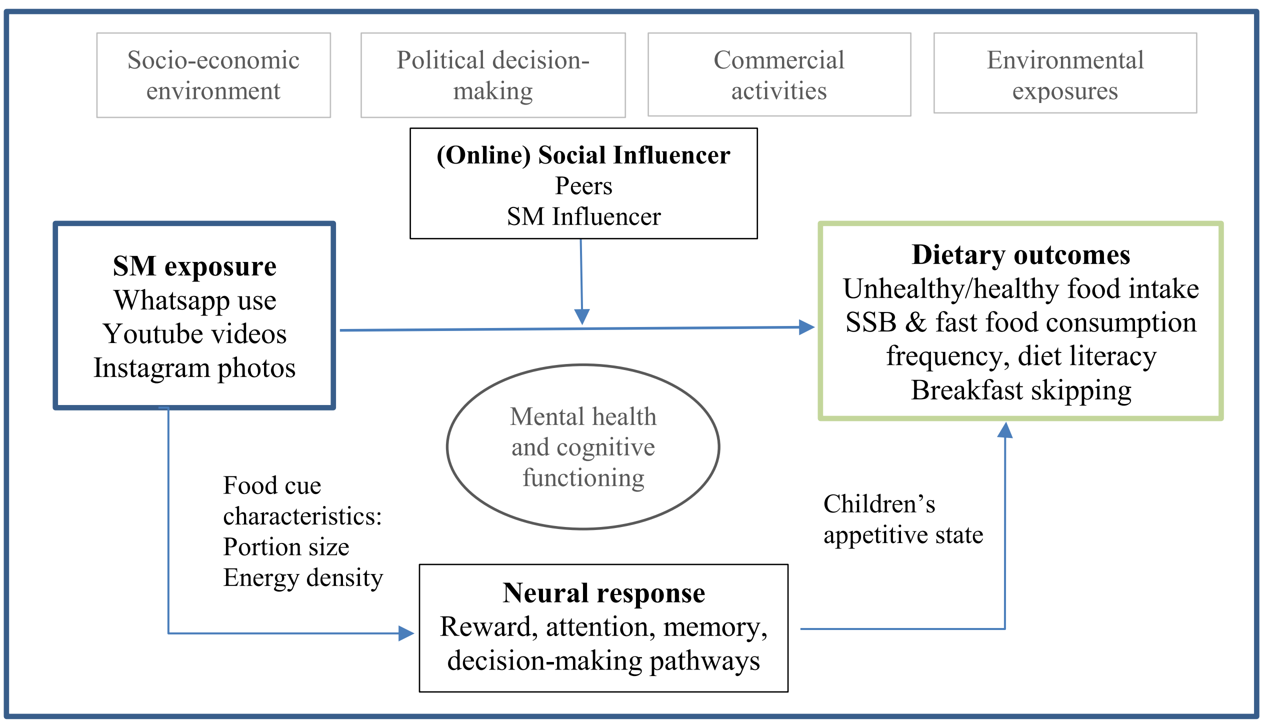

Figure 6. A proposed conceptual model that explains the link of SM exposure with dietary intake.[1]

[1] The role of social influencers's was not examined as an effect modifier, but instead as two different influencing exposures within the SM environment. The boxes in gray represent determinants of health outside of the digital environment that were not directly investigated in this thesis, but are encompassed within the digital ecosystem.

A prominent mechanism underlying the adverse effects of SM exposure on children's and adolescents' diets lies in the neuro-physiological response elicited by food cues embedded in the digital environment. The SLR (*paper 1*) showed that exposure to food vs. non-food images led to increased activation in brain areas specialized in attention, visual and information processing, memory functions, decision-making, gustation, and reward, independent of age and related brain maturation. This neural response was especially higher when children and adolescents were exposed to unhealthy food images than healthy ones and if they were in a hungry state. Exposure to unhealthy food images also led to reduced appetite regulation, independent of the satiety status. Moreover, viewing food vs. advertisements led to reduced activation in areas related to inhibitory control. These findings suggest that viewing unhealthy food images and food advertisements on smartphones and SM potentially increases children's and adolescents' appetite and desire to eat unhealthy foods, while it reduces their ability to inhibit the impulses of choosing the highly rewarding unhealthy foods over healthy ones, especially when in a hungry state (e.g., after waking up or after school). These findings have implications for eating and buying decisions, as lower inhibitory and executive control means a lower ability to control the impulses to purchase and consume unhealthy foods. This is also supported by the findings of *paper 3*, which showed that exposure to DM was negatively associated with the decision-making ability of children and adolescents, in the context of weighing short-term rewards against long-term adverse outcomes.

The portion size and the dietary ED of foods depicted in the digital images impacted the subsequent neural response of children, while this effect remains unknown among adolescents. When children were exposed to food images of large relative to small portion size, they showed higher activation in areas related to reward, associative learning, and decision-making and increased the energy intake compared to children with low activation. These findings are particularly problematic given the abundance of images and videos of foods in large portion-size all over SM platforms, exposure to which has been associated with unhealthy food choices [70,213]. When children were exposed to pictures of high-ED foods in large portions, they showed increased activation in regions specialized in inhibitory control and reduced the intake of high-ED foods. These results suggest that children may experience an increased conflict and more information processing on the social judgment related to the consumption of large portions of unhealthy foods, which in turn may lead to reduced intake of those foods. Of note, most fMRI-based studies are based on single experiments, and children's neural response to repeated exposure to food images might differ from the single exposure. Therefore, future repeated RCTs are needed to confirm the aforementioned effects.

Exposure to unhealthy food advertising by SM influencers was identified as an independent risk factor within the SM environment for unhealthy food choice and intake in children and adolescents. Similar advertising effects were observed when unhealthy products were advertised by video-gaming influencers in videogame live-streaming platforms like Twitch or Facebook Gaming Live was associated with higher purchase and consumption of the advertised foods, mediated through positive attitudes towards those foods [214]. Findings confirm that SM influencers can successfully shape children's and adolescents' food preferences by endorsing brand products in their SM posts [215]. This is supported by the para-social interaction theory [216], which suggests that children and adolescents develop a close emotional relationship with SM influencers, are likelier to adopt their behavior in their daily life, and hence, are more vulnerable to the adverse advertising effects [217,218].

The evidence examining the effects of SM exposure on healthy food intake and nutrition literacy was inconsistent, where negative and positive associations were observed depending on the exposure source. Findings suggest that mere exposure to SM influencers' advertising of healthy foods might not suffice to improve children's food intake [69]. Instead, the characteristics of the SM influencer seemed to play an important role. SM influencers displaying a sedentary lifestyle and promoting unhealthy foods on Instagram appeared to have a "counter-productive" effect on their followers' food choices, as higher consumption of healthy snacks was observed in the exposed children. This is supported by the social cognition theory, where negative consequences related to unhealthy food consumption, like a sedentary lifestyle, may impact children's healthy food choices, and they may no longer show a preference for those foods, and instead choose healthier food options [219]. Future interventions on SM may use this finding as it supports the Healthy Food Promotion Model, which emphasizes the role of the delivered message and situational factors on children's susceptibility to food cues [220]. Of note, only one study in the SLR examined the impact of SM influencer characteristics on children's food intake. Hence more research is warranted, also considering other aspects, such as the number of followers and likes an SM influencer has, which may lead to different responses among followers [221].

The peer influence among adolescents may also help tailor nutritional interventions targeting youth. Peers (friends or acquaintances) compared to SM influencers (i.e., internet celebrities) showed a higher potential for promoting vegetable intake among adolescents on SM. One reason may be that electronic recommendations from peers (eWord of Mouth) in the form of "likes" and "shares" are highly trustworthy; therefore, peers can significantly shape consumption-related decision-making in adolescents [222]. Second, peers are considered a more trusted source than influencers because adolescents know that no commercial interest is involved [223]. Third, adolescents, especially girls, may feel under pressure from peers; therefore, they try to convey a positive influence by eating healthy foods [224]. The results of this thesis indicate that despite the limited and inconsistent evidence, SM may help to promote healthy eating in youth. Previous interventions that used SM for improving adolescents' nutritional behaviors were mainly based on outdated SM forms rather than commercial platforms like Instagram or Facebook [41,42]. These interventions were more successful at improving the intake of favorable foods (fruits and vegetables) rather than decreasing the intake of unhealthy foods [41]. Hence, nutritional interventions targeting children and adolescents on SM should consider "active ingredients" like the source of advertising (peer or SM influencer), the type of message (encouraging healthy food intake or discouraging intake of unhealthy foods), and the contextual factors (SM influencers with a sedentary or active lifestyle).

5.2. Digital environment may alter children's and adolescents' sensory taste preferences

In line with my hypotheses, exposure to DM is positively associated with sensory taste preferences for sweet, fatty, and salty-tasting foods, which can be considered proxies for unhealthy food preferences. These associations were stronger among adolescents, particularly females. Moreover, exposure to DM was negatively associated with bitter taste preference, a proxy for healthy food preferences, with stronger associations among male adolescents. These findings align with a previous study where eating while watching TV was associated with decreased preference for bitter-tasting foods and a higher preference for sweet-tasting foods [225]. Results shed light on a potential mechanism via which DM exposure may impact children's and adolescents' eating behaviors and weight status. Exposure to DM and the food cues in the digital environment may influence children's sensory taste preference by favoring the preference for sweet, fatty, and salty-tasting foods over bitter-tasting ones. Given the influence of taste preferences on food intake, this might lead to higher intake of unhealthy foods, which can later impact children's weight status.

Three potential mechanisms underpin the associations between DM exposure and sensory taste preferences. **First**, branding and advertising of foods high in fat and sugar influence children's taste perceptions [73]. Previous studies reported that watching branded food videos on YouTube increased the preference for sweets and fried foods [152], while it reduced the liking of fruits and vegetables [151]. **Second**, unhealthy food images (rich in fat and sugar) attract children's attention more than healthy ones, and increase activation in brain areas involved in reward, motivation, and memory [145]. Children and adolescents also have an innate predisposition to prefer sugar- and fat-rich foods but reject bitter-rich ones, which is explained by neuropsychological factors related to the sensory appeal of these foods [226], reflecting their basic biology [167]. The neural response to unhealthy food images, and the innate preference for sugary and fatty foods, may further explain the association of DM exposure with sweet and fatty taste preferences. **Third,** personality traits related to impulsivity and decision-making in reward-related contexts may lie on the pathway of the associations between DM exposure and taste preferences. High impulsivity, poor self-regulation, and extraversion have been associated with a preference for unhealthy foods [227] and excessive SM use among children [228]. The findings of *paper 3* showed that exposure to smartphone and internet was positively associated with emotion-driven impulsiveness and negatively with the decision-making ability of children and adolescents. Previous findings from the I.Family study showed that adolescents with higher emotion-driven impulsiveness have a higher tendency to consume energy-dense snacks, potentially due to the higher sensory taste preference for these foods and as a strategy to relieve negative emotions [113].

Of note, the cross-sectional nature of these findings requires more cautious and in-depth interpretation, as it is impossible to provide conclusions on causality. Taste preferences are highly influenced by genetic factors [229] but still develop during the maturation of the taste apparatus [230]. In the present thesis, genetic factors influencing taste preferences, expect for family influences, were not account for. Hence, future studies should examine how genetic variants interplay with (digital) environmental factors to impact sensory taste preferences and subsequent eating behaviors in the long term. With regard to bitter taste preference, latest research has shown that regardless of bitter taste sensitivity (taste genotype: receptor *TAS2R38 and gustin (CA6),* or taste phenotype: PROP taster status and fungiform papilla density), repeated exposure to bitter taste by eating turnip frequently seemed to be a good strategy to increase both intake and liking of this vegetable in children [231]. This indicates that external environmental factors influence bitter taste preference, irrespective of genetic factors.

5.3. Digital media and cognitive functioning: the potential detrimental role of media multitasking

In agreement with my hypotheses and previous studies [120,232], this thesis provides evidence that exposure to contemporary DM, including smartphones, internet, and media multitasking, may be an independent risk factor for children's and adolescents' cognitive functioning. Findings showed that exposure to these media is cross-sectionally and positively associated with youth's emotion-driven impulsiveness and cognitive inflexibility. Exposure to smartphone and media multitasking was also negatively associated with decision-making ability. These findings suggest that prolonged exposure to the digital environment and simultaneously using multiple screens may impact children's and adolescents' response to impulses, their ability to shift between tasks, and to make advantageous long-term choices while in reward-seeking contexts. This elucidates a further potential mechanism by which DM may affect youth's cognitive development and subsequent health behaviors and outcomes. Several possible underlying mechanisms may explain these associations, which are also illustrated in **Figure 6**.

First, the stress induced by the digital environment may affect children's emotional regulation. The perpetual flow of information provided by DM, the pressure of being constantly online and connected, and the urge to keep up with new online trends (videos, music, games) [233] may exceed children's cognitive capacities to effectively process all that information, hence leading to digital stress [234]. Children and adolescents are vulnerable to the stress induced by DM and/or SM, because the neuronal myelination and synaptic pruning within the parietal and prefrontal cortex (responsible for attention control and delayed reinforcement) are not completed until about the age of 25 years[235], leading to reduced emotional-regulation and poor control of impulses in response to stressors [236,237]. Neuro-developmental differences exist between children and adolescents, with the limbic subcortical system (affective/hot system) maturing early on and the control system (cold) developing later in adolescence [238]. This may explain the stronger association between DM exposure and impulsivity in adolescents, who are also more prone to engage in risky habits, even under digital stress.

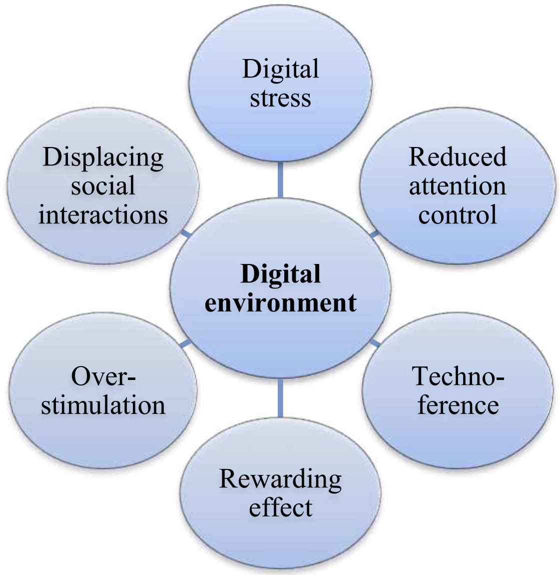

Figure 6. Properties of the digital environment that may underlie the potential impact of DM exposure on children's and adolescents' cognitive functioning.

Second, the potential effect of the digital environment on reducing children's attention control and mental multitasking ability. DM and media multitasking encourage high levels of flicking between information sources at the expense of brain circuitry used in sustained concentration [239]. fMRI-based studies performed in children and adolescents with prolonged smartphone exposure reported lower connectivity in the anterior cingulate cortex, a region involved in cognitive flexibility [120]. Moreover, positive short- [240] and long-term [241] associations between DM exposure and ADHD-related behaviors were previously reported in youth. In agreement with these studies, this thesis also provides evidence of the positive association between media multitasking and reported clinical ADHD diagnosis in IDEFICS/I.Family study participants, especially among boys and adolescents. As reported by Rideout et al., media multitasking is more common in adolescents compared to younger children [29]; hence, they may be at higher risk for being diagnosed with ADHD.

Third, the *technoference* property of digital devices. The negative association of DM exposure with decision-making ability suggests that DM interferes with children's capacities to make advantageous choices by weighing the short-term rewards against long-term negative outcomes, such as eating HFSS foods. This is especially relevant given the enriching (digital) food environment with HFSS food pictures. An overlap has been documented between the neural pathways involved in emotions that guide behavioral responses and those that regulate the overconsumption of highly palatable foods [242]. The role of smartphones, internet, and media multitasking on emotion-driven impulsiveness and decision-making ability might lie in the pathway of mindless eating during screen time, especially in reward-seeking contexts [243]. This mechanism could also explain the positive association between DM exposure and sensory taste preferences for sweet, fatty, and salty-tasting foods (*paper 2*), as children and adolescents tend to regulate both positive (happy) or negative (sad) emotions by snacking on palatable foods [244].

Forth, the rewarding effect of the digital environment. Smartphones and SM have facilitated prolific exposure to positive and negative social stimuli. Positive social stimuli like peer affirmations activate the reward pathways by releasing dopamine, the happiness-inducing hormone [245], hence reinforcing the behavior that preceded it. Dopamine is a neurotransmitter largely involved in substance use disorders. Internet and video-gaming dependency are also associated with dopamine levels among adolescents [246]. Additionally, fMRI studies show that DM activates the reward system through increased neural activation in the caudate and insula [120], providing quick and continuous gratifications and influencing the subsequent emotional and behavioral responses. It may be speculated that every time a child/teenager receives a like on their SM post or a red notification signaling a text message by a friend on WhatsApp, their brain secretes dopamine, and the reward system is activated. These “dopamine shots” may further contribute to the compulsive and excessive use of the internet, smartphones, and SM, which can enter a vicious cycle of engaging in sedentary behaviors over PA and unhealthy eating habits.

Fifth, the type of content children are exposed to may also impact their cognitive functioning. Repeated exposure to fast-paced content, like short-edited video segments in SM or fast-paced TV shows, might trigger sensory over-stimulation, which has been associated with diminished executive functioning in humans [247] and rodents [105]. Exposure to fast-paced content on SM might also trigger higher arousal levels seeking, which in turn leads to addictive and compulsive SM use while hampering engagement in activities that require sustained attention for longer duration, like homework [248]. TikTok, the SM platform used mainly by children and adolescents today, is entirely based on short, fast-paced videos generated by users. The popularity of these fast-paced videos is such that even Instagram, a traditionally photo-based SM platform, is now changing its core design by promoting mostly reels (i.e., fast-paced videos) [249]. The frequency of checking smartphones and the internet might also explain how these media impact children’s cognitive functioning. One longitudinal study conducted among Japanese children (6-18 years) observed that a higher frequency of internet use was associated with less age-related increases in the volume of grey and white brain matter after three years, which are areas responsible for attention control and executive functioning in humans [117].

Sixth, DM use displaces real-life social interactions. Longer duration of DM exposure is associated with reduced social interaction (parent-child, sibling, peers), which built the foundation of a range of personality and cognitive development processes, including decision-making ability and emotion-regulation [250]. The interference of technology with parent-child interactions competes with children's ability to concentrate and regulate their emotions, leading to internalizing and externalizing problems like reduced ability to control impulses [251]. Children living in one-parent families might be particularly at higher risk, as they often lack media supervision, with media used as a babysitting tool, substituting other screen-free, outdoor, or intellectual parent-child activities [248,252]. In *paper 3*, a more robust association was found between DM exposure (and media multitasking) and impulsivity and decision-making ability in children living in one-parent families relative to two-parent families. This suggests that one-parent families require support from governments, pediatricians, and educators: first, to promote early interaction with other children, for example, by offering a place in the kindergarten, and second, to implement strategies of media supervision at home, as well as screen-free, play-oriented activities, to ultimately counteract the adverse influence of DM exposure on children's cognition [30]. However, as the findings of this thesis cannot infer causality, future studies should examine the moderating role of family structure in the associations described above.

Until the direction of causality is confirmed, meaning whether DM causes deteriorated cognitive functioning in youth or whether youth with poor cognitive functioning tend to spend more time with DM, this thesis supports previous concerns that link excessive DM exposure with reduced cognitive abilities that are important for the formation and development of sound psycho-physiological resilience against unhealthy environments during childhood [248].

5.4. Digital media exposure is associated with metabolic syndrome in the long-term

In agreement with my hypotheses, increasing trajectories of childhood DM exposure were positively associated with the risk for metabolic syndrome, abdominal obesity, dyslipidemia, and insulin resistance over a follow-up of two to six years, independently of diet quality, PA and sedentary time, building upon cross-sectional studies[54,55,253]. These results also align with previous prospective findings from the IDEFICS/I.Family cohort, where DM exposure, measured as TV and

PC exposure, increased the risk for insulin resistance after two years [254]. Additional adjustment and post-hoc stratification by objectively-measured sedentary time did not attenuate the associations observed. One explanation could be that screen-time-related sedentary behavior in children is associated with reduced metabolic rate and lower energy expenditure compared to rest condition [255], potentially because children tend to fidget more while resting (or sitting quietly) than when watching TV [256]. Our findings shade light on a further methodological aspect whereby DM exposure is linked with metabolic disorders independently of sedentary time. Thus, time spent with DM should not simply be considered a proxy for sedentary time and vice versa. Instead, different types of sedentary behaviors should be separately examined in relation to health outcomes. Vitamin D insufficiency is another mechanism through which DM exposure may affect metabolic health. Spending prolonged time indoors and with DM are reported as predictors of vitamin D insufficiency in children aged 4-18 years [257]. Low levels of serum 25-hydroxyvitamin D in children are associated with higher odds for abdominal obesity, insulin resistance, and MetS [258,259,260], even in the long-term [261], as also observed in the IDEFICS/I.Family cohort [262].

In children with high and low MVPA, the increase of DM exposure over age (DM slope) was associated with higher z-scores of MetS and its components at follow-up, with more robust associations observed in the low MVPA group. These results indicate that: first, DM exposure is an independent risk factor for children's metabolic health, irrespective of MVPA durations; and second, high MVPA may partially compensate for the negative impact of time spent with DM and improving children's metabolic health, as previously reported [263,264]. In children with no MVPA, baseline DM exposure (DM intercept), but not DM slope, was positively associated with the MetS z-score and its components. These findings indicate that a high baseline exposure to DM, although stable with increasing age, can deteriorate children's metabolic health in the long term. Paradoxically, the increase of DM over age (DM slope) showed a protective effect for high waist circumference. In post-hoc analyses (unpublished results), the potential moderating effect of light PA duration or psychosocial wellbeing in children with no MVPA was tested. The moderation analyses provided similar results, and no explanation for the protective effect of DM exposure could be found. Of note, DM use for educational or entertainment purposes was not distinguished in the IDEFICS/I.Family cohort. Hence, it may be speculated that children with no MVPA are spending prolonged time studying, even with DM itself, or are engaged in other leisure activities like drawing, reading, or playing board games. These activities provide positive health influences in children, such as better self-regulation [265-267]. As no previous study has examined the association between DM exposure and metabolic disturbances by levels of MVPA to compare findings of this thesis with, future studies are warranted to explore the mechanisms that explain the beneficial association between DM exposure and metabolic outcomes in children with no MVPA. The findings hint at another methodological aspect, suggesting that only adjustment for PA duration in the association between DM exposure and metabolic outcomes is incorrect, and more complex analyses by levels of PA intensity are required. Although results should be replicated in other child cohorts, they serve as a first evidence that supports the proposal for considering DM as a third (independent) group of risk factors undermining children's health.

5.5. Sex differences in the association of digital media exposure with sensory taste preferences, cognitive functioning, and metabolic outcomes

The association of DM exposure with outcomes of interest differed by sex. An inverse association of DM exposure with bitter taste preference was observed in boys but not in girls. This difference could be explained by factors related to the socio-cultural environment, like peer pressure and perception of body weight that may influence adolescent girls to eat more vegetables, but not adolescent boys [224]. Repeated exposure to vegetables and the related molecules responsible for bitter taste can increase the tolerance and preference for bitter-tasting foods in early life [230,231]. Recent evidence shows that these effects can be observed even before children are born [268]. Fetuses who were repeatedly exposed to kale - a green vegetable rich in bitter molecules [269] - showed less "disgusting" facial grimaces inside the uterus [268]. This suggests that children (boys and girls) should be exposed to bitter foods at an early age and, if not possible, repeatedly during their development. This could potentially hinder the negative role of exposure to unhealthy food cues in the digital environment in early life. Moreover, although boys were expected to have higher impulsivity scores than girls, findings showed that prolonged exposure to smartphone and internet in combination with medium TV and low PC exposure was more strongly associated with emotion-driven impulsiveness in girls compared to boys. This could be explained by the fact that girls use smartphones and the internet mainly for communication and SM, while boys use them for playing games [29]. SM exposure has been associated with adverse effects on girls' and adolescents' psycho-emotional well-being [270] and body-image [271], which lead to both emotional overeating and restrictive eating as maladaptive coping strategies to relieve negative emotions [272].

The long-term association between DM exposure and metabolic outcomes differed by sex and country. Boys developed higher and steeper age-dependent DM trajectories compared to girls, which aligns with studies conducted in US children where boys developed steeper DM trajectories while growing up than girls [34]. We found that boys with increasing DM trajectory were at higher risk for MetS and dyslipidemia later in life compared to girls. These findings build upon previous studies where boys had higher screen time and triglycerides levels but lower HDL-c compared to girls [273]. Post-hoc analyses (unpublished data) showed that the association between DM exposure and MetS z-score was positive among boys with both no MVPA and with high MVPA duration. No clear pattern was observed in girls with increasing levels of MVPA. Again, findings indicate that boys are at higher risk for MetS than girls, independent of MVPA. Further explanation may be found on the mechanisms of self-regulation and their role in health [274]. DM exposure [275] and media multitasking [232] are inversely associated with self-regulatory traits in children like inhibitory control or tolerating frustrations, which are, in turn, less observed in boys than in girls [276]. This is further supported by findings of *paper 3*, where media multitasking was associated with higher cognitive inflexibility score and lower decision-making ability score in boys but only weakly in girls. The link between DM exposure and poor cognitive functioning could be one additional mechanism leading to higher MetS risk in boys. Lower self-regulation in children is a risk factor for obesogenic behaviors [277], high cholesterol levels [278], and cardiometabolic risk later in adolescence[274]. The stronger association of baseline DM exposure and abdominal obesity among girls compared to boys could be due to the stronger association of DM exposure with the emotion-driven impulsiveness score of girls compared to boys, as observed in paper 3. Impulsivity has been associated with obesity among pre-schoolers [279] and adolescents [280] through diet and screen time, with the latter having a higher mediating effect in girls than boys [279].

Acknowledging that the digital environment is an emerging research field and that many of the mechanisms explaining the associations observed in this thesis are unknown, looking at the findings of this thesis in light of Hill's criteria for causality [281] requires careful interpretation [282]. The results support the criteria of strength (as important associations were observed across all papers), biologic gradient (a dose-response relationship was observed between DM exposure and outcomes of interest), consistency (the found associations are observed in other populations of children and adolescents, although in different contexts/settings) and experimental evidence (as provided in the context of known literature in the introduction and discussion sections). Most of the associations investigated in this thesis are crossectional and do not meet the most important criteria for causality, i.e., temporality. However, the found associations can still be meaningful, as the evidence provided throughout this thesis suggests that it is biologically plausibile to relate DM exposure to metabolic disturbances, poor cognitive functioning, unhealthy food intake, and unfavorable taste preferences in children and adolescents.

5.6. Strengths and limitations

A primary strength of this thesis is the large sample size of children and adolescents participating in the IDEFICS/I.Family cohort, providing harmonized and phenotypic data. The large age range of children (2-18 years old) allowed the assessment of trajectories of DM exposure over age and the examination of age-group differences in the associations between DM exposure and the outcomes of interest. Including children and adolescents from nine European countries enabled the assessment of patterns of DM exposure across the continent and the examinations of country-specific differences in the associations between exposures and outcomes of interest. Although the country-specific samples were not representative of the respective populations, the pan-European design increases the variation of exposure and outcome, and thus enhances the ability to detect associations. Including information on various DM types, instead of only TV, like smartphones, internet, computers/game consoles, and related media multitasking, allowed to capture a better overview of the DM use in children. This also helped to consider the role of modern DM types on the outcomes of interest. The different media variables pointed to the same direction of associations with the outcomes investigated, indicating an internal consistency of the data. The research conducted in paper 2 and paper 3 was the first to examine the role of DM exposure on sensory taste preferences and cognitive functioning, respectively, with free-living participants. The research in *paper 4* was the first to examine the longitudinal association of DM exposure with later incident metabolic syndrome in European children and adolescents.

Using objectively-measured data on anthropometric measures and metabolic risk factors based on fasting blood samples is another strength of this thesis. The availability of accelerometer-measured MVPA and sedentary time increased the data accuracy and reduced misreporting due to socially-desirable answers on PA [283]. Moreover, obtaining information on various covariates, including sex, age, puberty status, BMI, diet quality, unhealthy snack consumption frequency, parental ISCED, psycho-social well-being, sleep duration, country of residence, migration background, family structure and family media rules enabled to control for potential confounders of the associations of interest. Finally, the sophisticated statistical analyses applied in this thesis also represent an advantage. The two-step trajectory approach using linear mixed models with two levels (repeated measurement occasions, nested within individuals) enabled the examination of changes in DM use duration over age in children measured at different ages. These models also allow for changes in scale and variance of the exposure measurements over time. Using the latent class analysis to identify underlying patterns of DM use allowed a better understanding of the impact of DM exposure on children's cognition.

There are methodological limitations to the investigations presented in the current thesis. First, only one paper (*paper 4*) examined the longitudinal association between DM exposure and health outcomes (i.e., metabolic syndrome). The investigations in *paper 2* and *paper 3* were based on cross-sectional data. This hampered the assessment of the temporal sequence in which dependent and independent factors occurred. Therefore, reverse causation can not be excluded, meaning whether certain personality traits or genetic factors predicted specific patterns of DM exposure. Recent evidence suggests that genetic variants and neuro-biological mechanisms commonly observed in behavioral addictions are related to the excessive use of smartphones, internet, and video-games [284,285,286]. Future cohort studies should investigate how DM exposure over time impacts health outcomes and cognitive functioning while accounting for genetic and psychological characteristics. Despite the described limitation, in paper 3, we controlled for factors like psychosocial well-being and partially accounted for family influences, and the observed associations between DM exposure and cognitive functioning remained robust.

As DM use was self-reported by adolescents and proxy-reported by parents of younger children, a social-desirability and recall bias may have resulted in over- and under-estimation of DM exposure [287]. This might have attenuated the associations between DM exposure and respective outcomes. However, previous studies have shown that self-reported DM use by adolescents adequately distinguishes between high and low use (e.g., for smartphones) [288]. Similarly, due to self-reported data, a social-desirability and recall bias could not be excluded for diet quality and snack consumption frequency, because adolescents are likely to under-report foods and beverages with high energy content, such as high-fat and high-sugar foods [289]. Moreover, when parents report their children's food preferences and consumption frequency, they may report food preferences similar to their own [290], while under- and over-reporting foods consumed depending on the perceived child's weight status and the socially desirable foods [291]. This might have attenuated the examined associations. However, previous studies have shown that parental misreporting is higher for reporting energy intake than for reporting food group consumption frequency [292].

In the IDEFICS/I.Family cohort, no information on SM use and its specific platforms was obtained. Therefore, the impact of SM exposure on metabolic disturbances and cognitive functioning was not examined in this thesis. As discussed in the introduction chapter, SM has invaded children's and adolescents' lives, and future studies should examine the short and long-term impact of SM exposure on metabolic and mental health and cognitive development. Moreover, information on the internet and smartphone exposure was included only in W3 of the cohort. Thus, no longitudinal analyses could be conducted with these modern DM. Smartphone exposure was measured based on a 24-hour recall question. Therefore, it was not possible to measure smartphone exposure duration over weekdays and weekend days, which prevented its inclusion in the age-dependent DM exposure trajectories. In this thesis, media multitasking was defined as the simultaneous use of a computer with other media. The latest evidence suggests that smartphone and SM use are also significant contributors to media multitasking [293]. Therefore, the observed association of media multitasking with cognitive functioning and ADHD could be much more prominent in real life. Future studies should consider all sources of screen time and media multitasking to capture the complete picture of DM exposure during childhood. Also, we did not distinguish between internet (and smartphone) use for education and entertainment purposes. Recent evidence suggests that the purpose of using DM has differential effects on children's health [27,294]. This could explain the lack of association of internet exposure with cognitive inflexibility and decision-making observed.

6. Conclusions and Public Health Implications

The ultimate aim of this thesis was to investigate the role that exposure to contemporary digital media has on children's and adolescents' dietary and health outcomes and to provide evidence for future health interventions and the formulation of related regulatory measures in the digital environment. The findings suggest that exposure to SM leads to deteriorated food intake and poor eating behaviors, independent of age. Additionally, prolonged exposure to digital devices and the internet is associated with a higher preference for sweet, salty, and fatty-tasting foods in girls and a lower preference for bitter-tasting foods in boys, independent of dietary intake. Moreover, exposure to smartphones, internet, and media multitasking is positively associated with emotion-driven impulsiveness and cognitive inflexibility and negatively related to decision-making ability. Finally, increasing trajectories of DM exposure during childhood is associated with a higher risk for metabolic syndrome and its components over a follow-up of two to six years, particularly in boys. These results are of great public health importance given the ubiquity of DM devices, the easy accessibility of internet-based content, and the fact that children and adolescents use DM increasingly without parental control. This thesis deepens our knowledge of the potential role of the digital environment as an emerging risk factor affecting the health status of children and adolescents in Europe and beyond. Children's health is a vital baseline investment for sustainable health futures, hence, I present here unique opportunities for implementing health interventions targeting children in the digital environment. Until the directionality and causal nature of the associations investigated is confirmed, the following recommendations may be useful considering a precautionary approach concerning children's health in a digital world.

6.1. Limiting recreational digital media use during childhood to improve metabolic and cognitive health

The findings of this thesis suggest that increasing DM exposure during childhood is an independent risk factor for metabolic syndrome, abdominal obesity, insulin resistance, and dyslipidemia later in life. Although more longitudinal studies need to replicate these long-term associations, they suggest that reducing DM exposure early in life may benefit children's and adolescents' metabolic health, supporting previous recommendations from WHO [31]. Moreover, increasing exposure to smartphones and the internet was negatively associated with measures of cognitive functioning. Engagement in media multitasking was associated with high cognitive inflexibility and impulsivity score, especially among children and adolescents living in one-parent households, and with higher odds of clinical ADHD diagnosis, especially in boys. These findings are of public health relevance, given that a 1 SD increase in cognitive test score during early childhood is associated with a 24% reduced risk of death over a follow-up of 17-69 years [110]. Moreover, sound cognitive development is a primary factor related to mental health and healthy behaviors later in life. The findings stress the necessity of protecting children and adolescents against the adverse effects of the digital environment, especially given the high neuroplasticity of their brains, which, more than ever before, leaves children and adolescents vulnerable to the external (digital) environment. The findings are of ultimate relevance also in context of the COVID-19 pandemic, which has led to increased DM exposure and physical inactivity, reduced sleep and diet quality and poor mental health in young populations [295], calling for urgent interventions to address determinants of children's health, including the excessive DM exposure.

Previous interventions on reducing DM use in children have achieved significant improvement not only in DM exposure itself [296] but also in sleep duration [297], lipid levels, hyperinsulinemia, depressive symptoms [298], and energy intake [299], all factors previously associated with metabolic syndrome. Interventions tackling the reduction of children's recreational screen time have also shown significant reduction of BMI z-score after two years, especially among families of low SES [299]. Multi-dimensional interventions for improving household routines (e.g., TV watching, shared family meals, and adequate sleeping time) are particularly of promise, as they reduced the BMI of young children living in low-income families [300]. Recent meta-analytic evidence showed that interventions tackling the reduction of TV exposure in children were highly cost-effective for reducing childhood obesity [301]. Another meta-analysis of interventions targeting the reduction of DM exposure in children aged 0-18 years showed that "active ingredients" such as smaller sample size, shorter intervention durations (<12 weeks vs. 54 weeks), and incorporation of behavioral change techniques such as goal setting, goal review, and self-monitoring were associated with larger intervention effects [302]. Other studies show that enhancing autonomous motivation in adolescents might be a helpful intervention target for trials aiming to reduce adolescents' recreational DM use [303,304]. Moreover, interventions need to account for mothers' and fathers' media parenting practices, such as using screens for controlling behavior or during mealtimes, as these practices were both associated with children's DM use [305].

Specific actions by parents, teachers, and pediatricians may support children and adolescents in limiting their DM exposure, providing opportunities to develop and increase resilience against the adverse effects of the digital environment. Family practitioners and pediatricians can help families to build effective family media use plans [306]. Another suggestion is for clinicians to incorporate the history of children's DM exposure in their routine health visits as they do for nutrition, tobacco, or alcohol consumption and to provide age-specific recommendations to limit DM exposure [306]. Parents may use active parenting strategies, such as discussing with their children how to limit DM use or how the algorithm-based designs of the DM/SM work. Other strategies could include removing the DM devices (television, PC/game console, smartphone) from the child's bedroom [307], prohibiting screens during meals, supervising their children's DM use also by using tools such as parental controlling applications that monitor the content children are exposed to in their mobile devices, discouraging media multitasking (e.g., using smartphones while TV) and modeling a healthy DM use themselves. Teachers can increase children's and adolescents' agency by teaching them digital and health literacy and defense strategies against harmful practices within the digital environment. Eventually, given the importance of DM in youth's lives, countries should introduce DM education already in kindergarten and in the school curricula to increase children's digital literacy and empower them with skills to identify and deal with malicious designs and predatory (marketing) activities online.

6.2. Multinational corporations, governments, policy-makers, and children's health

Acknowledging the power of multinational corporations to transnationally influence political decision-making and exacerbate social and health inequalities [308], the findings of this thesis help to extend this discussion to children and their right to health. As stated in article 24 of the UN Convention on the Rights of the Child, children have the fundamental right to enjoy the highest attainable standard of health [309], but states are far from guaranteeing this right to them. Multinational corporations often have more resources than state governments, and they often neglect or discredit the harmful effects of their unhealthy products on children's health (e.g., tobacco or SSB). This has also caused many governments to favor economic development and the job market over regulating the industry of unhealthy products [44]. The case of regulating the tobacco industry or introducing taxation to SSB are examples of the power of industry over policy-making [310], also in high-income countries. With regard to protecting children's right to health in a digitalized world, there is a need to employ a precautionary approach in regulating the digital environment [311]. According to the precautionary principle, when an activity or product has the potential to harm people's health, precautionary measures should be taken to mitigate the negative effects of that activity, even when the relationship cause-effect has not been fully established [312]. This precautionary approach holds true more than ever given the complex and constantly evolving nature of the digital environment.

6.2.1. Regulation of advertisements for unhealthy food and beverages targeting children and adolescents on social media

The evidence synthesized (i.e., SLR) in this thesis support the need for introducing comprehensive regulatory measures to tackle unhealthy food and beverage advertising directed to children and adolescents on SM. Manipulative, unethical, algorithm-based targeted advertising techniques are increasingly employed on SM, exploiting children's and adolescents' cognitive vulnerabilities. To target children and adolescents, food marketers use analytics of users' emotions (via emojis), online behaviors (liking, sharing, commenting, duration of staying on a particular page), and location data via GPS embedded in smartphones [313]. International institutions such as the Council of Europe have already acknowledged the need for more legislative efforts across all countries to protect children's and adolescents' informational self-determination and well-being in the online environment [314]. However, only a few countries have introduced mandatory regulations that restrict the advertising of unhealthy food and beverages on SM, including Chile, Portugal, and the UK [315]. Still, they apply only to children up to the age of 12, leaving adolescents unprotected. It is widely accepted that existing food industry self-regulations (voluntary "pledges") do not work due to conflicts of interest [316,317]. The findings of this thesis support recent calls from the WHO-UNICEF-Lancet Commission to develop an Optional Protocol of the UN Convention on the Right of the Child, to protect children aged 0-18 against predatory commercial practices of tobacco, alcohol, SSB, gambling, and damaging effects of SM exposure [44].

As shown in this thesis (*section 4.1.3, page 35*), advertisement disclosures do not suffice to protect children and adolescents from the effects of food and beverage advertising on SM. Therefore, stricter regulations are needed. YouTube Kids, the child-friendly YouTube version, can be seen as a forerunner since it bans advertisements for food and beverages and filters adult-directed content [318]. However, children can still be exposed to unhealthy food brands on YouTube Kids through product placement on the promoted videos, highlighting that food marketers find novel ways to target children online; therefore, stricter and complex regulations are needed. It should also be noted that major SM platforms, including Facebook, Instagram, WhatsApp, and LinkedIn, but not TikTok, have prohibited the advertisements of tobacco, alcohol, and weight loss products [318]. First, this highlights the feasibility and willingness of SM companies to take serious actions in protecting children and adolescents against unhealthy products online. Second, more political pressure should be directed to TikTok, not only for restricting advertisements for unhealthy food and beverages but also for tobacco, alcohol, weight loss products, and gambling. The borderless nature of SM calls for globally-coordinated actions to limit children's and adolescents' exposure to SM advertising of unhealthy products by bringing all stakeholders around the same table: policymakers, digital and SM corporations, health and youth organizations, schools, parents, and the research community.

6.3. Tailored interventions to promote healthy food intake on social media

The SLR (*paper 1*) showed limited evidence on the positive role of SM exposure and SM influencers' advertising to improve children's nutrition literacy and intake of healthy foods. However, the role of peers and the SM influencer's lifestyle (active or sedentary) were identified as important "active ingredients" to consider when developing interventions promoting healthy foods in children and adolescents. Interventions are also encouraged to promote healthy foods in an appealing way. As described (section 4.1.3, page 33), food images attract children's attention and activate reward pathways and decision-making-related brain areas. To increase the rewarding value of healthy foods (e.g., vegetables, legumes), food promotion strategies on SM should address youth's emotional and cognitive needs for identity and belonging [220], as advertising campaigns delivering emotional messages have stronger effects than those delivering rationale messages [319].

Another suggestion is to motivate SM influencers and celebrities to promote healthy behaviors on their SM networks. First, the developers of health interventions should consider the motivation of the social influencer (SM celebrity or peer) to engage in the health behaviors themselves and then promote it in their SM profile by applying principles of the self-determination theory [320]. Second, intervention developers may consider influencers who actually engage in healthy behaviors in their daily life. For example, the football star Cristiano Ronaldo, the celebrity/influencer with the highest number of followers on Instagram (489 million), is well-known for his healthy lifestyle in terms of PA, eating, and drinking (he does not consume alcohol, nor SSB). In a pre-match press conference during the football world championship in 2021, Ronaldo removed two Coca-Cola bottles from his table and said, "Water… no Coca-Cola" [321], while holding up an unlabelled bottle of water. This simple sentence and gesture were considered a contributing factor to a 1.6% plunge in the stock price of Coca-Cola company, with its market value dropping by $4 billion in the days following the event [322]. Although it is unknown if Ronaldo's action impacted viewers' consumption of the sugary drink, this highlights the power of SM influencers to promote healthy behaviors in larger audiences, and the importance of considering their lifestyle when developing health interventions.

6.4. Future Research and Outlook

The findings of this thesis provide evidence of the association of DM exposure with metabolic syndrome, cognitive functioning, and dietary outcomes. As technology evolves, newer digital devices, applications, SM platforms, and more complex, interactive features are being developed and quickly embraced by young populations; hence further research questions emerge. For instance, TikTok did not exist until five years ago, but it is today the most used SM platform among children and adolescents [26]. In 2022, a new SM platform emerged - BeReal - which is also becoming popular among adolescents and young adults. This stresses the need for more empirical data to keep up with the pace of technological advancement, to understand health determinants that are exclusively present in the online environment, and their interplay with other known determinants (e.g., social determinants). Potential promising methods that obtain information on DM exposure and its patterns include i) Ecological Momentary Assessment (EMA), measuring exposure to DM/SM in several instances of the day over one week; ii) objectively-measured smartphone and SM use via log-on data; iii) smartphone application trackers which monitor whether the screen is lit (timing and duration) on a second-to-second basis [323], in addition to screen-media (online) diaries. Moreover, we should acknowledge the hurdle for the research community to measure the accurate patterns of SM exposure and SM advertising due to the shift of power over data ownership and control to big SM corporations. Hence, it is necessary for health entities such as WHO to initiate collaborations with the digital and SM companies to establish shared infrastructures for making algorithms transparent. This would enable researchers around the globe to measure the true extent of SM exposure and advertising to provide recommendations and holistic solutions for making algorithms less "addictive". The COVID-19 pandemic provided an example of the willingness of SM companies to cooperate with WHO and governments to tackle fake news and misinformation sharing on SM [311]. In the following, I present avenues for future research on the impact of DM and SM exposure on children's health and related behaviors.

6.4.1. Patterns of social media use in association with food intake and mental health

The patterns of using the internet and SM and their seasonal use are also important to consider in association with food intake and mental health. As shown in paper 1, smartphone and SM use for entertainment has higher deteriorating effects on children's and adolescents' eating behaviors and mental health compared to their use for academic purposes. SM use for entertainement might be higher during the summer (i.e., school holidays) than the rest of the year. The rationale is that during summer, children and adolescents are mainly free from segmented, restrictive, and compulsory daily activities compared to what school demands. They can make more autonomous choices in their behaviors, such as spending time with their smartphones [324]. This can lead to higher viewing instances of advertisements for unhealthy products and increased online social comparisons, like higher exposure to peers' travel images or comparisons over the "summer body" type, which may have a higher deteriorating impact on eating behaviors and mental health. As these data were not available when this thesis's research was conducted, future studies are strongly suggested to explore these hypotheses, which would help to identify periods when children and adolescents are most vulnerable to the exacerbating effects of DM exposure.

6.4.2. Watching mukbang videos on social media and eating behaviors

A relatively new and under-researched phenomenon on SM is "*mukbang*" videos, which means "eating broadcast" in Korean [325]. In mukbang videos, the video blogger eats a large amount of food in front of the camera while talking to the viewers. Initially a popular trend among the South Korean youth to avoid loneliness (i.e., online-based facilitation of eating) [326], thanks to YouTube and Instagram, mukbang videos have now become viral and are watched by millions worldwide [327]. The mukbang video bloggers intentionally consume large portions of food - often branded products, such as McDonald's, Milka chocolate bars, or Coca-Cola cans - chew loudly or place highly appetizing foods close to the viewing audience [325]. These visual and auditory stimuli may trigger viewers' cravings for foods, impact their eating behaviors, and promote eating disorders. These concerns are also supported by findings of *paper 1*, where exposure to food images in high portions led to increased brain activation in areas related to salience and decision-making, and higher food intake at ad-libitum. A recent content analysis of mukbang videos on YouTube showed that most of them promoted fast-food, unhealthy snacks, instant noodles, and alcohol consumption [325]. Another study conducted among university students in South Korea reported that watching mukbang videos was positively associated with self-reported consumption frequency of unhealthy foods [328]. Further research is urgently needed to investigate the effects of watching mukbang videos on children's and adolescents' food intake, food preferences, and the risk for eating disorders.

6.4.3. Long-term impact of social media exposure on children's mental health

Studies examining the longitudinal association between SM exposure and mental health outcomes like depression and psychosocial well-being have produced equivocal findings, where positive [100] and lack of associations were reported [329,330]. Thus, further cohort studies with longer follow-up duration are needed to understand the age-dependent association between SM exposure in early childhood and/or preadolescence to mental health outcomes later in adolescence and young adulthood. The transition periods during the development must be considered, as many factors related to peers, puberty, school, and the larger social, physical, and political environment might attenuate the association between SM exposure and later mental health. The long-term role of DM exposure, media multitasking, and exposure to fast-paced SM content on cognitive functioning and development needs to be further explored in cohort studies. Additionally, birth-cohort studies should investigate the role of DM exposure and especially media multitasking during early childhood on ADHD development later in life. Further research is also required to understand the moderators and/or mediators of the associations between SM exposure and mental health outcomes in children, adolescents, and young adults, which can inform the development of tailored health interventions. Promising multidisciplinary interventions may built upon the perspectives of public health and human-computer interaction science, while considering co-creation approaches by including the primary stakeholders, i.e., youth, in the early stages of intervention development.

6.4.4. The role of family environment on the association of digital media exposure with mental health and eating behaviors of children and adolescents

How family environment and lifestyle - including the role of siblings, parenting strategies, media supervision at home, frequency of family meals, or doing activities together - moderates or mediates the association between DM exposure and health outcomes in children requires more research attention. Having an older sibling is a predictor of prolonged DM exposure [35] and of experiencing sibling bulling in childhood [331]. The latter has in turn been associated with poor mental health in adolescence [332] and early adulthood [333]. Still, siblings' moderating or mediating role in the association between SM exposure and mental health outcomes remains unknown. Moreover, lack of family meals was reported to moderate the association between SM exposure and poor well-being among youth [334]. Yet, this has not been investigated in children. Another study showed that restrictive parenting strategies, like parents controlling their child's time spent on SM, were associated with better mental health in preadolescents. This was mediated by reduced browsing time and fewer appearance comparisons on SM [335]. This finding suggests that parenting strategies can potentially mitigate the negative effects of SM exposure on children's mental health. Parents can also shape their children's media use habits by restricting or allowing DM duration and the type of DM exposure (e.g., whether the child can have an SM account). Instagram has acknowledged the role of parental mediation strategies and recently introduced a "parental supervision" feature, which allows parents and their teenagers to initiate supervision and gives parents access to their teens' SM accounts. Eventually, parents can see their teen's time spent on the application, their following and followers lists, and can also set daily time limits or breaks to help them manage their time on Instagram [336]. However, to what extent teenagers will accept this supervision feature remains to be seen, due to their drive for autonomy, independence, and privacy. Hence, further research needs to explore how and which parenting strategies can moderate the impact of SM exposure on children's and adolescents' mental health.

6.4.5. Digital blue lights, metabolic health and eating behaviors of children

In the current digital era, smartphones are commonly used during the hours before sleeping, especially among youth [337]. Smartphones emit blue light, which contains short wavelength emissions (~450-500 nm), but a lot remains unknown about its potential role in human health. In rodents, exposure to blue light leads to acute impairment of glucose tolerance and increased sugar intake [338]. In adolescents and young adults, several studies have linked exposure to blue light emitted by DM with disruptions of the circadian rhythm, increased sleep latency but reduced sleep duration and quality [339], and suppression of melatonin production [340]. Furthermore, one experimental study conducted in young adults showed that using digital devices at night (before sleep) compared to reading a hard-copy book resulted in suppression of leptin and reduced sleep quality [341]. Although further research is needed to understand if these effects are present in children and adolescents, these findings are worrisome given the central role of leptin in obesity and metabolic processes. Leptin, the satiety-inducing hormone, plays a crucial role in inhibiting food intake, regulating body weight, and energy homeostasis [342]. On the other hand, melatonin is involved in leptin synthesis and its release by the adipose tissue [343]. A deteriorated production of these hormones and potential disruptions of the underlying biological processes due to DM exposure warrant further investigations in children and adolescents.

Post-scriptum: If your child was alone in the streets of Berlin at night, wouldn't you be worried and take actions to protect them?

Given the novel, complex and ever-evolving nature of the digital environment, many of its associated risks remain unknown, therefore we need be cautious about exposing children to this not-fully known milieu, especially those at an early age. The findings of this thesis should serve as an alarm bell for parents, policy makers and the digital media industry, to take serious actions to protect children and adolescents online. In fact, many more threats are posed to children's health and rights in the digital space, which could not be addressed in the current thesis. We need to understand the long-term effects of growing up in a digital environment on suicidal behaviors, gambling, grooming, sexual, psychological, and emotional abuse, permanent social jet lag, cybersecurity, financial abuse, and many more [44]. The main take-home message of this thesis lies in the importance of continuously examining the determinants of health and related behaviors in a not-fully-known digital environment, in order to prevent future health emergencies in youth and to reduce the human, social and economic burden of diseases later in life. Children are the future of human existence, and they need to be protected, especially in a digital environment where its benefits and risks remain, yet, unknown.

References

1. United Nations. Transforming our world: the 2030 Agenda for Sustainable Development. 2015.
2. World Health Organization. Children: new threats to health. Accessed 11.07.2022. https://www.who.int/news-room/fact-sheets/detail/children-new-threats-to-health
3. The Lancet Diabetes & Endocrinology. Childhood obesity: a growing pandemic. *The Lancet Diabetes & Endocrinology*. 2022;10(1):1. doi:10.1016/S2213-8587(21)00314-4
4. Abarca-Gómez L, Abdeen ZA, Hamid ZA, et al. Worldwide trends in body-mass index, underweight, overweight, and obesity from 1975 to 2016: a pooled analysis of 2416 population-based measurement studies in 128·9 million children, adolescents, and adults. *The Lancet*. 2017;390(10113):2627-2642. doi:10.1016/S0140-6736(17)32129-3
5. World Health Organization. Obesity and overweight. Accessed 12.07.2022. https://www.who.int/en/news-room/fact-sheets/detail/obesity-and-overweight
6. Skinner AC, Perrin EM, Moss LA, Skelton JA. Cardiometabolic Risks and Severity of Obesity in Children and Young Adults. *New England Journal of Medicine*. 2015;373(14):1307-1317. doi:10.1056/NEJMoa1502821
7. Alberti KG, Eckel RH, Grundy SM, et al. Harmonizing the Metabolic Syndrome. *Circulation*. 2009;120(16):1640-1645. doi:doi:10.1161/CIRCULATIONAHA.109.192644
8. Noubiap JJ, Nansseu JR, Lontchi-Yimagou E, et al. Global, regional, and country estimates of metabolic syndrome burden in children and adolescents in 2020: a systematic review and modelling analysis. *The Lancet Child & Adolescent Health*. 2022/03/01/ 2022;6(3):158-170. doi:https://doi.org/10.1016/S2352-4642(21)00374-6
9. Magge SN, Goodman E, Armstrong SC. The Metabolic Syndrome in Children and Adolescents: Shifting the Focus to Cardiometabolic Risk Factor Clustering. *Pediatrics*. 2017;140(2):e20171603. doi:10.1542/peds.2017-1603
10. Bremer AA, Mietus-Snyder M, Lustig RH. Toward a Unifying Hypothesis of Metabolic Syndrome. *Pediatrics*. 2012;129(3):557-570. doi:10.1542/peds.2011-2912
11. Reedy J, Krebs-Smith SM. Dietary Sources of Energy, Solid Fats, and Added Sugars among Children and Adolescents in the United States. *Journal of the American Dietetic Association*. 2010/10/01/ 2010;110(10):1477-1484. doi:https://doi.org/10.1016/j.jada.2010.07.010
12. Ambrosini GL, Huang RC, Mori TA, et al. Dietary patterns and markers for the metabolic syndrome in Australian adolescents. *Nutrition, Metabolism and Cardiovascular Diseases*. 2010/05/01/ 2010;20(4):274-283. doi:https://doi.org/10.1016/j.numecd.2009.03.024
13. Funtikova AN, Navarro E, Bawaked RA, Fíto M, Schröder H. Impact of diet on cardiometabolic health in children and adolescents. *Nutr J*. Nov 14 2015;14:118. doi:10.1186/s12937-015-0107-z
14. Ambrosini GL, Oddy WH, Huang RC, Mori TA, Beilin LJ, Jebb SA. Prospective associations between sugar-sweetened beverage intakes and cardiometabolic risk factors in adolescents1,2,3. *The American Journal of Clinical Nutrition*. 2013/08/01/ 2013;98(2):327-334. doi:https://doi.org/10.3945/ajcn.112.051383
15. Koren D, Levitt Katz LE, Brar PC, Gallagher PR, Berkowitz RI, Brooks LJ. Sleep architecture and glucose and insulin homeostasis in obese adolescents. *Diabetes Care*. Nov 2011;34(11):2442-7. doi:10.2337/dc11-1093
16. Yu Y, Lu BS, Wang B, et al. Short Sleep Duration and Adiposity in Chinese Adolescents. *Sleep*. 2007;30(12):1688-1697. doi:10.1093/sleep/30.12.1688
17. Steele RM, van Sluijs EM, Cassidy A, Griffin SJ, Ekelund U. Targeting sedentary time or moderate- and vigorous-intensity activity: independent relations with adiposity in a population-based sample of 10-y-old British children. *The American Journal of Clinical Nutrition*. 2009;90(5):1185-1192. doi:10.3945/ajcn.2009.28153
18. Ekelund U, Brage S, Froberg K, et al. TV Viewing and Physical Activity Are Independently Associated with Metabolic Risk in Children: The European Youth Heart Study. *PLOS Medicine*. 2006;3(12):e488. doi:10.1371/journal.pmed.0030488

19. Thumann BF, Börnhorst C, Ahrens W, et al. Cross-Sectional and Longitudinal Associations Between Psychosocial Well-Being and Cardiometabolic Markers in European Children and Adolescents. *Psychosom Med*. Oct 2020;82(8):764-773. doi:10.1097/psy.0000000000000845
20. World Health Organization. Adolescent mental health. Accessed 11.07.2022. https://www.who.int/news-room/fact-sheets/detail/adolescent-mental-health
21. Anderson DR, Subrahmanyam K. Digital Screen Media and Cognitive Development. *Pediatrics*. Nov 2017;140(Suppl 2):S57-s61. doi:10.1542/peds.2016-1758C
22. Zimmerman FJ, Christakis DA. Children's Television Viewing and Cognitive Outcomes: A Longitudinal Analysis of National Data. *Archives of Pediatrics & Adolescent Medicine*. 2005;159(7):619-625. doi:10.1001/archpedi.159.7.619
23. Adelantado-Renau M, Moliner-Urdiales D, Cavero-Redondo I, Beltran-Valls MR, Martínez-Vizcaíno V, Álvarez-Bueno C. Association Between Screen Media Use and Academic Performance Among Children and Adolescents: A Systematic Review and Meta-analysis. *JAMA Pediatrics*. 2019;doi:10.1001/jamapediatrics.2019.3176
24. The Lancet Child & Adolescent Health. Growing up in a digital world: benefits and risks. *The Lancet Child & Adolescent Health*. 2018;2(2):79. doi:10.1016/S2352-4642(18)30002-6
25. Kuss DJ, Griffiths MD. Social Networking Sites and Addiction: Ten Lessons Learned. *International Journal of Environmental Research and Public Health*. 2017;14(3):311.
26. Statista. Social media - Statistics & Facts. Statista. Accessed 07.07, 2022. https://www.statista.com/topics/1164/social-networks/#topicHeader__wrapper
27. Reid Chassiakos YL, Radesky J, Christakis D, Moreno MA, Cross C. Children and Adolescents and Digital Media. *Pediatrics*. Nov 2016;138(5)doi:10.1542/peds.2016-2593
28. Rideout V RM. *The Common Sense census: Media use by kids age zero to eight, 2020*. 2020. https://www.commonsensemedia.org/research/the-common-sense-census-media-use-by-kids-age-zero-to-eight-2020
29. Rideout VJ, Robb MB. *The common sense census: Media use by tweens and teens*. Common Sense Media; 2019.
30. Council of Communications and Media, Hill D, et al. Media and Young Minds. *Pediatrics*. 2016;138(5)doi:10.1542/peds.2016-2591
31. World Health Organization. WHO guidelines on physical activity and sedentary behaviour. 2020.
32. Mascheroni G, Ólafsson K. Net children go mobile: Risks and opportunities. 2014;
33. Stahlmann K, Hebestreit A, DeHenauw S, et al. A cross-sectional study of obesogenic behaviours and family rules according to family structure in European children. *Int J Behav Nutr Phys Act*. 2020/03/05 2020;17(1):32. doi:10.1186/s12966-020-00939-2
34. Trinh MH, Sundaram R, Robinson SL, et al. Association of Trajectory and Covariates of Children's Screen Media Time. *JAMA Pediatr*. Nov 25 2019;174(1):71-8. doi:10.1001/jamapediatrics.2019.4488
35. Durham K, Wethmar D, Brandstetter S, et al. Digital Media Exposure and Predictors for Screen Time in 12-Month-Old Children: A Cross-Sectional Analysis of Data From a German Birth Cohort. Original Research. *Frontiers in Psychiatry*. 2021-November-29 2021;12doi:10.3389/fpsyt.2021.737178
36. Raj D, Mohd Zulkefli N, Mohd Shariff Z, Ahmad N. Determinants of Excessive Screen Time among Children under Five Years Old in Selangor, Malaysia: A Cross-Sectional Study. *Int J Environ Res Public Health*. Mar 17 2022;19(6)doi:10.3390/ijerph19063560
37. Carson V, Janssen I. Associations between factors within the home setting and screen time among children aged 0–5 years: a cross-sectional study. *BMC Public Health*. 2012/07/23 2012;12(1):539. doi:10.1186/1471-2458-12-539
38. Bogl LH, Mehlig K, Ahrens W, et al. Like me, like you – relative importance of peers and siblings on children's fast food consumption and screen time but not sports club participation depends on age. *Int J Behav Nutr Phys Act*. 2020/04/15 2020;17(1):50. doi:10.1186/s12966-020-00953-4
39. Uhls YT, Ellison NB, Subrahmanyam K. Benefits and Costs of Social Media in Adolescence. *Pediatrics*. Nov 2017;140(Suppl 2):S67-s70. doi:10.1542/peds.2016-1758E

40. Mitchell KJ, Ybarra ML, Korchmaros JD, Kosciw JG. Accessing sexual health information online: use, motivations and consequences for youth with different sexual orientations. *Health Educ Res*. Feb 2014;29(1):147-57. doi:10.1093/her/cyt071
41. Hsu MSH, Rouf A, Allman-Farinelli M. Effectiveness and Behavioral Mechanisms of Social Media Interventions for Positive Nutrition Behaviors in Adolescents: A Systematic Review. *J Adolesc Health*. Nov 2018;63(5):531-545. doi:10.1016/j.jadohealth.2018.06.009
42. Chau MM, Burgermaster M, Mamykina L. The use of social media in nutrition interventions for adolescents and young adults-A systematic review. *Int J Med Inform*. Dec 2018;120:77-91. doi:10.1016/j.ijmedinf.2018.10.001
43. Wright M, Reitegger F, Cela H, Papst A, Gasteiger-Klicpera B. Interventions with Digital Tools for Mental Health Promotion among 11–18 Year Olds: A Systematic Review and Meta-Analysis. *Journal of Youth and Adolescence*. 2023/04/01 2023;52(4):754-779. doi:10.1007/s10964-023-01735-4
44. Clark H, Coll-Seck AM, Banerjee A, et al. A future for the world's children? A WHO–UNICEF–Lancet Commission. *The Lancet*. 2020;395(10224):605-658. doi:10.1016/S0140-6736(19)32540-1
45. Radesky J, Hiniker A, McLaren C, et al. Prevalence and Characteristics of Manipulative Design in Mobile Applications Used by Children. *JAMA Network Open*. 2022;5(6):e2217641-e2217641. doi:10.1001/jamanetworkopen.2022.17641
46. Rozendaal E, Buijzen M, Valkenburg P. Comparing Children's and Adults' Cognitive Advertising Competences in the Netherlands. *Journal of Children and Media*. 2010/02/01 2010;4(1):77-89. doi:10.1080/17482790903407333
47. Smith R, Kelly B, Yeatman H, Boyland E. Food Marketing Influences Children's Attitudes, Preferences and Consumption: A Systematic Critical Review. *Nutrients*. Apr 18 2019;11(4)doi:10.3390/nu11040875
48. Bornhorst C, Wijnhoven TM, Kunesova M, et al. WHO European Childhood Obesity Surveillance Initiative: associations between sleep duration, screen time and food consumption frequencies. *BMC Public Health*. Apr 30 2015;15:442. doi:10.1186/s12889-015-1793-3
49. Robinson TN, Banda JA, Hale L, et al. Screen Media Exposure and Obesity in Children and Adolescents. *Pediatrics*. Nov 2017;140(Suppl 2):S97-s101. doi:10.1542/peds.2016-1758K
50. Lissner L, Lanfer A, Gwozdz W, et al. Television habits in relation to overweight, diet and taste preferences in European children: the IDEFICS study. journal article. *European Journal of Epidemiology*. September 01 2012;27(9):705-715. doi:10.1007/s10654-012-9718-2
51. Olafsdottir S, Berg C, Eiben G, et al. Young children's screen activities, sweet drink consumption and anthropometry: results from a prospective European study. *Eur J Clin Nutr*. Feb 2014;68(2):223-8. doi:10.1038/ejcn.2013.234
52. Kenney EL, Gortmaker SL. United States Adolescents' Television, Computer, Videogame, Smartphone, and Tablet Use: Associations with Sugary Drinks, Sleep, Physical Activity, and Obesity. *J Pediatr*. Mar 2017;182:144-149. doi:10.1016/j.jpeds.2016.11.015
53. Goodman W, Jackson SE, McFerran E, Purves R, Redpath I, Beeken RJ. Association of Video Game Use With Body Mass Index and Other Energy-Balance Behaviors in Children. *JAMA Pediatrics*. 2020;174(6):563-572. doi:10.1001/jamapediatrics.2020.0202
54. Mark AE, Janssen I. Relationship between screen time and metabolic syndrome in adolescents. *J Public Health (Oxf)*. Jun 2008;30(2):153-60. doi:10.1093/pubmed/fdn022
55. Kang H-T, Lee H-R, Shim J-Y, Shin Y-H, Park B-J, Lee Y-J. Association between screen time and metabolic syndrome in children and adolescents in Korea: The 2005 Korean National Health and Nutrition Examination Survey. *Diabetes Research and Clinical Practice*. 2010/07/01/ 2010;89(1):72-78. doi:https://doi.org/10.1016/j.diabres.2010.02.016
56. Sayin FK, Buyukinan M. Sleep Duration and Media Time Have a Major Impact on Insulin Resistance and Metabolic Risk Factors in Obese Children and Adolescents. *Child Obes*. Aug 2016;12(4):272-8. doi:10.1089/chi.2015.0126
57. Ford C, Ward D, White M. Television viewing associated with adverse dietary outcomes in children ages 2-6. *Obes Rev*. Dec 2012;13(12):1139-47. doi:10.1111/j.1467-789X.2012.01028.x

58. Börnhorst C, Wijnhoven TM, Kunešová M, et al. WHO European Childhood Obesity Surveillance Initiative: associations between sleep duration, screen time and food consumption frequencies. *BMC Public Health*. Apr 30 2015;15:442. doi:10.1186/s12889-015-1793-3
59. Chaput JP, Visby T, Nyby S, et al. Video game playing increases food intake in adolescents: a randomized crossover study. *Am J Clin Nutr*. Jun 2011;93(6):1196-203. doi:10.3945/ajcn.110.008680
60. Emond JA, Longacre MR, Drake KM, et al. Exposure to Child-Directed TV Advertising and Preschoolers' Intake of Advertised Cereals. *Am J Prev Med*. Feb 2019;56(2):e35-e43. doi:10.1016/j.amepre.2018.09.015
61. van den Berg SW, Boer JMA, Scholtens S, et al. Quantification of the energy gap in young overweight children. The PIAMA birth cohort study. *BMC Public Health*. 2011/05/17 2011;11(1):326. doi:10.1186/1471-2458-11-326
62. Boyland EJ, Nolan S, Kelly B, et al. Advertising as a cue to consume: a systematic review and meta-analysis of the effects of acute exposure to unhealthy food and nonalcoholic beverage advertising on intake in children and adults. *Am J Clin Nutr*. Feb 2016;103(2):519-33. doi:10.3945/ajcn.115.120022
63. Harris JL, Bargh JA, Brownell KD. Priming effects of television food advertising on eating behavior. *Health Psychol*. Jul 2009;28(4):404-13. doi:10.1037/a0014399
64. Borzekowski DL, Robinson TN. The 30-second effect: an experiment revealing the impact of television commercials on food preferences of preschoolers. *J Am Diet Assoc*. Jan 2001;101(1):42-6. doi:10.1016/s0002-8223(01)00012-8
65. Potvin Kent M, Pauzé E, Roy EA, de Billy N, Czoli C. Children and adolescents' exposure to food and beverage marketing in social media apps. *Pediatric obesity*. 2019;14(6):e12508.
66. Qutteina Y, Hallez L, Mennes N, De Backer C, Smits T. What Do Adolescents See on Social Media? A Diary Study of Food Marketing Images on Social Media. Original Research. *Frontiers in Psychology*. 2019-November-22 2019;10(2637)doi:10.3389/fpsyg.2019.02637
67. Baldwin HJ, Freeman B, Kelly B. Like and share: associations between social media engagement and dietary choices in children. *Public Health Nutr*. Dec 2018;21(17):3210-3215. doi:10.1017/s1368980018001866
68. Folkvord F, Anschutz DJ, Buijzen M, Valkenburg PM. The effect of playing advergames that promote energy-dense snacks or fruit on actual food intake among children. Article. *Am J Clin Nutr*. Feb 2013;97(2):239-245. doi:10.3945/ajcn.112.047126
69. Coates AE, Hardman CA, Halford JC, Christiansen P, Boyland EJ. Social media influencer marketing and children's food intake: a randomized trial. *Pediatrics*. 2019;143(4)
70. Spence C, Okajima K, Cheok AD, Petit O, Michel C. Eating with our eyes: From visual hunger to digital satiation. *Brain Cogn*. Dec 2016;110:53-63. doi:10.1016/j.bandc.2015.08.006
71. Spielvogel I, Matthes J, Naderer B, Karsay K. A treat for the eyes. An eye-tracking study on children's attention to unhealthy and healthy food cues in media content. *Appetite*. Jun 1 2018;125:63-71. doi:10.1016/j.appet.2018.01.033
72. Schüssler P, Kluge M, Yassouridis A, Dresler M, Uhr M, Steiger A. Ghrelin Levels Increase After Pictures Showing Food. *Obesity*. 2012;20(6):1212-1217. doi:10.1038/oby.2011.385
73. Robinson TN, Borzekowski DL, Matheson DM, Kraemer HC. Effects of fast food branding on young children's taste preferences. *Arch Pediatr Adolesc Med*. Aug 2007;161(8):792-7. doi:10.1001/archpedi.161.8.792
74. Bruce AS, Pruitt SW, Ha O-R, et al. The Influence of Televised Food Commercials on Children's Food Choices: Evidence from Ventromedial Prefrontal Cortex Activations. *The Journal of Pediatrics*. 2016/10/01/ 2016;177:27-32.e1. doi:https://doi.org/10.1016/j.jpeds.2016.06.067
75. Ohla K, Toepel U, le Coutre J, Hudry J. Visual-Gustatory Interaction: Orbitofrontal and Insular Cortices Mediate the Effect of High-Calorie Visual Food Cues on Taste Pleasantness. *PLOS ONE*. 2012;7(3):e32434. doi:10.1371/journal.pone.0032434
76. Sprengeler O, Pohlabeln H, Bammann K, et al. Trajectories of objectively measured physical activity and childhood overweight: longitudinal analysis of the IDEFICS/I.Family cohort. *Int J Behav Nutr Phys Act*. 2021/08/09 2021;18(1):103. doi:10.1186/s12966-021-01171-2

77. Metcalf BS, Hosking J, Jeffery AN, Voss LD, Henley W, Wilkin TJ. Fatness leads to inactivity, but inactivity does not lead to fatness: a longitudinal study in children (EarlyBird 45). *Archives of Disease in Childhood*. 2011;96(10):942-947. doi:10.1136/adc.2009.175927

78. Metcalf BS, Voss LD, Hosking J, Jeffery AN, Wilkin TJ. Physical activity at the government-recommended level and obesity-related health outcomes: a longitudinal study (Early Bird 37). *Archives of Disease in Childhood*. 2008;93(9):772-777. doi:10.1136/adc.2007.135012

79. Väistö J, Eloranta AM, Viitasalo A, et al. Physical activity and sedentary behaviour in relation to cardiometabolic risk in children: cross-sectional findings from the Physical Activity and Nutrition in Children (PANIC) Study. *Int J Behav Nutr Phys Act*. Apr 26 2014;11:55. doi:10.1186/1479-5868-11-55

80. Cliff DP, Jones RA, Burrows TL, et al. Volumes and bouts of sedentary behavior and physical activity: associations with cardiometabolic health in obese children. *Obesity (Silver Spring)*. May 2014;22(5):E112-8. doi:10.1002/oby.20698

81. Ramsey Buchanan L, Rooks-Peck CR, Finnie RKC, et al. Reducing Recreational Sedentary Screen Time: A Community Guide Systematic Review. *Am J Prev Med*. Mar 2016;50(3):402-415. doi:10.1016/j.amepre.2015.09.030

82. Hale L, Guan S. Screen time and sleep among school-aged children and adolescents: a systematic literature review. *Sleep Med Rev*. Jun 2015;21:50-8. doi:10.1016/j.smrv.2014.07.007

83. Touitou Y, Touitou D, Reinberg A. Disruption of adolescents' circadian clock: The vicious circle of media use, exposure to light at night, sleep loss and risk behaviors. *J Physiol Paris*. Nov 2016;110(4 Pt B):467-479. doi:10.1016/j.jphysparis.2017.05.001

84. Oshima N, Nishida A, Shimodera S, et al. The Suicidal Feelings, Self-Injury, and Mobile Phone Use After Lights Out in Adolescents. *Journal of Pediatric Psychology*. 2012;37(9):1023-1030. doi:10.1093/jpepsy/jss072

85. Magee L, Hale L. Longitudinal associations between sleep duration and subsequent weight gain: A systematic review. *Sleep Medicine Reviews*. 2012/06/01/ 2012;16(3):231-241. doi:https://doi.org/10.1016/j.smrv.2011.05.005

86. Mosavat M, Mirsanjari M, Arabiat D, Smyth A, Whitehead L. The Role of Sleep Curtailment on Leptin Levels in Obesity and Diabetes Mellitus. *Obesity Facts*. 2021;14(2):214-221. doi:10.1159/000514095

87. Chaput J-P, Tremblay MS, Katzmarzyk PT, et al. Sleep patterns and sugar-sweetened beverage consumption among children from around the world. *Public Health Nutrition*. 2018;21(13):2385-2393. doi:10.1017/S1368980018000976

88. Winpenny EM, Rowthorn H, Hollidge S, et al. Shorter sleep among adolescents is associated with lower fruit and vegetable consumption the following day. *Int J Behav Nutr Phys Act*. 2023/02/07 2023;20(1):12. doi:10.1186/s12966-023-01420-6

89. Dashti HS, Scheer FAJL, Jacques PF, Lamon-Fava S, Ordovás JM. Short Sleep Duration and Dietary Intake: Epidemiologic Evidence, Mechanisms, and Health Implications. *Advances in Nutrition*. 2015/11/01/ 2015;6(6):648-659. doi:https://doi.org/10.3945/an.115.008623

90. Thumann BF, Michels N, Felső R, et al. Associations between sleep duration and insulin resistance in European children and adolescents considering the mediating role of abdominal obesity. *PLOS ONE*. 2020;15(6):e0235049. doi:10.1371/journal.pone.0235049

91. Qureshi F, Derks IPM, Jaddoe VWV, et al. Mental Health in Early Childhood and Changes in Cardiometabolic Dysregulation by Preadolescence. *Psychosomatic Medicine*. 2021;83(3):256-264. doi:10.1097/psy.0000000000000927

92. Hinkley T, Verbestel V, Ahrens W, et al. Early childhood electronic media use as a predictor of poorer well-being: a prospective cohort study. *JAMA Pediatr*. May 2014;168(5):485-92. doi:10.1001/jamapediatrics.2014.94

93. Bickham DS, Hswen Y, Rich M. Media use and depression: exposure, household rules, and symptoms among young adolescents in the USA. *Int J Public Health*. Feb 2015;60(2):147-55. doi:10.1007/s00038-014-0647-6

94. Cha S-S, Seo B-K. Smartphone use and smartphone addiction in middle school students in Korea: Prevalence, social networking service, and game use. *Health Psychology Open*. 2018;5(1):2055102918755046. doi:10.1177/2055102918755046
95. Müller KW, Dreier M, Beutel ME, Duven E, Giralt S, Wölfling K. A hidden type of internet addiction? Intense and addictive use of social networking sites in adolescents. *Computers in Human Behavior*. 2016/02/01/ 2016;55:172-177. doi:https://doi.org/10.1016/j.chb.2015.09.007
96. Pew Research Center. *Teens, Social Media and Technology 2022*. 2022. https://www.pewresearch.org/internet/2022/08/10/teens-social-media-and-technology-2022/
97. Fioravanti G, Casale S, Benucci SB, et al. Fear of missing out and social networking sites use and abuse: A meta-analysis. *Computers in Human Behavior*. 2021/09/01/ 2021;122:106839. doi:https://doi.org/10.1016/j.chb.2021.106839
98. Banyai F, Zsila A, Kiraly O, et al. Problematic Social Media Use: Results from a Large-Scale Nationally Representative Adolescent Sample. *PLoS One*. 2017;12(1):e0169839. doi:10.1371/journal.pone.0169839
99. Boers E, Afzali MH, Newton N, Conrod P. Association of Screen Time and Depression in Adolescence. *JAMA Pediatrics*. 2019;173(9):853-859. doi:10.1001/jamapediatrics.2019.1759
100. Viner RM, Gireesh A, Stiglic N, et al. Roles of cyberbullying, sleep, and physical activity in mediating the effects of social media use on mental health and wellbeing among young people in England: a secondary analysis of longitudinal data. *The Lancet Child & Adolescent Health*. 2019/10/01/ 2019;3(10):685-696. doi:https://doi.org/10.1016/S2352-4642(19)30186-5
101. Spies Shapiro LA, Margolin G. Growing Up Wired: Social Networking Sites and Adolescent Psychosocial Development. *Clinical Child and Family Psychology Review*. 2014/03/01 2014;17(1):1-18. doi:10.1007/s10567-013-0135-1
102. Steinsbekk S, Wichstrøm L, Stenseng F, Nesi J, Hygen BW, Skalická V. The impact of social media use on appearance self-esteem from childhood to adolescence – A 3-wave community study. *Computers in Human Behavior*. 2021/01/01/ 2021;114:106528. doi:https://doi.org/10.1016/j.chb.2020.106528
103. Tiggemann M, Zaccardo M. 'Strong is the new skinny': A content analysis of #fitspiration images on Instagram. *Journal of Health Psychology*. 2018;23(8):1003-1011. doi:10.1177/1359105316639436
104. Prichard I, Kavanagh E, Mulgrew KE, Lim MSC, Tiggemann M. The effect of Instagram #fitspiration images on young women's mood, body image, and exercise behaviour. *Body Image*. 2020/06/01/ 2020;33:1-6. doi:https://doi.org/10.1016/j.bodyim.2020.02.002
105. Christakis Dimitri A, Ramirez Julian SB, Ferguson Susan M, Ravinder S, Ramirez J-M. How early media exposure may affect cognitive function: A review of results from observations in humans and experiments in mice. *Proceedings of the National Academy of Sciences*. 2018/10/02 2018;115(40):9851-9858. doi:10.1073/pnas.1711548115
106. Altschul DM, Starr JM, Deary IJ. Cognitive function in early and later life is associated with blood glucose in older individuals: analysis of the Lothian Birth Cohort of 1936. *Diabetologia*. 2018/09/01 2018;61(9):1946-1955. doi:10.1007/s00125-018-4645-8
107. Olsson GM, Hulting A-L, Montgomery SM. Cognitive Function in Children and Subsequent Type 2 Diabetes. *Diabetes Care*. 2008;31(3):514-516. doi:10.2337/dc07-1399
108. Richards M, Black S, Mishra G, Gale CR, Deary IJ, Batty DG. IQ in childhood and the metabolic syndrome in middle age: Extended follow-up of the 1946 British Birth Cohort Study. *Intelligence*. 2009/11/01/ 2009;37(6):567-572. doi:https://doi.org/10.1016/j.intell.2008.09.004
109. Dobson KG, Chow CHT, Morrison KM, Van Lieshout RJ. Associations Between Childhood Cognition and Cardiovascular Events in Adulthood: A Systematic Review and Meta-analysis. *Canadian Journal of Cardiology*. 2017/02/01/ 2017;33(2):232-242. doi:https://doi.org/10.1016/j.cjca.2016.08.014
110. Calvin CM, Deary IJ, Fenton C, et al. Intelligence in youth and all-cause-mortality: systematic review with meta-analysis. *International Journal of Epidemiology*. 2011;40(3):626-644. doi:10.1093/ije/dyq190
111. Batty GD, Deary IJ, Schoon I, Gale CR. Mental ability across childhood in relation to risk factors for premature mortality in adult life: the 1970 British Cohort Study. *Journal of Epidemiology and Community Health*. 2007;61(11):997-1003. doi:10.1136/jech.2006.054494

112. Batty GD, Deary IJ, Schoon I, Gale CR. Childhood Mental Ability in Relation to Food Intake and Physical Activity in Adulthood: The 1970 British Cohort Study. *Pediatrics*. 2007;119(1):e38-e45. doi:10.1542/peds.2006-1831
113. Coumans JMJ, Danner UN, Intemann T, et al. Emotion-driven impulsiveness and snack food consumption of European adolescents: Results from the I.Family study. *Appetite*. Apr 1 2018;123:152-159. doi:10.1016/j.appet.2017.12.018
114. Do S, Coumans JMJ, Börnhorst C, et al. Associations Between Psychosocial Well-Being, Stressful Life Events and Emotion-Driven Impulsiveness in European Adolescents. *Journal of Youth and Adolescence*. 2021/11/09 2021;doi:10.1007/s10964-021-01533-w
115. Coumans JMJ, Danner UN, Ahrens W, et al. The association of emotion-driven impulsiveness, cognitive inflexibility and decision-making with weight status in European adolescents. *Int J Obes*. 2018/04/01 2018;42(4):655-661. doi:10.1038/ijo.2017.270
116. Hutton JS, Dudley J, Horowitz-Kraus T, DeWitt T, Holland SK. Associations Between Screen-Based Media Use and Brain White Matter Integrity in Preschool-Aged Children. *JAMA Pediatrics*. 2020;174(1):e193869-e193869. doi:10.1001/jamapediatrics.2019.3869
117. Takeuchi H, Taki Y, Asano K, et al. Impact of frequency of internet use on development of brain structures and verbal intelligence: Longitudinal analyses. *Human Brain Mapping*. 2018;39(11):4471-4479. doi:https://doi.org/10.1002/hbm.24286
118. Camerini A-L, Marciano L. Media Use and Academic Achievement. *The International Encyclopedia of Media Psychology*. 1-12.
119. van der Schuur WA, Baumgartner SE, Sumter SR, Valkenburg PM. The consequences of media multitasking for youth: A review. *Computers in Human Behavior*. 2015/12/01/ 2015;53:204-215. doi:https://doi.org/10.1016/j.chb.2015.06.035
120. Marciano L, Camerini A-L, Morese R. The Developing Brain in the Digital Era: A Scoping Review of Structural and Functional Correlates of Screen Time in Adolescence. Review. *Frontiers in Psychology*. 2021-August-27 2021;12(3761)doi:10.3389/fpsyg.2021.671817
121. Baumgartner SE, van der Schuur WA, Lemmens JS, te Poel F. The Relationship Between Media Multitasking and Attention Problems in Adolescents: Results of Two Longitudinal Studies. *Human Communication Research*. n/a(n/a)doi:https://doi.org/10.1111/hcre.12111
122. Uncapher MR, Lin L, Rosen LD, et al. Media Multitasking and Cognitive, Psychological, Neural, and Learning Differences. *Pediatrics*. Nov 2017;140(Suppl 2):S62-s66. doi:10.1542/peds.2016-1758D
123. Moher D, Liberati A, Tetzlaff J, Altman DG. Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. *PLoS Med*. Jul 21 2009;6(7):e1000097. doi:10.1371/journal.pmed.1000097
124. Ouzzani M, Hammady H, Fedorowicz Z, Elmagarmid A. Rayyan—a web and mobile app for systematic reviews. *Systematic Reviews*. 2016/12/05 2016;5(1):210. doi:10.1186/s13643-016-0384-4
125. Wells GA, Shea B, O'Connell Da, et al. The Newcastle-Ottawa Scale (NOS) for assessing the quality of nonrandomised studies in meta-analyses. Oxford; 2000.
126. Moola, S. , Munn Z, Tufanaru C, et al. Chapter 7: Systematic reviews of etiology and risk. In: Aromataris E MZE, ed. *JBI Manual for Evidence SynthesisJBI*. 2020.
127. Sterne JAC, Savović J, Page MJ, et al. RoB 2: a revised tool for assessing risk of bias in randomised trials. *BMJ*. 2019;366:l4898. doi:10.1136/bmj.l4898
128. Bradbury KM, Turel O, Morrison KM. Electronic device use and beverage related sugar and caffeine intake in US adolescents. *PLoS ONE*. 2019 2019;14(10)
129. Cullen KW, Thompson D, Boushey C, Konzelmann K, Chen T-A. Evaluation of a web-based program promoting healthy eating and physical activity for adolescents: Teen Choice: Food and Fitness. *Health Education Research*. 2013 2013;28(4):704-714.
130. English LK, Fearnbach SN, Lasschuijt M, et al. Brain regions implicated in inhibitory control and appetite regulation are activated in response to food portion size and energy density in children. *Int J Obes*. 2016 2016;40(10):1515-1522.
131. English LK, Fearnbach SN, Wilson SJ, et al. Food portion size and energy density evoke different patterns of brain activation in children. *Am J Clin Nutr*. 2017 2017;105(2):295-305.

132. Fearnbach SN, English LK, Lasschuijt M, et al. Brain response to images of food varying in energy density is associated with body composition in 7- to 10-year-old children: Results of an exploratory study. *Physiology and Behavior*. 2016 2016;162:3-9.
133. Jensen CD, Duraccio KM, Carbine KA, Barnett KA, Kirwan CB. Motivational impact of palatable food correlates with functional brain responses to food images in adolescents. *Journal of Pediatric Psychology*. 2017 2017;42(5):578-587.
134. Masterson TD, Bermudez MA, Austen M, et al. Food commercials do not affect energy intake in a laboratory meal but do alter brain responses to visual food cues in children. *Appetite*. 2019;132:154-165.
135. Samara A, Li X, Pivik RT, Badger TM, Ou X. Brain activation to high-calorie food images in healthy normal weight and obese children: A fMRI study. *BMC Obesity*. 2018 2018;5(1)
136. Stice E, Yokum S, Burger KS, Epstein LH, Small DM. Youth at risk for obesity show greater activation of striatal and somatosensory regions to food. *Journal of Neuroscience*. 2011 2011;31(12):4360-4366.
137. Keller KL, English LK, Fearnbach SN, et al. Brain response to food cues varying in portion size is associated with individual differences in the portion size effect in children. *Appetite*. 2018;125:139-151.
138. Sampasa-Kanyinga H, Chaput JP, Hamilton HA. Associations between the use of social networking sites and unhealthy eating behaviours and excess body weight in adolescents. *Br J Nutr*. Dec 14 2015;114(11):1941-7. doi:10.1017/s0007114515003566
139. Sadler JR, Shearrer GE, Papantoni A, Yokum ST, Stice E, Burger KS. Correlates of Neural Adaptation to Food Cues and Taste: The Role of Obesity Risk Factors. *Soc Cogn Affect Neurosci*. Mar 3 2021;doi:10.1093/scan/nsab018
140. Allen HA, Chambers A, Blissett J, et al. Relationship between parental feeding practices and neural responses to food cues in adolescents. *PLoS ONE*. 2016 2016;11(8)
141. Coates AE, Hardman CA, Halford JCG, Christiansen P, Boyl, EJ. The effect of influencer marketing of food and a "protective" advertising disclosure on children's food intake. *Pediatric Obesity*.2019;14(10)
142. Sharps MA, Hetherington MM, Blundell-Birtill P, Rolls BJ, Evans CEL. The effectiveness of a social media intervention for reducing portion sizes in young adults and adolescents. *Digital Health*. 2019 2019;5
143. Watson P, Wiers RW, Hommel B, Ridderinkhof KR, de Wit S. An associative account of how the obesogenic environment biases adolescents' food choices. *Appetite*. 2016 2016;96:560-571.
144. Charbonnier L, van Meer F, Johnstone AM, et al. Effects of hunger state on the brain responses to food cues across the life span. *NeuroImage*. 2018 2018;171:246-255.
145. Van Meer F, Van Der Laan LN, Charbonnier L, Viergever MA, Adan RAH, Smeets PAM. Developmental differences in the brain response to unhealthy food cues: An fMRI study of children and adults. *Am J Clin Nutr*. 2016 2016;104(6):1515-1522.
146. Smit CR, Buijs L, van Woudenberg TJ, Bevel, er KE, Buijzen M. The Impact of Social Media Influencers on Children's Dietary Behaviors. *Frontiers in Psychology*. 2020 2020;10
147. Folkvord F, de Bruijne M. The effect of the promotion of vegetables by a social influencer on adolescents' subsequent vegetable intake: A pilot study. *International Journal of Environmental Research and Public Health*. 2020 2020;17(7)
148. Busch V, Manders LA, de Leeuw JR. Screen time associated with health behaviors and outcomes in adolescents. *Am J Health Behav*. Nov 2013;37(6):819-30. doi:10.5993/AJHB.37.6.11
149. Murphy G, Corcoran C, Tatlow-Golden M, Boyl, E, Rooney B. See, like, share, remember: Adolescents' responses to unhealthy-, healthy- and non-food advertising in social media. *International Journal of Environmental Research and Public Health*. 2020 2020;17(7)
150. De Jans S, Spielvogel I, Naderer B, Hudders L. Digital food marketing to children: How an influencer's lifestyle can stimulate healthy food choices among children. Article. *Appetite*. 2021;162105182. doi:10.1016/j.appet.2021.105182
151. Ngqangashe Y, Backer CJS. The differential effects of viewing short-form online culinary videos of fruits and vegetables versus sweet snacks on adolescents' appetites. *Appetite*. Nov 1 2021;166:105436. doi:10.1016/j.appet.2021.105436

152. Qutteina Y, Hallez L, Raedschelders M, De Backer C, Smits T. Food for teens: how social media is associated with adolescent eating outcomes. *Public Health Nutr*. Jul 30 2021:1-13. doi:10.1017/s1368980021003116
153. Marsh S, Ni Mhurchu C, Jiang Y, Maddison R. Modern screen-use behaviors: the effects of single- and multi-screen use on energy intake. *J Adolesc Health*. May 2015;56(5):543-9. doi:10.1016/j.jadohealth.2015.01.009
154. Gascoyne C, Scully M, Wakefield M, Morley B. Food and drink marketing on social media and dietary intake in Australian adolescents: Findings from a cross-sectional survey. Article. *Appetite*. 2021;166105431. doi:10.1016/j.appet.2021.105431
155. Delfino LD, Dos Santos Silva DA, Tebar WR, et al. Screen time by different devices in adolescents: Association with physical inactivity domains and eating habits. *J Sports Med Phys Fit*. 2018 2018;58(3):318-325.
156. Hansstein FV, Hong Y, Di C. The relationship between new media exposure and fast food consumption among Chinese children and adolescents in school: a rural–urban comparison. *Global Health Promotion*. 2017 2017;24(3):40-48.
157. Lwin MO, Malik S, Ridwan H, Sum Au CS. Media exposure and parental mediation on fast-food consumption among children in metropolitan and suburban Indonesian. *Asia Pacific Journal of Clinical Nutrition*. 2017 2017;26(5):899-905.
158. Teo E, Goh D, Vijayakumar KM, Liu JCJ. To message or browse? Exploring the impact of phone use patterns on male adolescents' consumption of palatable snacks. *Frontiers in Psychology*. 2018 2018;8
159. Byun D, Kim R, Oh H. Leisure-time and study-time Internet use and dietary risk factors in Korean adolescents. *Am J Clin Nutr*. 2021;114(5):1791-1801. doi:10.1093/ajcn/nqab229
160. Kim HR, Han MA. Associations between problematic smartphone use, unhealthy behaviors, and mental health status in Korean adolescents: Based on data from the 13th Korea youth risk behavior survey (2017). Article. *Psychiatry Investig*. 2020;17(12):1216-1225. doi:10.30773/pi.2020.0007
161. Ahrens W, Bammann K, Siani A, et al. The IDEFICS cohort: design, characteristics and participation in the baseline survey. *Int J Obes (Lond)*. Apr 2011;35 Suppl 1:S3-15. doi:10.1038/ijo.2011.30
162. Bammann K, Lissner L, Pigeot I, Ahrens W. *Instruments for health surveys in children and adolescents*. Springer; 2019.
163. Jilani H, Pohlabeln H, De Henauw S, et al. Relative Validity of a Food and Beverage Preference Questionnaire to Characterize Taste Phenotypes in Children Adolescents and Adults. *Nutrients*. Jun 27 2019;11(7)doi:10.3390/nu11071453
164. Rauber F, Da Costa Louzada ML, Steele EM, Millett C, Monteiro CA, Levy RB. Ultra-Processed Food Consumption and Chronic Non-Communicable Diseases-Related Dietary Nutrient Profile in the UK (2008–2014). *Nutrients*. 2018;10(5):587.
165. Ambrosini GL, Johns DJ, Northstone K, Emmett PM, Jebb SA. Free Sugars and Total Fat Are Important Characteristics of a Dietary Pattern Associated with Adiposity across Childhood and Adolescence. *The Journal of Nutrition*. 2016;146(4):778-784. doi:10.3945/jn.115.224659
166. Liem DG, Russell CG. The Influence of Taste Liking on the Consumption of Nutrient Rich and Nutrient Poor Foods. *Front Nutr*. 2019;6:174. doi:10.3389/fnut.2019.00174
167. Mennella JA, Bobowski NK. The sweetness and bitterness of childhood: Insights from basic research on taste preferences. *Physiol Behav*. Dec 1 2015;152(Pt B):502-7. doi:10.1016/j.physbeh.2015.05.015
168. Jilani HS, Intemann T, Bogl LH, et al. Familial aggregation and socio-demographic correlates of taste preferences in European children. *BMC Nutrition*. 2017/12/06 2017;3(1):87. doi:10.1186/s40795-017-0206-7
169. Juraska JM, Willing J. Pubertal onset as a critical transition for neural development and cognition. *Brain Res*. Jan 1 2017;1654(Pt B):87-94. doi:10.1016/j.brainres.2016.04.012
170. Berg EA. A Simple Objective Technique for Measuring Flexibility in Thinking. *The Journal of General Psychology*. 1948/07/01 1948;39(1):15-22. doi:10.1080/00221309.1948.9918159

171. Mueller ST, Piper BJ. The Psychology Experiment Building Language (PEBL) and PEBL Test Battery. *Journal of Neuroscience Methods*. 2014/01/30/ 2014;222:250-259. doi:https://doi.org/10.1016/j.jneumeth.2013.10.024
172. Crone EA, van der Molen MW. Developmental Changes in Real Life Decision Making: Performance on a Gambling Task Previously Shown to Depend on the Ventromedial Prefrontal Cortex. *Developmental Neuropsychology*. 2004/06/01 2004;25(3):251-279. doi:10.1207/s15326942dn2503_2
173. Bechara A, Damasio AR, Damasio H, Anderson SW. Insensitivity to future consequences following damage to human prefrontal cortex. *Cognition*. 1994/04/01/ 1994;50(1):7-15. doi:https://doi.org/10.1016/0010-0277(94)90018-3
174. Whiteside SP, Lynam DR. The Five Factor Model and impulsivity: using a structural model of personality to understand impulsivity. *Personality and Individual Differences*. 2001/03/01/ 2001;30(4):669-689. doi:https://doi.org/10.1016/S0191-8869(00)00064-7
175. Cole TJ, Lobstein T. Extended international (IOTF) body mass index cut-offs for thinness, overweight and obesity. *Pediatr Obes*. Aug 2012;7(4):284-94. doi:10.1111/j.2047-6310.2012.00064.x
176. Stomfai S, Ahrens W, Bammann K, et al. Intra- and inter-observer reliability in anthropometric measurements in children. *Int J Obes*. 2011/04/01 2011;35(1):S45-S51. doi:10.1038/ijo.2011.34
177. Alpert BS. Validation of the Welch Allyn Spot Vital Signs blood pressure device according to the ANSI/AAMI SP10: 2002. Accuracy and cost-efficiency successfully combined. *Blood Pressure Monitoring*. 2007;12(5):345-347. doi:10.1097/MBP.0b013e3282c9abf7
178. Barba G, Buck C, Bammann K, et al. Blood pressure reference values for European non-overweight school children: the IDEFICS study. *Int J Obes (Lond)*. Sep 2014;38 Suppl 2:S48-56. doi:10.1038/ijo.2014.135
179. De Henauw S, Michels N, Vyncke K, et al. Blood lipids among young children in Europe: results from the European IDEFICS study. *Int J Obes*. 2014/09/01 2014;38(2):S67-S75. doi:10.1038/ijo.2014.137
180. Ahrens W, Moreno LA, Mårild S, et al. Metabolic syndrome in young children: definitions and results of the IDEFICS study. *Int J Obes*. 2014/09/01 2014;38(2):S4-S14. doi:10.1038/ijo.2014.130
181. Peplies J, Jiménez-Pavón D, Savva SC, et al. Percentiles of fasting serum insulin, glucose, HbA1c and HOMA-IR in pre-pubertal normal weight European children from the IDEFICS cohort. *Int J Obes*. 2014/09/01 2014;38(2):S39-S47. doi:10.1038/ijo.2014.134
182. Nagy P, Kovacs E, Moreno LA, et al. Percentile reference values for anthropometric body composition indices in European children from the IDEFICS study. *Int J Obes (Lond)*. Sep 2014;38 Suppl 2:S15-25. doi:10.1038/ijo.2014.131
183. Suling M, Hebestreit A, Peplies J, et al. Design and results of the pretest of the IDEFICS study. *Int J Obes*. 2011/04/01 2011;35(1):S30-S44. doi:10.1038/ijo.2011.33
184. Rideout Victoria J., Foehr Uhlla G., and Roberts Donald F. Ph.D. Generation M2: Media in the Lives of 8- to 18-Year-Olds. Accessed 16.12.2022. https://www.kff.org/other/poll-finding/report-generation-m2-media-in-the-lives/
185. UNESCO. International Standard Classification of Education ISCED 2011. 2011.
186. van Jaarsveld CH, Fidler JA, Simon AE, Wardle J. Persistent impact of pubertal timing on trends in smoking, food choice, activity, and stress in adolescence. *Psychosom Med*. Nov 2007;69(8):798-806. doi:10.1097/PSY.0b013e3181576106
187. Carskadon MA, Acebo C. A self-administered rating scale for pubertal development. *Journal of Adolescent Health*. 1993/05/01/ 1993;14(3):190-195. doi:https://doi.org/10.1016/1054-139X(93)90004-9
188. Tanner JM. Growth and Maturation during Adolescence. *Nutrition Reviews*. 1981;39(2):43-55. doi:10.1111/j.1753-4887.1981.tb06734.x
189. Lanfer A, Hebestreit A, Ahrens W, et al. Reproducibility of food consumption frequencies derived from the Children's Eating Habits Questionnaire used in the IDEFICS study. *Int J Obes (Lond)*. Apr 2011;35 Suppl 1:S61-8. doi:10.1038/ijo.2011.36
190. Bel-Serrat S, Mouratidou T, Pala V, et al. Relative validity of the Children's Eating Habits Questionnaire-food frequency section among young European children: the IDEFICS Study. *Public Health Nutr*. Feb 2014;17(2):266-76. doi:10.1017/s1368980012005368

191. Waijers PMCM, Feskens EJM, Ocké MC. A critical review of predefined diet quality scores. *British Journal of Nutrition*. 2007;97(2):219-231. doi:10.1017/S0007114507250421
192. Arvidsson L, Eiben G, Hunsberger M, et al. Bidirectional associations between psychosocial well-being and adherence to healthy dietary guidelines in European children: prospective findings from the IDEFICS study. *BMC Public Health*. Dec 14 2017;17(1):926. doi:10.1186/s12889-017-4920-5
193. Lee AM, Gurka MJ, DeBoer MD. Trends in Metabolic Syndrome Severity and Lifestyle Factors Among Adolescents. *Pediatrics*. 2016;137(3):e20153177. doi:10.1542/peds.2015-3177
194. Konstabel K, Veidebaum T, Verbestel V, et al. Objectively measured physical activity in European children: the IDEFICS study. *Int J Obes*. 2014/09/01 2014;38(2):S135-S143. doi:10.1038/ijo.2014.144
195. Buck C, Eiben G, Lauria F, et al. Urban Moveability and physical activity in children: longitudinal results from the IDEFICS and I.Family cohort. *Int J Behav Nutr Phys Act*. 2019/12/11 2019;16(1):128. doi:10.1186/s12966-019-0886-2
196. Santaliestra-Pasías AM, Dios JEL, Sprengeler O, et al. Food and beverage intakes according to physical activity levels in European children: the IDEFICS (Identification and prevention of Dietary and lifestyle induced health EFfects In Children and infantS) study. *Public Health Nutrition*. 2018;21(9):1717-1725. doi:10.1017/S1368980018000046
197. Choi L, Liu Z, Matthews CE, Buchowski MS. Validation of accelerometer wear and nonwear time classification algorithm. *Medicine and science in sports and exercise*. 2011;43(2):357-364. doi:10.1249/MSS.0b013e3181ed61a3
198. Evenson KR, Catellier DJ, Gill K, Ondrak KS, McMurray RG. Calibration of two objective measures of physical activity for children. *Journal of Sports Sciences*. 2008/12/15 2008;26(14):1557-1565. doi:10.1080/02640410802334196
199. Carson V, Janssen I. Volume, patterns, and types of sedentary behavior and cardio-metabolic health in children and adolescents: a cross-sectional study. *BMC public health*. 2011;11:274-274. doi:10.1186/1471-2458-11-274
200. Saunders TJ, Tremblay MS, Mathieu ME, et al. Associations of sedentary behavior, sedentary bouts and breaks in sedentary time with cardiometabolic risk in children with a family history of obesity. *PLoS One*. 2013;8(11):e79143. doi:10.1371/journal.pone.0079143
201. Bogl L-H, Kaprio J, Brünings-Kuppe C, Lissner L, Ahrens W. Interview on Kinship and Household. *Instruments for Health Surveys in Children and Adolescents*. Springer; 2019:291-301.
202. Trent K, Spitze GD. GROWING UP WITHOUT SIBLINGS AND ADULT SOCIABILITY BEHAVIORS. *J Fam Issues*. 2011;32(9):1178-1204. doi:10.1177/0192513X11398945
203. Yang J, Hou X, Wei D, Wang K, Li Y, Qiu J. Only-child and non-only-child exhibit differences in creativity and agreeableness: evidence from behavioral and anatomical structural studies. *Brain Imaging and Behavior*. 2017/04/01 2017;11(2):493-502. doi:10.1007/s11682-016-9530-9
204. Bullinger M, Brütt AL, Erhart M, Ravens-Sieberer U. Psychometric properties of the KINDL-R questionnaire: results of the BELLA study. *Eur Child Adolesc Psychiatry*. Dec 2008;17 Suppl 1:125-32. doi:10.1007/s00787-008-1014-z
205. Liu Y, De A. Multiple Imputation by Fully Conditional Specification for Dealing with Missing Data in a Large Epidemiologic Study. *Int J Stat Med Res*. 2015;4(3):287-295. doi:10.6000/1929-6029.2015.04.03.7
206. Šidák Z. Rectangular Confidence Regions for the Means of Multivariate Normal Distributions. *Journal of the American Statistical Association*. 1967/06/01 1967;62(318):626-633. doi:10.1080/01621459.1967.10482935
207. Lanza ST, Cooper BR. Latent Class Analysis for Developmental Research. https://doi.org/10.1111/cdep.12163. *Child Development Perspectives*. 2016/03/01 2016;10(1):59-64. doi:https://doi.org/10.1111/cdep.12163
208. Weller BE, Bowen NK, Faubert SJ. Latent Class Analysis: A Guide to Best Practice. *Journal of Black Psychology*. 2020/05/01 2020;46(4):287-311. doi:10.1177/0095798420930932
209. Pohlabeln H, Rach S, De Henauw S, et al. Further evidence for the role of pregnancy-induced hypertension and other early life influences in the development of ADHD: results from the IDEFICS study. *Eur Child Adolesc Psychiatry*. Aug 2017;26(8):957-967. doi:10.1007/s00787-017-0966-2

210. Börnhorst C, Siani A, Russo P, et al. Early Life Factors and Inter-Country Heterogeneity in BMI Growth Trajectories of European Children: The IDEFICS Study. *PLOS ONE*. 2016;11(2):e0149268. doi:10.1371/journal.pone.0149268
211. Sayers A, Heron J, Smith A, et al. Joint modelling compared with two stage methods for analysing longitudinal data and prospective outcomes: A simulation study of childhood growth and BP. *Stat Methods Med Res*. 2017;26(1):437-452. doi:10.1177/0962280214548822
212. Folkvord F, van 't Riet J. The persuasive effect of advergames promoting unhealthy foods among children: A meta-analysis. *Appetite*. 2018/10// 2018;129:245-251. doi:10.1016/j.appet.2018.07.020
213. Seal A, Gavaravarapu SM, Konapur A. Can foodporn prime healthy eating? Thinking beyond digital gazing and satiety. *European Journal of Clinical Nutrition*. 2022/04/11 2022;doi:10.1038/s41430-022-01139-w
214. Evans R, Christiansen P, Masterson T, Pollack C, Albadri S, Boyland E. Recall of food marketing on videogame livestreaming platforms: Associations with adolescent diet-related behaviours and health. *Appetite*. 2023/04/29/ 2023:106584. doi:https://doi.org/10.1016/j.appet.2023.106584
215. De Veirman M, Hudders L, Nelson MR. What Is Influencer Marketing and How Does It Target Children? A Review and Direction for Future Research. Review. *Frontiers in Psychology*. 2019-December-03 2019;10(2685)doi:10.3389/fpsyg.2019.02685
216. Horton D, Richard Wohl R. Mass communication and para-social interaction: Observations on intimacy at a distance. *psychiatry*. 1956;19(3):215-229.
217. Lou C, Kim HK. Fancying the New Rich and Famous? Explicating the Roles of Influencer Content, Credibility, and Parental Mediation in Adolescents' Parasocial Relationship, Materialism, and Purchase Intentions. Original Research. *Frontiers in Psychology*. 2019-November-15 2019;10doi:10.3389/fpsyg.2019.02567
218. Balaban DC, Szambolics J, Chirică M. Parasocial relations and social media influencers' persuasive power. Exploring the moderating role of product involvement. *Acta Psychologica*. 2022/10/01/ 2022;230:103731. doi:https://doi.org/10.1016/j.actpsy.2022.103731
219. Bandura A. Social-learning theory of identificatory processes. *Handbook of socialization theory and research*. 1969;213:262.
220. Folkvord F. *The psychology of food marketing and overeating*. Routledge; 2019.
221. Kay S, Mulcahy R, Parkinson J. When less is more: the impact of macro and micro social media influencers' disclosure. *Journal of Marketing Management*. 2020/02/12 2020;36(3-4):248-278. doi:10.1080/0267257X.2020.1718740
222. De Jans S, Cauberghe V, Hudders L. How an Advertising Disclosure Alerts Young Adolescents to Sponsored Vlogs: The Moderating Role of a Peer-Based Advertising Literacy Intervention through an Informational Vlog. *Journal of Advertising*. 2018/10/02 2018;47(4):309-325. doi:10.1080/00913367.2018.1539363
223. De Veirman M, Cauberghe V, Hudders L. Marketing through Instagram influencers: the impact of number of followers and product divergence on brand attitude. *International Journal of Advertising*. 2017/09/03 2017;36(5):798-828. doi:10.1080/02650487.2017.1348035
224. Salvy S-J, Elmo A, Nitecki LA, Kluczynski MA, Roemmich JN. Influence of parents and friends on children's and adolescents' food intake and food selection. *The American Journal of Clinical Nutrition*. 2010;93(1):87-92. doi:10.3945/ajcn.110.002097
225. Rodrigues L, Silverio R, Costa AR, et al. Taste sensitivity and lifestyle are associated with food preferences and BMI in children. *International Journal of Food Sciences and Nutrition*. 2020/10/02 2020;71(7):875-883. doi:10.1080/09637486.2020.1738354
226. Drewnowski A. Energy intake and sensory properties of food. *Am J Clin Nutr*. Nov 1995;62(5 Suppl):1081s-1085s. doi:10.1093/ajcn/62.5.1081S
227. Zhou Z, SooHoo M, Zhou Q, Perez M, Liew J. Temperament as Risk and Protective Factors in Obesogenic Eating: Relations Among Parent Temperament, Child Temperament, and Child Food Preference and Eating. *J Genet Psychol*. Jan-Feb 2019;180(1):75-79. doi:10.1080/00221325.2019.1575180

228. Yañez AM, Bennasar-Veny M, Leiva A, García-Toro M. Implications of personality and parental education on healthy lifestyles among adolescents. *Sci Rep*. May 13 2020;10(1):7911. doi:10.1038/s41598-020-64850-3
229. Mennella JA. Ontogeny of taste preferences: basic biology and implications for health. *The American Journal of Clinical Nutrition*. 2014;99(3):704S-711S. doi:10.3945/ajcn.113.067694
230. Mennella JA, Jagnow CP, Beauchamp GK. Prenatal and Postnatal Flavor Learning by Human Infants. *Pediatrics*. 2001;107(6):e88-e88. doi:10.1542/peds.107.6.e88
231. Mohd Nor ND, Houston-Price C, Harvey K, Methven L. The effects of taste sensitivity and repeated taste exposure on children's intake and liking of turnip (Brassica rapa subsp. rapa); a bitter Brassica vegetable. *Appetite*. 2021/02/01/ 2021;157:104991. doi:https://doi.org/10.1016/j.appet.2020.104991
232. Wiradhany W, Koerts J. Everyday functioning-related cognitive correlates of media multitasking: a mini meta-analysis. *Media Psychology*. 2021/03/04 2021;24(2):276-303. doi:10.1080/15213269.2019.1685393
233. Sha P, Sariyska R, Riedl R, Lachmann B, Montag C. Linking Internet Communication and Smartphone Use Disorder by taking a closer look at the Facebook and WhatsApp applications. *Addictive Behaviors Reports*. 2019/06/01/ 2019;9:100148. doi:https://doi.org/10.1016/j.abrep.2018.100148
234. Hefner D, Vorderer P. Permanent connectedness and multitasking. *The Routledge handbook of media use and well-being: International perspectives on theory and research on positive media effects*. 2016:237-249.
235. Arain M, Haque M, Johal L, et al. Maturation of the adolescent brain. *Neuropsychiatr Dis Treat*. 2013;9:449-61. doi:10.2147/ndt.S39776
236. Defoe IN, Dubas JS, Figner B, van Aken MA. A meta-analysis on age differences in risky decision making: adolescents versus children and adults. *Psychol Bull*. Jan 2015;141(1):48-84. doi:10.1037/a0038088
237. Steele RG, Hall JA, Christofferson JL. Conceptualizing Digital Stress in Adolescents and Young Adults: Toward the Development of an Empirically Based Model. *Clin Child Fam Psychol Rev*. Mar 2020;23(1):15-26. doi:10.1007/s10567-019-00300-5
238. Schweizer S, Gotlib IH, Blakemore SJ. The role of affective control in emotion regulation during adolescence. *Emotion*. Feb 2020;20(1):80-86. doi:10.1037/emo0000695
239. Firth JA, Torous J, Firth J. Exploring the Impact of Internet Use on Memory and Attention Processes. *International journal of environmental research and public health*. 2020;17(24):9481. doi:10.3390/ijerph17249481
240. Nikkelen SW, Valkenburg PM, Huizinga M, Bushman BJ. Media use and ADHD-related behaviors in children and adolescents: A meta-analysis. *Dev Psychol*. Sep 2014;50(9):2228-41. doi:10.1037/a0037318
241. Ra CK, Cho J, Stone MD, et al. Association of Digital Media Use With Subsequent Symptoms of Attention-Deficit/Hyperactivity Disorder Among Adolescents. *Jama*. Jul 17 2018;320(3):255-263. doi:10.1001/jama.2018.8931
242. Jacques A, Chaaya N, Beecher K, Ali SA, Belmer A, Bartlett S. The impact of sugar consumption on stress driven, emotional and addictive behaviors. *Neuroscience & Biobehavioral Reviews*. 2019/08/01/ 2019;103:178-199. doi:https://doi.org/10.1016/j.neubiorev.2019.05.021
243. Sina E, Boakye D, Christianson L, Ahrens W, Hebestreit A. Social Media and Children's and Adolescents' Diets: A Systematic Review of the Underlying Social and Physiological Mechanisms. *Advances in Nutrition*. 2022;13(3):913-937. doi:10.1093/advances/nmac018
244. Michels N, Sioen I, Braet C, et al. Stress, emotional eating behaviour and dietary patterns in children. *Appetite*. 2012/12/01/ 2012;59(3):762-769. doi:https://doi.org/10.1016/j.appet.2012.08.010
245. Krach S, Paulus FM, Bodden M, Kircher T. The rewarding nature of social interactions. *Front Behav Neurosci*. 2010;4:22. doi:10.3389/fnbeh.2010.00022
246. Liu M, Luo J. Relationship between peripheral blood dopamine level and internet addiction disorder in adolescents: a pilot study. *Int J Clin Exp Med*. 2015;8(6):9943-8.
247. Lillard AS, Peterson J. The Immediate Impact of Different Types of Television on Young Children's Executive Function. *Pediatrics*. 2011;128(4):644-649. doi:10.1542/peds.2010-1919

248. Lissak G. Adverse physiological and psychological effects of screen time on children and adolescents: Literature review and case study. *Environmental Research*. 2018/07/01/ 2018;164:149-157. doi:https://doi.org/10.1016/j.envres.2018.01.015
249. Instagram. Continuing our video investment on Instagram. Meta Accessed 14.10, 2022. https://creators.instagram.com/blog/instagram-reels-creators-simplify-video
250. Pempek TA, Lauricella AR. Chapter 3 - The Effects of Parent-Child Interaction and Media Use on Cognitive Development in Infants, Toddlers, and Preschoolers. In: Blumberg FC, Brooks PJ, eds. *Cognitive Development in Digital Contexts*. Academic Press; 2017:53-74.
251. McDaniel BT, Radesky JS. Technoference: Parent Distraction With Technology and Associations With Child Behavior Problems. *Child Dev*. Jan 2018;89(1):100-109. doi:10.1111/cdev.12822
252. Barr R. Growing up in the digital age: Early learning and family media ecology. *Curr Dir Psychol Sci*. Aug 2019;28(4):341-346. doi:10.1177/0963721419838245
253. Hardy LL, Denney-Wilson E, Thrift AP, Okely AD, Baur LA. Screen Time and Metabolic Risk Factors Among Adolescents. *JAMA Pediatrics*. 2010;164(7):643-649. doi:10.1001/archpediatrics.2010.88
254. Peplies J, Börnhorst C, Günther K, et al. Longitudinal associations of lifestyle factors and weight status with insulin resistance (HOMA-IR) in preadolescent children: the large prospective cohort study IDEFICS. *The international journal of behavioral nutrition and physical activity*. 2016;13(1):97-97. doi:10.1186/s12966-016-0424-4
255. Klesges RC, Shelton ML, Klesges LM. Effects of Television on Metabolic Rate: Potential Implications For Childhood Obesity. *Pediatrics*. 1993;91(2):281-286.
256. Dietz WH, Bandini LG, Morelli JA, Peers KF, Ching PL. Effect of sedentary activities on resting metabolic rate. *Am J Clin Nutr*. Mar 1994;59(3):556-9. doi:10.1093/ajcn/59.3.556
257. Absoud M, Cummins C, Lim MJ, Wassmer E, Shaw N. Prevalence and predictors of vitamin D insufficiency in children: a Great Britain population based study. *PLoS One*. 2011;6(7):e22179. doi:10.1371/journal.pone.0022179
258. Challa AS, Makariou SE, Siomou EC. The relation of vitamin D status with metabolic syndrome in childhood and adolescence: an update. *Journal of Pediatric Endocrinology and Metabolism*. 2015;28(11-12):1235-1245. doi:doi:10.1515/jpem-2014-0485
259. Lee SH, Kim SM, Park HS, et al. Serum 25-hydroxyvitamin D levels, obesity and the metabolic syndrome among Korean children. *Nutrition, Metabolism and Cardiovascular Diseases*. 2013/08/01/ 2013;23(8):785-791. doi:https://doi.org/10.1016/j.numecd.2012.04.013
260. Pacifico L, Anania C, Osborn JF, et al. Low 25(OH)D3 levels are associated with total adiposity, metabolic syndrome, and hypertension in Caucasian children and adolescents. *European Journal of Endocrinology*. 2011;165(4):603-611. doi:10.1530/eje-11-0545
261. Williams DM, Fraser A, Sayers A, et al. Associations of childhood 25-hydroxyvitamin D2 and D3 and cardiovascular risk factors in adolescence: prospective findings from the Avon Longitudinal Study of Parents and Children. *Eur J Prev Cardiol*. Mar 2014;21(3):281-90. doi:10.1177/2047487312465688
262. Wolters M, Marron M, Foraita R, et al. Longitudinal associations between vitamin D status and cardiometabolic risk markers among children and adolescents. *The Journal of Clinical Endocrinology and Metabolism*. 2023;doi:(Under revision)
263. Gralla MH, McDonald SM, Breneman C, Beets MW, Moore JB. Associations of Objectively Measured Vigorous Physical Activity With Body Composition, Cardiorespiratory Fitness, and Cardiometabolic Health in Youth: A Review. *Am J Lifestyle Med*. Jan-Feb 2019;13(1):61-97. doi:10.1177/1559827615624417
264. Stabelini Neto A, de Campos W, dos Santos GC, Mazzardo Junior O. Metabolic syndrome risk score and time expended in moderate to vigorous physical activity in adolescents. *BMC Pediatrics*. 2014/02/14 2014;14(1):42. doi:10.1186/1471-2431-14-42
265. Savina E. Does play promote self-regulation in children? *Early Child Development and Care*. 2014/11/02 2014;184(11):1692-1705. doi:10.1080/03004430.2013.875541
266. Brechet C, D'Audigier L, Audras-Torrent L. The use of drawing as an emotion regulation technique with children. *Psychology of Aesthetics, Creativity, and the Arts*. 2020;

267. Hernández MM, Eisenberg N, Valiente C, et al. Self-Regulation and Academic Measures Across the Early Elementary School Grades: Examining Longitudinal and Bidirectional Associations. *Early Education and Development*. 2018/10/03 2018;29(7):914-938. doi:10.1080/10409289.2018.1496722
268. Ustun B, Reissland N, Covey J, Schaal B, Blissett J. Flavor Sensing in Utero and Emerging Discriminative Behaviors in the Human Fetus. *Psychol Sci*. Sep 21 2022:9567976221105460. doi:10.1177/09567976221105460
269. Johnson SL, Moding KJ, Grimm KJ, Flesher AE, Bakke AJ, Hayes JE. Infant and Toddler Responses to Bitter-Tasting Novel Vegetables: Findings from the Good Tastes Study. *The Journal of Nutrition*. 2021;151(10):3240-3252. doi:10.1093/jn/nxab198
270. Svensson R, Johnson B, Olsson A. Does gender matter? The association between different digital media activities and adolescent well-being. *BMC Public Health*. 2022/02/10 2022;22(1):273. doi:10.1186/s12889-022-12670-7
271. McLean SA, Jarman HK, Rodgers RF. How do "selfies" impact adolescents' well-being and body confidence? A narrative review. *Psychol Res Behav Manag*. 2019;12:513-521. doi:10.2147/PRBM.S177834
272. Shriver LH, Dollar JM, Calkins SD, Keane SP, Shanahan L, Wideman L. Emotional Eating in Adolescence: Effects of Emotion Regulation, Weight Status and Negative Body Image. *Nutrients*. 2021;13(1):79.
273. Barstad LH, Juliusson PB, Johnson LK, Hertel JK, Lekhal S, Hjelmesaeth J. Gender-related differences in cardiometabolic risk factors and lifestyle behaviors in treatment-seeking adolescents with severe obesity. *BMC Pediatr*. Feb 14 2018;18(1):61. doi:10.1186/s12887-018-1057-3
274. Dollar JM, Calkins SD, Shriver L, Keane SP, Shanahan L, Wideman L. Emerging self-regulatory skills in childhood predict cardiometabolic risk in adolescence. *Compr Psychoneuroendocrinol*. Aug 2021;7doi:10.1016/j.cpnec.2021.100070
275. Lawrence AC, Narayan MS, Choe DE. Association of Young Children’s Use of Mobile Devices With Their Self-regulation. *JAMA Pediatrics*. 2020;174(8):793-795. doi:10.1001/jamapediatrics.2020.0129
276. Anderson SE, Whitaker RC. Association of Self-regulation With Obesity in Boys vs Girls in a US National Sample. *JAMA Pediatrics*. 2018;172(9):842-850. doi:10.1001/jamapediatrics.2018.1413
277. Aparicio E, Canals J, Arija V, De Henauw S, Michels N. The role of emotion regulation in childhood obesity: implications for prevention and treatment. *Nutr Res Rev*. Jun 2016;29(1):17-29. doi:10.1017/s0954422415000153
278. Miller HV, Barnes JC, Beaver KM. Self-control and health outcomes in a nationally representative sample. *Am J Health Behav*. Jan-Feb 2011;35(1):15-27. doi:10.5993/ajhb.35.1.2
279. Xu K, Zhang Y, Dong W, et al. The Mediation Role of Health Behaviors in the Association between Self-Regulation and Weight Status among Preschool Children: A Sex-Specific Analysis. *Nutrients*. 2022;14(9):1692.
280. Coumans JMJ, Danner UN, Ahrens W, et al. The association of emotion-driven impulsiveness, cognitive inflexibility and decision-making with weight status in European adolescents. *Int J Obes (Lond)*. Apr 2018;42(4):655-661. doi:10.1038/ijo.2017.270
281. Hill AB. The Environment And Disease: Association Or Causation? *Proc R Soc Med*. May 1965;58(5):295-300.
282. Rothman KJ, Greenland S. Hill's Criteria for Causality. *Encyclopedia of Biostatistics*. 2005.
283. Adams SA, Matthews CE, Ebbeling CB, et al. The Effect of Social Desirability and Social Approval on Self-Reports of Physical Activity. *American Journal of Epidemiology*. 2005;161(4):389-398. doi:10.1093/aje/kwi054
284. Kuss DJ, Griffiths MD. Internet and gaming addiction: a systematic literature review of neuroimaging studies. *Brain sciences*. 2012;2(3):347-374.
285. Weinstein A, Lejoyeux M. New developments on the neurobiological and pharmaco-genetic mechanisms underlying internet and videogame addiction. *The American Journal on Addictions*. 2015;24(2):117-125. doi:https://doi.org/10.1111/ajad.12110
286. Montag C, Reuter M. *Internet addiction*. Springer; 2017.

287. Scharkow M. The Accuracy of Self-Reported Internet Use—A Validation Study Using Client Log Data. *Communication Methods and Measures*. 2016/01/02 2016;10(1):13-27. doi:10.1080/19312458.2015.1118446
288. Mireku MO, Mueller W, Fleming C, et al. Total recall in the SCAMP cohort: Validation of self-reported mobile phone use in the smartphone era. *Environ Res*. Feb 2018;161:1-8. doi:10.1016/j.envres.2017.10.034
289. Perl MA, Mandić ML, Primorac L, Klapec T, Perl A. Adolescent acceptance of different foods by obesity status and by sex. *Physiol Behav*. Nov 15 1998;65(2):241-5. doi:10.1016/s0031-9384(98)00117-6
290. Skinner JD, Carruth BR, Bounds W, Ziegler PJ. Children's food preferences: a longitudinal analysis. *Journal of the American Dietetic Association*. 2002;102(11):1638-1647.
291. Börnhorst C, Huybrechts I, Ahrens W, et al. Prevalence and determinants of misreporting among European children in proxy-reported 24 h dietary recalls. *British Journal of Nutrition*. 2013;109(7):1257-1265. doi:10.1017/S0007114512003194
292. Subar AF, Freedman LS, Tooze JA, et al. Addressing Current Criticism Regarding the Value of Self-Report Dietary Data1,2. *The Journal of Nutrition*. 2015/12/01/ 2015;145(12):2639-2645. doi:https://doi.org/10.3945/jn.115.219634
293. Voorveld HA, Segijn CM, Ketelaar PE, Smit EG. Investigating the prevalence and predictors of media multitasking across countries. 2014;
294. Cardoso-Leite P, Buchard A, Tissieres I, Mussack D, Bavelier D. Media use, attention, mental health and academic performance among 8 to 12 year old children. *PLOS ONE*. 2021;16(11):e0259163. doi:10.1371/journal.pone.0259163
295. Gardner LA, Debenham J, Newton NC, et al. Lifestyle risk behaviours among adolescents: a two-year longitudinal study of the impact of the COVID-19 pandemic. *BMJ Open*. Jun 1 2022;12(6):e060309. doi:10.1136/bmjopen-2021-060309
296. Wu L, Sun S, He Y, Jiang B. The effect of interventions targeting screen time reduction: A systematic review and meta-analysis. *Medicine (Baltimore)*. Jul 2016;95(27):e4029. doi:10.1097/md.0000000000004029
297. Martin KB, Bednarz JM, Aromataris EC. Interventions to control children's screen use and their effect on sleep: A systematic review and meta-analysis. *J Sleep Res*. Jun 2021;30(3):e13130. doi:10.1111/jsr.13130
298. Robinson TN, Matheson DM, Kraemer HC, et al. A Randomized Controlled Trial of Culturally Tailored Dance and Reducing Screen Time to Prevent Weight Gain in Low-Income African American Girls: Stanford GEMS. *Archives of Pediatrics & Adolescent Medicine*. 2010;164(11):995-1004. doi:10.1001/archpediatrics.2010.197
299. Epstein LH, Roemmich JN, Robinson JL, et al. A Randomized Trial of the Effects of Reducing Television Viewing and Computer Use on Body Mass Index in Young Children. *Archives of Pediatrics & Adolescent Medicine*. 2008;162(3):239-245. doi:10.1001/archpediatrics.2007.45
300. Haines J, McDonald J, O'Brien A, et al. Healthy Habits, Happy Homes: randomized trial to improve household routines for obesity prevention among preschool-aged children. *JAMA Pediatr*. Nov 2013;167(11):1072-9. doi:10.1001/jamapediatrics.2013.2356
301. Kenney EL, Mozaffarian RS, Long MW, et al. Limiting Television to Reduce Childhood Obesity: Cost-Effectiveness of Five Population Strategies. *Childhood Obesity*. 2021/10/01 2021;17(7):442-448. doi:10.1089/chi.2021.0016
302. Jones A, Armstrong B, Weaver RG, Parker H, von Klinggraeff L, Beets MW. Identifying effective intervention strategies to reduce children's screen time: a systematic review and meta-analysis. *Int J Behav Nutr Phys Act*. Sep 16 2021;18(1):126. doi:10.1186/s12966-021-01189-6
303. Babic MJ, Smith JJ, Morgan PJ, et al. Intervention to reduce recreational screen-time in adolescents: Outcomes and mediators from the 'Switch-Off 4 Healthy Minds' (S4HM) cluster randomized controlled trial. *Prev Med*. Oct 2016;91:50-57. doi:10.1016/j.ypmed.2016.07.014
304. Smith JJ, Morgan PJ, Lonsdale C, Dally K, Plotnikoff RC, Lubans DR. Mediators of change in screen-time in a school-based intervention for adolescent boys: findings from the ATLAS cluster randomized controlled trial. *J Behav Med*. Jun 2017;40(3):423-433. doi:10.1007/s10865-016-9810-2

305. Tang L, Darlington G, Ma DWL, Haines J. Mothers' and fathers' media parenting practices associated with young children's screen-time: a cross-sectional study. *BMC Obes*. 2018;5:37. doi:10.1186/s40608-018-0214-4
306. Hill D AN, Chassiakos YR, et al. Media and Young Minds. *Pediatrics*. 2016;138(5):e20162591. doi:10.1542/peds.2016-2591
307. McKetta S, Rich M. The fault, dear viewer, lies not in the screens, but in ourselves: relationships between screen media and childhood overweight/obesity. *Pediatr Clin North Am*. Dec 2011;58(6):1493-508, xii. doi:10.1016/j.pcl.2011.09.010
308. Ottersen OP, Dasgupta J, Blouin C, et al. The political origins of health inequity: prospects for change. *Lancet*. Feb 15 2014;383(9917):630-67. doi:10.1016/s0140-6736(13)62407-1
309. United Nations. Convention on the Rights of the Child (1989).
310. Tangcharoensathien V, Chandrasiri O, Kunpeuk W, Markchang K, Pangkariya N. Addressing NCDs: Challenges From Industry Market Promotion and Interferences. *Int J Health Policy Manag*. May 1 2019;8(5):256-260. doi:10.15171/ijhpm.2019.02
311. Kickbusch I, Piselli D, Agrawal A, et al. The Lancet and Financial Times Commission on governing health futures 2030: growing up in a digital world. *Lancet*. Nov 6 2021;398(10312):1727-1776. doi:10.1016/s0140-6736(21)01824-9
312. Jackson W, Steingraber S. *Protecting public health and the environment: implementing the precautionary principle*. Island Press; 1999.
313. Holmberg C, J EC, Hillman T, Berg C. Adolescents' presentation of food in social media: An explorative study. *Appetite*. Apr 1 2016;99:121-129. doi:10.1016/j.appet.2016.01.009
314. Council of Europe. Rights of children in the digital environment. Council of Europe. Accessed 20.07., 2022. https://www.coe.int/en/web/children/the-digital-environment
315. Obesity Policy Coalition. Policy brief: restrictions on marketing unhealthy food to children—international comparison. *Obesity Policy Coalition*. 2019;
316. Galbraith-Emami S, Lobstein T. The impact of initiatives to limit the advertising of food and beverage products to children: a systematic review. *Obes Rev*. Dec 2013;14(12):960-74. doi:10.1111/obr.12060
317. Potvin Kent M, Pauzé E. The effectiveness of self-regulation in limiting the advertising of unhealthy foods and beverages on children's preferred websites in Canada. *Public Health Nutr*. Jun 2018;21(9):1608-1617. doi:10.1017/s1368980017004177
318. Sacks G, Looi ESY. The advertising policies of major social media platforms overlook the imperative to restrict the exposure of children and adolescents to the promotion of unhealthy foods and beverages. *International Journal of Environmental Research and Public Health*. 2020 2020;17(11):1-11.
319. Binet L, Field P. Empirical Generalizations about Advertising Campaign Success. *Journal of Advertising Research*. 2009;49(2):130-133. doi:10.2501/s0021849909090163
320. Smit CR, Bevelander KE, de Leeuw RNH, Buijzen M. Motivating Social Influencers to Engage in Health Behavior Interventions. Perspective. *Frontiers in Psychology*. 2022-July-22 2022;13doi:10.3389/fpsyg.2022.885688
321. Financial Times. Ronaldo's Coke moment signals shifting balance of power in sport. https://www.ft.com/content/e11ec659-d386-47f5-b284-c6951fa45870
322. Business Insider. Coca-Cola lost $4 billion in market value after soccer star Cristiano Ronaldo suggested people drink water instead. https://markets.businessinsider.com/news/stocks/euro-2020-cristiano-ronaldo-coca-cola-market-value-snubs-drink-2021-6-1030526880.
323. Rasmussen MGB, Pedersen J, Olesen LG, Kristensen PL, Brønd JC, Grøntved A. Feasibility of two screen media reduction interventions: Results from the SCREENS pilot trial. *PLOS ONE*. 2021;16(11):e0259657. doi:10.1371/journal.pone.0259657
324. Brazendale K, Beets MW, Weaver RG, et al. Understanding differences between summer vs. school obesogenic behaviors of children: the structured days hypothesis. *Int J Behav Nutr Phys Act*. 2017/07/26 2017;14(1):100. doi:10.1186/s12966-017-0555-2

325. Kang E, Lee J, Kim KH, Yun YH. The popularity of eating broadcast: Content analysis of “mukbang” YouTube videos, media coverage, and the health impact of “mukbang” on public. *Health Informatics Journal*. 2020;26(3):2237-2248. doi:10.1177/1460458220901360
326. Kircaburun K, Harris A, Calado F, Griffiths MD. The Psychology of Mukbang Watching: A Scoping Review of the Academic and Non-academic Literature. *International Journal of Mental Health and Addiction*. 2021/08/01 2021;19(4):1190-1213. doi:10.1007/s11469-019-00211-0
327. Kircaburun K, Balta S, Emirtekin E, Tosuntas ŞB, Demetrovics Z, Griffiths MD. Compensatory Usage of the Internet: The Case of Mukbang Watching on YouTube. *Psychiatry investigation*. 2021/04// 2021;18(4):269-276. doi:10.30773/pi.2019.0340
328. Yun S, Kang H, Lee H. Mukbang- and Cookbang-watching status and dietary life of university students who are not food and nutrition majors. *Nutr Res Pract*. Jun 2020;14(3):276-285. doi:10.4162/nrp.2020.14.3.276
329. Beeres DT, Andersson F, Vossen HGM, Galanti MR. Social Media and Mental Health Among Early Adolescents in Sweden: A Longitudinal Study With 2-Year Follow-Up (KUPOL Study). *Journal of Adolescent Health*. 2021/05/01/ 2021;68(5):953-960. doi:https://doi.org/10.1016/j.jadohealth.2020.07.042
330. Coyne SM, Rogers AA, Zurcher JD, Stockdale L, Booth M. Does time spent using social media impact mental health?: An eight year longitudinal study. *Computers in Human Behavior*. 2020/03/01/ 2020;104:106160. doi:https://doi.org/10.1016/j.chb.2019.106160
331. Dantchev S, Wolke D. Trouble in the nest: Antecedents of sibling bullying victimization and perpetration. *Developmental Psychology*. 2019;55:1059-1071. doi:10.1037/dev0000700
332. Toseeb U, Wolke D. Sibling Bullying: A Prospective Longitudinal Study of Associations with Positive and Negative Mental Health during Adolescence. *Journal of Youth and Adolescence*. 2022/05/01 2022;51(5):940-955. doi:10.1007/s10964-021-01495-z
333. Dantchev S, Hickman M, Heron J, Zammit S, Wolke D. The Independent and Cumulative Effects of Sibling and Peer Bullying in Childhood on Depression, Anxiety, Suicidal Ideation, and Self-Harm in Adulthood. Original Research. *Frontiers in Psychiatry*. 2019-September-24 2019;10doi:10.3389/fpsyt.2019.00651
334. Jagtiani MR, Kelly Y, Fancourt D, Shelton N, Scholes S. #StateOfMind: Family Meal Frequency Moderates the Association Between Time on Social Networking Sites and Well-Being Among U.K. Young Adults. *Cyberpsychol Behav Soc Netw*. Dec 2019;22(12):753-760. doi:10.1089/cyber.2019.0338
335. Fardouly J, Magson NR, Johnco CJ, Oar EL, Rapee RM. Parental Control of the Time Preadolescents Spend on Social Media: Links with Preadolescents’ Social Media Appearance Comparisons and Mental Health. *Journal of Youth and Adolescence*. 2018/07/01 2018;47(7):1456-1468. doi:10.1007/s10964-018-0870-1
336. Instagram. "For Parents: Helping your teen navigate Instagram safely" Accessed 18.10., 2022. https://about.instagram.com/community/parents
337. Gradisar M, Wolfson AR, Harvey AG, Hale L, Rosenberg R, Czeisler CA. The sleep and technology use of Americans: findings from the National Sleep Foundation's 2011 Sleep in America poll. *J Clin Sleep Med*. Dec 15 2013;9(12):1291-9. doi:10.5664/jcsm.3272
338. Masís-Vargas A, Hicks D, Kalsbeek A, Mendoza J. Blue light at night acutely impairs glucose tolerance and increases sugar intake in the diurnal rodent Arvicanthis ansorgei in a sex-dependent manner. *Physiol Rep*. Oct 2019;7(20):e14257. doi:10.14814/phy2.14257
339. Silvani MI, Werder R, Perret C. The influence of blue light on sleep, performance and wellbeing in young adults: A systematic review. *Front Physiol*. 2022;13:943108. doi:10.3389/fphys.2022.943108
340. Ricketts EJ, Joyce DS, Rissman AJ, et al. Electric lighting, adolescent sleep and circadian outcomes, and recommendations for improving light health. *Sleep Med Rev*. Aug 2022;64:101667. doi:10.1016/j.smrv.2022.101667
341. Driller MW, Jacobson G, Uiga L. Hunger hormone and sleep responses to the built-in blue-light filter on an electronic device: a pilot study. *Sleep Sci*. Jul-Sep 2019;12(3):171-177. doi:10.5935/1984-0063.20190074
342. Casanueva FF, Dieguez C. Neuroendocrine regulation and actions of leptin. *Front Neuroendocrinol*. Oct 1999;20(4):317-63. doi:10.1006/frne.1999.0187

343. Alonso-Vale MI, Andreotti S, Peres SB, et al. Melatonin enhances leptin expression by rat adipocytes in the presence of insulin. *Am J Physiol Endocrinol Metab*. Apr 2005;288(4):E805-12. doi:10.1152/ajpendo.00478.2004

Appendix

Paper 1

Social media and children’s and adolescents’ diets - a systematic review of the underlying social and physiological mechanisms

Elida Sina, Daniel Boakye, Lara Christianson, Wolfgang Ahrens, Antje Hebestreit, Social Media and Children's and Adolescents' Diets: A Systematic Review of the Underlying Social and Physiological Mechanisms, *Advances in Nutrition*, Volume 13, Issue 3, May 2022, Pages 913–937, https://doi.org/10.1093/advances/nmac018

Social Media and Children's and Adolescents' Diets: A Systematic Review of the Underlying Social and Physiological Mechanisms

Elida Sina, Daniel Boakye, Lara Christianson, Wolfgang Ahrens, and Antje Hebestreit
Leibniz Institute for Prevention Research and Epidemiology—BIPS, Bremen, Germany

ABSTRACT

The association between social media (SM) and children's and adolescents' diet is poorly understood. This systematic literature review aims to explore the role of SM in children's and adolescents' diets and related behaviors, considering also the underlying mechanisms. We searched Medline, Scopus, and CINAHL (2008–December 2021) for studies assessing the relation of SM exposure with food intake, food preference, dietary behaviors, and the underlying mechanisms (e.g., brain activation to digital food images—as proxy for SM food images) among healthy children and adolescents aged 2–18 y. A total of 35 articles were included. Of 4 studies, 1 found that exposure to peers' videos on healthy eating, but not SM influencers', increased vegetable intake. Most studies reported that SM was associated with skipping breakfast, increased intake of unhealthy snacks and sugar-sweetened beverages, and lower fruit and vegetable intake, independent of age. Children and adolescents exposed to unhealthy compared with healthy digital food images showed increased brain response in reward- and attention-related regions. The mechanisms underpinning the abovementioned associations were *1*) physiological (appetitive state, increased neural response to portion size and energy density of food depicted) and *2*) social (food advertising via SM influencers and peers). SM exposure leads to unfavorable eating patterns both in children and adolescents. The identified mechanisms may help tailor future health interventions. Downregulating SM advertising and limiting SM exposure to children and adolescents may improve food intake and subsequent health outcomes. The protocol of this review was registered in PROSPERO as CRD42020213977 (https://www.crd.york.ac.uk/prospero/). *Adv Nutr* 2022;13:913–937.

Statement of Significance: This review is the first to examine the role exposure to social media has on children's and adolescents' diets, considering developmental differences. We identified the underlying social and physiological mechanisms, which will serve to tailor future health interventions.

Keywords: eating habits, fMRI, food advertising, social media, Instagram, Facebook, neural activity, influencer marketing, children, adolescents

Introduction

The prevalence of overweight and obesity among children aged 5–19 y has increased worldwide, from 4% in 1975 to 18% in 2016 (1). Eating behaviors driven by obesogenic environments, including the high availability, affordability, and the omnipresent marketing of energy-dense (ED) foods, especially in the digital environment, contribute to a poorer health status of children and adolescents. Prolonged television (TV) viewing is a well-documented factor associated with obesity risk (2), as it predominantly associates with unfavorable eating behaviors: increased consumption frequency of unhealthy foods, reduced consumption frequency of vegetables and fruits (3), high sweet and fat intake (4), and breakfast skipping (5).

With emerging technological developments, TV has been displaced by the use of smartphones. Their technological features facilitate ubiquitous access to internet and social media (SM) platforms (e.g., YouTube, Facebook, Instagram, etc.) (6, 7). Thus, children's smartphone use is more difficult for parents to control (8). The urge to constantly check highly entertaining online content and the upcoming notifications (i.e., from the SM applications) can influence children's and adolescents' attention span (6). This effect is especially worrisome in the eating environment, as mindless eating when in front of screens is associated with overeating, potentially leading to overweight and obesity (9). The Global Kids Online Report (10) showed that smartphones were the most popular devices children used to go online. According

 Adv Nutr 2022;13:913–937; doi: https://doi.org/10.1093/advances/nmac018.

to the Common Sense Census (11), nearly all (96%) 5–8-y-old children in the United States spent, on average, 1 h daily using mobile devices. Moreover, 70% of US adolescents reported using the internet—notably via smartphones—to access Instagram, whereas 50% reported being online "almost constantly" (12). Research shows that, despite the age restrictions of these SM platforms (≥13 y), 72% of US children aged ≤8 y use smartphones to watch videos on SM (11), while 9–11-y-old European children visit their SM account every day, ranging from 11% in Germany to 45% in Serbia (13).

The ubiquitous presence of SM in children's and adolescents' lives represents a powerful tool for companies to advertise their junk-food products through paid partnerships with bloggers (i.e., SM influencers) who are attractive role models for children and adolescents (14). The SM influencers may shape their followers' opinions by endorsing brand products in their SM posts (e.g., highly curated videos and images) (15). Increasingly, influencers also provide nutrition and weight-management information, although they lack evidence-based features and the involvement of health care experts, questioning their validity and safety (16).

Studies examining advertisement exposure on SM platforms among Canadian children aged 7–16 y found that they watch weekly almost 200 food/beverage advertisements (17), predominantly promoting unhealthy foods. Similar findings were observed in Australian and Belgian children and adolescents (18, 19). Children are particularly susceptible to marketing messages, as their cognitive development and the ability to recognize the selling, persuasive intent of advertisements is limited (20, 21). Food and beverage advertisements enhance brand recognition and may alter preferences for the advertised (mainly ultra-processed) foods (21). Moreover, SM has rendered the presence of highly appetizing and digitally enhanced (unhealthy) food images ubiquitous (22). Image- and video-based SM platforms (Instagram, YouTube, TikTok) are indeed the platforms with the highest use among children and adolescents (11, 12). Exposure to appetizing food images increases attention and neural activation in visual-processing and reward-related brain areas in humans (22). Moreover, eye-tracking research showed that images of unhealthy foods are processed differently (i.e., higher gaze duration) compared with images of healthy foods and nonedible products (e.g., sunscreen), and can be remembered regardless of the amount of visual attention that children allocate to them (23). Further, our innate preference for sweet and fat taste has been reported (24) and consumption of sugar-sweetened beverages (SSBs), for example, is associated with TV use (2). Thus, analyzing the role of food marketing in the SM environment is important for understanding the impact of brand-related SM posts on food preference and food choice.

A previous cross-sectional study reported that SM exposure was associated with higher odds of skipping breakfast and consuming SSBs (25). Moreover, influencer marketing of unhealthy foods increased children's immediate intake of these foods, whereas the equivalent marketing of healthy foods showed no effect (26). The mechanisms behind these associations remain unknown.

These observations suggest that exposure to SM content might influence children's and adolescents' diets and eating behaviors. Prior reviews in this area have been focused on the role of advergames, where advertising content is embedded in the videogame (27), and in the effectiveness of using SM for nutrition interventions in adolescents and young adults (28). However, no systematic review has synthetized the evidence on the role of SM in children's and adolescents' diets, accounting for developmental differences such as age, brain maturation, and puberty. Hence, we aimed to identify, appraise, and synthetize the current body of evidence and to address 2 main research gaps: *1*) to determine how exposure to SM influences children's and adolescents' diets, including food intake (consumption frequency and quantity of unhealthy, high-energy vs. healthy, low-energy foods), food preference, and/or liking of healthy vs. unhealthy foods, related behaviors (breakfast consumption), and nutrition literacy, and *2*) to identify the underlying explanatory mechanisms (e.g., brain response to food images) and technological features of SM such as advertising disclosure that may shape children's eating behaviors.

Methods

This systematic review was conducted and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) (29). The protocol was registered with the International Prospective Register of Systematic Review (PROSPERO; registration number: CRD42020213977).

Search strategy

Three literature databases—MEDLINE (via PubMed), Scopus, and CINAHL (via EBSCO)—were searched from 2008 to December 2021. As Facebook was publicly launched in 2006 and in 2008 the first Apple iPhone entered the market, we set 2008 as the beginning year in our search strategy. However, studies evaluating the use of SM for research purposes were not published until 5–6 y later (30, 31). No restrictions on language, study design, or publication type were imposed. Search terms were combined to identify articles targeting the following:

This research was supported by the Leibniz ScienceCampus Bremen Digital Public Health (lsc-diph.de), jointly funded by the Leibniz Association (W4/2018), the Federal State of Bremen, and the Leibniz Institute for Prevention Research and Epidemiology—BIPS.

Author disclosures: The authors report no conflicts of interest. The funders had no role in study selection, quality assessment, or synthesis of the results.

Supplemental Methods and Supplemental Tables 1–5 are available from the "Supplementary data" link in the online posting of the article and from the same link in the online table of contents at https://academic.oup.com/advances/.

Address correspondence to ES (e-mail: sec-epi@leibniz-bips.de).

Abbreviations used: dlPFC, dorsolateral prefrontal cortex; dmPFC, dorsomedial prefrontal cortex; ED, energy-dense; FFM, fat-free mass; mPFC, medial prefrontal cortex; IFG, inferior frontal gyrus; OFC, orbitofrontal cortex; PRISMA, Preferred Reporting Items for Systematic Reviews and Meta-Analysis; PS, portion size; PPHG, parahippocampal gyri; RCT, randomized controlled trial; SES, socioeconomic status; SSB, sugar-sweetened beverage; SM, social media; TV, television; vmPFC, ventromedial prefrontal cortex.

1. Healthy children and adolescents aged 2–18 y in any context
2. An association with food intake (unhealthy vs. healthy food intake, junk-food intake, fruit/vegetable intake, SSB intake), food preference/liking, nutrition literacy (or diet literacy) and related behaviors (breakfast skipping or breakfast consumption)
3. SM use (or social networking sites or Facebook, Instagram, Snapchat, TikTok, YouTube; or online SM food marketing/advertisement or influencers' marketing); or proxies such as internet and smartphone use and exposure to food images or food videos.

The rationale for the inclusion of internet and smartphone use is based on recent findings that show that children and adolescents mainly use their smartphone and internet to access SM, share content from their everyday activities (including food images), and have (online) social interactions with their peers and SM followers (11, 12). Exposure to digital food images/videos was included as a proxy exposure for highly saturated and palatable food images in the SM context, which can shape children's and adolescents' food preferences and choices (23, 26, 32). Using electroencephalography, Ohla and colleagues (33) showed that the mere exposure to images of energy-dense (ED) foods could enhance hedonic taste evaluation. After exposure to high- compared with low-calorie food images, participants reported the hedonically neutral electric taste signal as more pleasant, with effects being stronger in the reward-processing (insula) and decision-making [orbitofrontal cortex (OFC)] brain areas.

Studies conducted in children with disease (e.g., those having obesity, diabetes, eating disorders, or neurological disorders) in children aged <2 y or >18 y, lacking an SM component, or not measuring diet-related outcomes were excluded. Studies primarily targeting parents and/or families and those where the main exposure was computer, TV, advergames or mobile applications other than SM applications were also excluded. The complete search strategy for Medline is presented in **Supplemental Table 1**.

Study selection and synthesis of the results

Articles identified in each database were downloaded to EndNote X9. One of the authors (ES) removed duplicates and exported articles to the online Rayyan QCRI app (34). First, articles were screened based on title/abstract by ES and 3 independent reviewers (blind screening, in pairs), all with a strong public health background and, in a second step, based on full texts. At both stages, disagreements were resolved by consensus or adjudicated by 2 additional reviewers (AH, DB). References of included studies and relevant review articles were manually searched for citations. For missing full texts, the respective authors were contacted by e-mail (ES). For the eligible articles, the 4 initial reviewers independently extracted the data and disagreements were resolved by mutual consensus. A concluding decision for the final extract was made by ES and AH. The extracted data were recorded in a predefined data extraction template including the following—*1*) study details: title, authors, year, country, study design, and SM exposure (type of platform and/or food image/video, frequency/duration of use); *2*) participant information: age (mean and range), sex, sample size, parental socioeconomic status (SES), and ethnicity/migration background; and *3*) outcomes investigated and main primary and secondary findings. The results were synthetized narratively and key findings—clustered by age group (children: <12 y; adolescents ≥12 y)—were categorized as *1*) SM exposure and unhealthy food intake (i.e., consumption frequency and quantity) and dietary behaviors (e.g., breakfast skipping), *2*) SM exposure and healthy food intake (e.g., fruit and vegetable intake) and nutrition literacy, *3*) smartphone use, food intake, and dietary behaviors (e.g., breakfast consumption), *4*) exposure to digital food images and patterns of brain activation, and *5*) differences in the abovementioned associations by sex.

Risk of bias and assessment of study quality

The quality and risk of bias of the selected publications were assessed by 2 independent reviewers. For cohort studies, the Newcastle-Ottawa Scale was used (35), while the Joanna Briggs Institute appraisal tool (36) and the revised Cochrane risk-of-bias (RoB 2.0) tool were respectively used for assessing cross-sectional studies and randomized controlled trials (RCTs) (37). Further information on the specific domains/items of each appraisal tool is provided in the **Supplemental Methods**. An aggregate quality rating was given to each study, and for all discrepancies consensus was achieved via further discussions among ES and the 3 reviewers or by consulting an additional reviewer (AH/DB). We did not exclude studies based on their quality rating.

Results

Our database search identified a total of 5518 articles and an additional 4 articles were identified via manual search. After 1725 duplicates were removed, the remaining 3797 articles went through title and abstract screening. Of these, 237 articles met our criteria for full-text screening. At this stage, 202 studies were removed, with reasons outlined in **Figure 1** (29). The majority of studies were excluded because they did not include an SM component. A total of 35 studies were included in our review (**Table 1** and **Supplemental Table 2**).

Study characteristics

The majority of the studies were conducted in North America (25, 38–48) and Europe (26, 49–61). A minority were conducted in Australia (19, 62, 63), Brazil (64), and Asia (65–69). The sample size ranged from 11 to 54,603 participants. SM platforms examined were Instagram (26, 50, 51, 56, 59), YouTube (19, 55), Facebook (25, 58), and WhatsApp (67), whereas 6 studies focused on smartphone or internet use (57, 62, 64, 65, 68, 69). Food and beverage SM marketing was investigated in 10 studies; 5 of them focused on peer (51) and influencer marketing (26, 50, 56, 59). In the observational studies, SM exposure (frequency

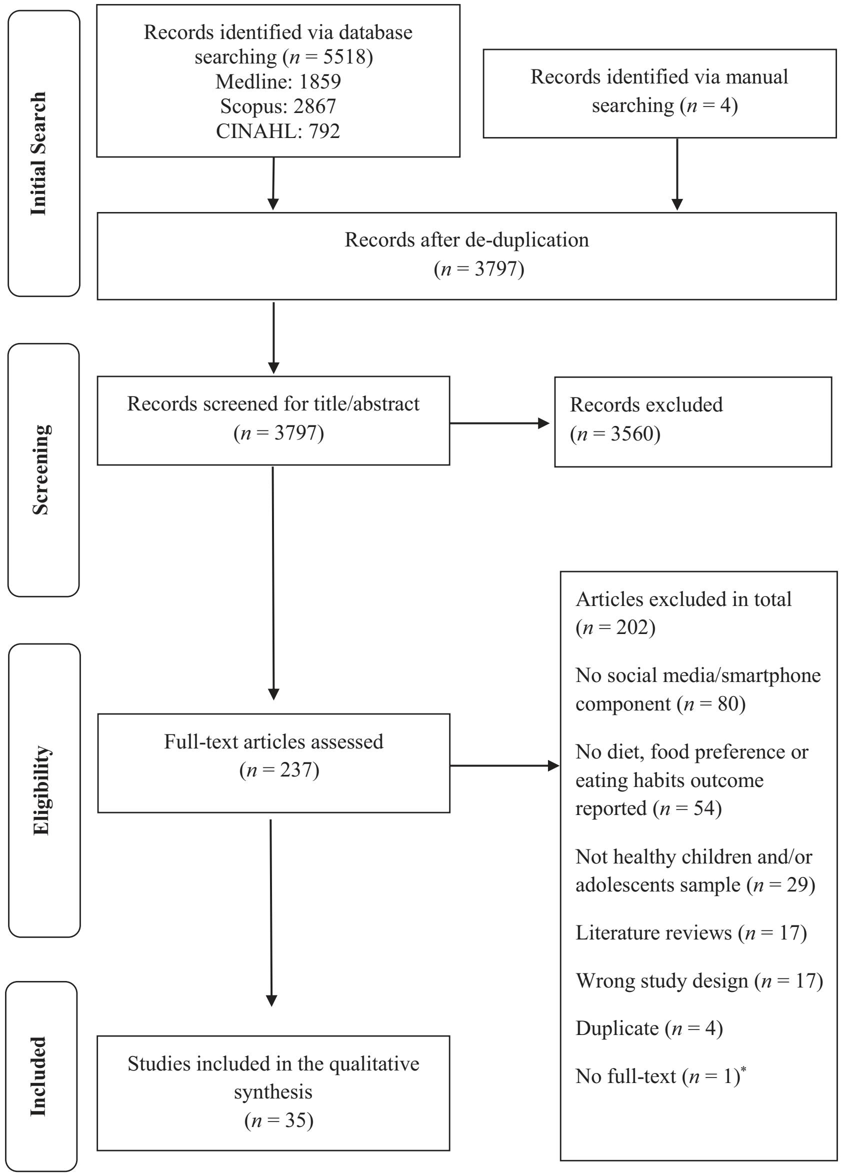

FIGURE 1 PRISMA flow diagram illustrating the selection process of the eligible studies. *The authors were contacted, but we did not receive an answer from them. PRISMA, Preferred Reporting Items for Systematic Reviews and Meta-Analysis.

and duration) was self-reported, whereas RCTs predefined the exposure duration to SM. Among RCTs, 12 were fMRI-based studies, which measured the exposure to unhealthy digital food images, while 1 of them considered food video commercials (hereinafter, food advertisements) (44). Detailed characteristics of the included studies are described in **Supplemental Table 2**.

Quality assessment

Over half of the included studies were interventional studies (i.e., RCTs: $n = 23$) (26, 39–54, 56, 58–60, 62, 67), whereas 12 studies were observational, of which 1 and 11 studies were respectively longitudinal (55) and cross-sectional (19, 25, 38, 57, 61, 63–66, 68, 69). Among the RCTs, 1 was rated high quality (i.e., low risk of bias) (62), 3 were medium quality (26, 50, 59), and 19 were rated low quality (39–49, 51–54, 56, 58, 60, 67) (Table 1 and **Supplemental Table 3**). The only longitudinal study included was rated low quality (55) (**Supplemental Table 4**). Among the cross-sectional studies, 7 were rated high quality (38, 57, 61, 63, 64, 68, 69), whereas 4 were rated medium quality (19, 25, 65, 66) (**Supplemental Table 5**).

SM exposure and unhealthy food intake and dietary behaviors.
Of the included studies, 8 investigated the association between SM and unhealthy diet intake (Table 1).

In adolescents, 3 cross-sectional studies reported a dose–response relation between SM exposure and daily intake of sugar and caffeine (38), the consumption frequency of SSBs, sweets, and fried foods (61), as well as a higher likelihood of skipping breakfast (25). In an RCT, Teo et al. (67) investigated the messaging feature of WhatsApp where participants were assigned to engage in texting with friends, while the control group was asked to read an online article. Adolescents in the WhatsApp messaging group consumed 58% more snacks (corn puffs) than those of the control group (67). Watching online videos was cross-sectionally associated with higher fast-food preference among Chinese adolescents, while those living in rural areas had higher frequency of eating at fast-food restaurants (65). Another RCT showed that watching SM culinary videos influenced food choice among Flemish adolescents (60). Exposure to a sweet snack video reduced the liking of fruits and vegetables and the likelihood of choosing a fruit over a cookie, which was mediated by intentions to eat sweet snacks. By contrast, the fruit and vegetable video did not influence food choice but resulted in higher intentions to prepare healthy snacks (60).

In children, the frequency of watching YouTube video-blogs significantly predicted unhealthy beverage consumption amount 2 y later (55). In a cross-sectional sample of Indonesian children, Lwin et al. (66) observed that SM exposure was related to fast-food consumption frequency in suburban, but not in urban, areas. However, active parental mediation strategy (discussing and advising) significantly lowered fast-food consumption frequency and increased nutrition knowledge for suburban children, but not for urban children (66).

Seven studies investigated the role of SM and SM influencers' marketing in children's and adolescents' unhealthy food intake.

In children, SM influencers' marketing led to unhealthy food intake. Coates et al. (26) revealed in an RCT that children exposed to a 1-min influencer's advertising segment (during a 5-min video on Instagram) of unhealthy food images, consumed more energy overall and from unhealthy snacks compared with those exposed to healthy food images and nonfood images. In a second study, they investigated the influencers' marketing of branded compared with unbranded unhealthy snacks with or without an advertising disclosure (50). Overall, children consumed more energy from the branded than the unbranded snack. When exposed to food marketing with relative to without a disclosure, they consumed more from the marketed snack compared with the alternative, indicating no interaction between food marketing with an advertising disclosure and children's awareness of advertising on energy intake. Masterson et al. (44) showed that exposure to advertisements (food vs. nonfood) was not associated with children's subsequent total energy intake. A cross-sectional study including children and adolescents aged 10–16 y in Australia showed that watching branded food videos on YouTube increased unhealthy food and beverage consumption, independent of age (19).

Among adolescents, exposure to branded food and beverage marketing on SM was cross-sectionally associated with increased intake of unhealthy drinks (fruit juice and sports and soft drinks) (63) and with increased preference for ED foods (sweets and fried foods) (61). Adolescents who engaged with food marketing posts on SM (liked, shared) had increased frequency intake of unhealthy foods and drinks, indicating that engagement with food marketing might have stronger effects on adolescents' diets than exposure per se (63). In fact, exposure to peers' Instagram images of ED snacks and SSBs had no effect on their respective consumption (51). In an RCT by Murphy et al. (58), adolescents had longer gaze duration to advertisements for unhealthy compared with healthy foods. Fixation duration was higher for unhealthy foods when posted by peers but higher for healthy foods when posted by celebrities. Nevertheless, participants could recall and recognize unhealthy food brands more than healthy ones when coming from celebrities and companies, but not peers, especially among older adolescents (58).

SM exposure, healthy food intake, and nutrition literacy. Only 5 studies investigated the role of SM on healthy food intake ($n = 3$) and nutrition literacy ($n = 2$; Table 1) among children and adolescents.

In children, greater exposure to SM was not associated with better knowledge about nutrition, but broadcast media instead influenced nutrition literacy (66). Two RCTs showed that Instagram influencer marketing of healthy snacks (e.g., banana) did not influence children's subsequent intake of these foods (26), even when promoted by an athletic instead of a sedentary influencer (59). However, exposure to unhealthy foods (donuts) promoted by the sedentary SM influencer led to an increased choice for healthy snacks (strawberries) (59).

In adolescents, Folkvord and de Bruijne (56) reported findings comparable to those observed in children (26), but due to methodological concerns, the results will not be explained in detail here (56). Remarkably, adolescents who were exposed to a blog on healthy nutrition and to videos of peers addressing barriers to healthy eating (i.e., role models) reported eating $\geq$3 servings of vegetables/d compared with those not exposed to videos of peers (39). Flemish adolescents frequently exposed to SM healthy food messages (e.g., fruits and vegetables, mainly posted by peers, celebrities, or influencers) had an increased intake of healthy foods and this association was mediated by higher food literacy (61). However, in that cross-sectional study, food literacy was not a mediator for the association between exposure to ED foods and ED food intake (e.g., sweets and fried foods).

Smartphone use, food intake, and dietary behaviors. Four cross-sectional studies and 1 RCT evaluated the role of smartphone and internet use on food intake, exclusively conducted in adolescents (Table 1). Prolonged smartphone use (>2 h/d) was associated with higher consumption

TABLE 1 Characteristics, quality assessment and main results of the included studies ($n = 35$) by age group, distinguishing between RCTs, longitudinal studies, and cross-sectional studies based on quality assessment[1]

Study (year, country) (ref); study design	Population (age range), n	Exposure	Outcome	Key primary results	Key secondary results	Quality assessment
Social media exposure, unhealthy food intake and dietary behaviors, by age group (interventional study)						
De Jans et al. (2021, Belgium) (59); RCT—between-subject study design	Children (8–12 y) $n = 190$	Instagram profiles of 2 fictitious lifestyle influencers (sedentary vs. athletic): exposure to unhealthy (donuts) vs. healthy (strawberries) snack food images	1) Ad libitum healthy food choice (healthy vs. unhealthy food)	- The ad libitum healthy food choice did not differ after exposure to healthy food promoted by athletic vs. sedentary influencer ($\beta = 0.28$, $P = 0.60$) - Exposure to unhealthy food promoted by sedentary compared to athletic influencer led to higher choice of healthy snacks ($\beta = -1.31$, $P = 0.02$)	The interaction effect of influencer lifestyle and snack type were not significant in relation to source credibility ($\beta = 0.24$, $P = 0.27$), influencer admiration ($\beta = 0.19$, $P = 0.52$), or para-social interaction ($\beta = 0.22$, $P = 0.46$)	Medium
Coates et al. (2019a, UK) (26); RCT—between-subject study design	Children (9–11 y) $n = 186$	Instagram profiles of 2 popular YouTube video bloggers: exposure to unhealthy (cookies) vs. healthy (banana) food images vs. branded nonfood pictures (sneakers)	1) Caloric intake ad libitum from a selection of snack foods 2) Caloric intake from unhealthy foods and healthy foods	- Children exposed to unhealthy foods on Instagram consumed 26% more energy (mean = 448 ± 141 kcal/d) compared to the control group (mean = 357 ± 147 kcal/d; $P = 0.001$) and 15% more than children exposed to healthy foods on Instagram (mean = 389 ± 146 kcal/d; $P = 0.05$), after adjusting for hunger, previous influencer exposure, and liking of Instagram profiles	- Children in the unhealthy condition consumed 32% more energy from unhealthy snacks (mean = 385±141 kcal/d) vs. control (mean = 292 ± 147 kcal/d; $P = 0.001$) and 20% more than the healthy group (mean = 320 ± 144 kcal/d; $P = 0.03$) - No effect of Instagram on energy intake from healthy snacks	Medium
Coates et al. (2019b, UK) (50); RCT—between-subject study design	Children (9–11 y) $n = 151$	Exposure to YouTube video-bloggers featuring influencer marketing of: branded nonfood	1) Unhealthy snack intake ad libitum 2) Total energy intake of snacks branded and	- Children exposed to food advertising with ($P < 0.001$, $d = 1.40$) and without	- Children who viewed food advertising with a disclosure (and not those without)	Medium

(*Continued*)

TABLE 1 (*Continued*)

Study (year, country) (ref); study design	Population (age range), *n*	Exposure	Outcome	Key primary results	Key secondary results	Quality assessment
		product (Apple i-Phone 8) or branded unhealthy snack (McVitie's chocolate digestives) either (a) with or (b) without an advertising disclosure	unbranded 3) Energy intake of snacks in the groups with advertising disclosure vs. without	($P < 0.001$, $d = 1.07$) a disclosure consumed more energy from the advertised snack vs. the alternative, independently of age, sex, and hunger; the control did not differ ($P = 0.186$, $d = 0.45$) - Children consumed more energy from the branded snack than the alternative (unbranded snack)	consumed 41% more of the advertised snack ($P = 0.004$, $\eta_p{}^2 = 0.06$), than the control - No interaction between marketing with advertising disclosure and children's awareness of advertising (no awareness vs. awareness) on energy intake	
Ngqangashe et al. (2021, Belgium) (60); RCT	Adolescents (12–14 y) $n = 126$	Buzzfed's Tasty culinary videos on YouTube on preparation of snacks: 1) fruit and vegetable 2) sweets (unhealthy)	1) Food choice (fruit vs. cookie) 2) Food liking (fruits and vegetables vs. sweets)	- Exposure to the fruit and vegetable video did not influence food choice ($\beta = -0.11$, $P = 0.83$), but resulted in higher intentions to prepare healthy snacks and reduced liking of sweets	-Exposure to the sweet snack video reduced the liking of fruits and vegetables and reduced the likelihood of choosing a fruit over a cookie, mediated by intentions to eat sweet snacks	Low
Marsh et al. (2015, New Zealand) (62); randomized 2-arm parallel trial[2]	Adolescents (13–18 y) $n = 78$	Multiscreen use (simultaneous use of television, iPad, smartphone) vs. single screen (television)	1a) Total EI for foods/drinks. 1b) EI for high- vs. low-ED foods 2) Appetite changes	a) Total EI did not differ between multi-screen (758 kcal/d, SE = 75) vs. single-screen group (681 kcal/d, SE = 75; difference=77 kcal/d; 95% CI = −166 to +320), after adjusting for age, sex, BMI, and appetite at baseline b) EI from healthy vs. unhealthy foods did not differ between groups	Change from baseline in appetite scores did not differ significantly between the multi- and single-screen groups (−1.0; 95% CI = −7.0 to +5.0)	High

(*Continued*)

TABLE 1 (*Continued*)

Study (year, country) (ref); study design	Population (age range), *n*	Exposure	Outcome	Key primary results	Key secondary results	Quality assessment
Sharps et al. (2019, UK) (51); RCT	Adolescents (13–16 y) $n = 144$	Peers' Instagram images of high-ED snacks and SSBs	1) Changes in desired portion sizes 2) Changes in consumption and liking of snacks and SSBs	No significant main effect of condition, no main effect of time and no interactions ($P > 0.05$) for changes in desired portion sizes of high-ED snacks or SSBs, after adjusting for age, sex, and BMI.	There were no main effects or interactions for frequency of consumption or liking of snacks and SSBs	Low
Teo et al. (2018, Singapore) (67); RCT	7th-10th grade (mean age = 14.6 y), $n = 50$	Intervention group: WhatsApp use/texting Control group: reading a neutral article	Food intake (corn puff snacks)	Participants in the WhatsApp group consumed 58% more snacks (mean increase of 29–73 kcal) than in the control group	NA	Low
Exposure to food images and brain activation, by age group (interventional study)						
Sadler et al. (2021, USA) (48); within-subjects, repeated-measures crossover design; fMRI study	Adolescents (14–17 y) of high vs. low risk for obesity (of obese vs. lean parents) $n = 154$	1) Food stimuli: images of milkshake and water glasses that signalled the delivery of a chocolate milkshake or a tasteless solution (TS)	1) Brain activation to food stimuli by: a) unpaired milkshake vs. tasteless cue b) milkshake vs. tasteless receipt c) after repeated exposure to respective milkshake cues 2) Role of parental obesity	a) Exposure to unpaired milkshake cues vs. tasteless cue increased response in the bilateral caudate, the occipital fusiform cortex, and the anterior cingulate cortex - This activation remained after repeated exposure (in the bilateral posterior cingulate cortex and the bilateral caudate) b) Increased activation emerged in the bilateral pre/post central gyrus in response to the milkshake receipt vs. tasteless receipt	After repeated exposure: high- vs. low-risk participants showed greater activation the right caudate, independent of time. Exploratory analyses showed a significant effect of paternal but not maternal obesity in the right caudate after repeated exposure to milkshake cues	Low

(*Continued*)

TABLE 1 (*Continued*)

Study (year, country) (ref); study design	Population (age range), *n*	Exposure	Outcome	Key primary results	Key secondary results	Quality assessment
				- After repeated exposure, activation remained in the bilateral oral somatosensory cortex (pre/post central gyrus)		
Masterson et al. (2019, USA) (44); within-subjects, repeated-measures crossover design; fMRI study	Children (7–9 y) $n = 25$	1) Advertisements for food vs. toy vs. no exposure. 2) Images of low- vs. high-ED foods Control: blurred images	1) Total meal energy intake 2) Brain response as mediator	- Meal intake did not differ between advertisement condition in healthy children, after adjusting for sex, BMI *z*-score, parental education, SES, time of meals, and pre-meal fullness	Food vs. toy advertisements reduced brain response to high- vs. low-ED food images in the left fusiform gyrus, left supramarginal gyrus, and 1 region of left OFC	Low
Keller et al. (2018, USA) (47); within-subjects, repeated-measures crossover design; fMRI study	Children (7–11 y) $n = 39$	Food images of varying ED and PS: i) Large PS High ED, ii) Small PS High ED, iii) Large PS Low ED, iv) Small PS Low ED Control conditions: furniture and scrambled images	1) Brain response to large vs. small PS food images in association with total food intake 2a) Brain response to large vs. small PS high-ED foods 2b) Brain response to large vs. small PS low-ED foods	- Large vs. small PS: Activation in the left vmPFC and left OFC was associated with increased intake from baseline (32% more) than children with low activation, after adjusting for age, sex, BMI *z*-score, test-meal food liking, and pre-meal fullness level . Children who had high vmPFC and OFC activation also reached peak consumption at smaller PS than children with low activation	a) Activation in right IFG and caudate was negatively associated with high-ED food intake (87% less from baseline) with increasing PS . Activation in left OFC was associated with increased food intake from baseline. b) None of regions tested was associated with children's intake of low-ED foods in increasing PS	Low
Charbonnier et al. (2018, The Netherlands, Scotland, and Greece) (53); within-subject, crossover trial; fMRI study	Children (8–10 y); adolescents (13–17 y) $n = 55$	Food images: high-ED foods, low-ED foods, nonfood images	1) Brain activation between and across hungry vs. sated conditions 2) Liking of high vs. low-calorie foods	- Brain activation to high- vs. low-calorie food image viewing was greater in the hungry compared to sated state in the	- No significant main effect of hunger state on food vs. nonfood image viewing related brain activation	Low

(*Continued*)

TABLE 1 (*Continued*)

Study (year, country) (ref); study design	Population (age range), *n*	Exposure	Outcome	Key primary results	Key secondary results	Quality assessment
				dorsomedial and medial prefrontal cortex (dmPFC) and right dlPFC, after adjusting for age, country, and scan order - Higher liking for high- vs. low-ED foods both in children and teens	- Food vs. nonfood image viewing: no differences in brain activation between children and adolescents	
Samara et al. (2018, USA) (45); RCT; fMRI study	Children (8–10 y) $n = 11$	High-calorie food images vs. nonfood images	Brain activation	- Increased activation in the visual cortex, left and right PPHG, and the dmPFC in response to food vs. nonfood images	NA	Low
English et al. (2017, USA) (41); RCT; fMRI study	Children (7–10 y) $n = 36$	Food images varying in ED and PS: i) Large PS/High ED, ii) Small PS/High ED, iii) Large PS/Low ED, iv) Small PS/Low ED	1) Brain activation across conditions (varying in PS and ED) 2) Brain response and: a) food intake in response to food images varying in PS; b) appetitive traits	- Large vs. small PS: decreased activation in the bilateral IFG; a PS × ED interaction was shown in the superior temporal gyrus, but no longer significant after adjusting for pre-fMRI fullness or food liking - High vs. low ED: Increased activation in the caudate, cingulate, and precentral gyrus; and decreased activation in the insula and superior temporal gyrus, after adjusting for BMI *z*-score	a) Activation to high- vs. low-ED cues in the decline interacted with PS to influence energy intake. b) Activation to high- vs. low-ED was negatively correlated with scores on the enjoyment of food subscale in the anterior insula and with food-responsiveness scores in the decline (cognitive processing)	Low
Fearnbach et al. (2016, USA) (42); RCT; fMRI study	Children (7–10 y) $n = 36$	Food images varying in ED: high ED, low ED, vs. control	1) Brain activation across conditions 2) Mediating role of FFM (i.e., body composition)	High- vs. low-ED foods elicited greater activation in the left thalamus	Neural activation was positively associated with child FFM in the right substantia nigra when exposed to high- vs. low-ED food images, after adjusting for BMI *z*-score and food liking	Low

(*Continued*)

TABLE 1 (*Continued*)

Study (year, country) (ref); study design	Population (age range), *n*	Exposure	Outcome	Key primary results	Key secondary results	Quality assessment
English et al. (2016, USA) (40); RCT; fMRI study	Children (7–10 y) $n = 36$	Food images varying in ED and PS: Large PS/High ED, Small PS/High ED, Large PS/Low ED, and Small PS/Low ED Control stimuli: furniture, scrambled images	1) Brain activation across conditions (varying in PS and ED) 2) Brain response to food vs. nonfood images 3) Liking and wanting of high- vs. low-ED foods	- Large vs. small PS: increased activation in the right and left IFG; no longer significant after adjusting for pre-scan fullness and food liking . High vs. low ED: decreased activation in the left hypothalamus, after adjusting for fullness, but no longer significant after adjusting for both fullness and food image liking	Higher mean liking and wanting ratings for high ED vs. low ED	Low
Van Meer et al. (2016, The Netherlands) (54); RCT; fMRI study	Children (10–12 y) $n = 27$	Unhealthy vs. healthy food images	1) Brain responses to unhealthy vs. healthy food images 2) Role of BMI	Higher response to unhealthy vs. healthy food images in the right temporal/occipital gyri and left precentral gyrus and left hippocampus, independent of age and sex	Negative correlation between BMI and the brain response to unhealthy vs. healthy food images in the bilateral dlPFC	Low
Murphy et al. (2020, Ireland) (58); RCT	Adolescents: Study 1: 13–14 y; $n = 72$ Study 2: 13–17 y; $n = 79$	1) Advertising content: exposure to Facebook unhealthy, healthy vs. non-food advertising 2) Source of advertisement: peer, celebrity, company	Study 1: 1) Recall and brand recognition; 2) Social responses to healthy vs. unhealthy foods (post sharing) Study 2: Eye-tracking measures of attention: 1) Attention to advertising (fixation duration and count); 2) Fixation duration by ads source	Study 1: Participants could recall and recognize unhealthy food brands more than healthy posts (5×), when coming from celebrities and companies, but not peers, after adjusting for age, sex, product type and internet use Study 2: adolescents looked at ads for	Study 1: Adolescents responded more positively to unhealthy food brands, compared to healthy and nonfoods in terms of social attitudes: post sharing Study 2: Fixation duration was higher for unhealthy foods when posted by peers, but higher for	Low

(*Continued*)

TABLE 1 (*Continued*)

Study (year, country) (ref); study design	Population (age range), n	Exposure	Outcome	Key primary results	Key secondary results	Quality assessment
				unhealthy foods for longer (fixation duration) vs. healthy foods - Fixation count and duration to posts overall was greater for older adolescents	healthy foods when posted by celebrities, after adjusting for sex, age, internet use	
Allen et al. (2016, UK) (49); RCT; fMRI study	Adolescents (12–18 y) $n = 21$	Food images: High-fat, high-sugar (e.g., cake); high-fat, low-sugar (e.g., fried chicken); low-fat, high-sugar (e.g., sweets, apples); low-fat, low-sugar (e.g., carrots) Control: nonfood	1a) Appeal of food 1b) Brain activation 2) Mediator: parental feeding practices	a) Participants rated high-fat/high-sugar and low-fat/high-sugar foods as more appealing compared to high-fat/low-sugar and low-fat/low-sugar foods, independent of age and sex ; b) Participants showed heightened activation to food compared to nonfood images in the insula and operculum (gustation and reward)	- Food images related to restrictive feeding: Greater activity in visual regions (posterior) including the left occipital pole, left lateral occipital cortex, right temporal occipital fusiform)	Low
Jensen et al. (2016, USA) (43); RCT; fMRI study	Adolescents (14–20 y) $n = 12$	Food images: high-energy foods (e.g., SSBs, fried potatoes); low-energy foods (e.g., fresh fruits, vegetables); Control: nonfood objects (e.g., flowers)	1) Neural activation depending on Power of Food Score— i) food available; ii) food present, but not tasted; iii) food tasted—as a measure of appetite and food motivational reward	For high-energy foods, higher PFS decreased brain response in the dlPFC, mPFC, and right inferior parietal lobule (inhibitory control), but not for low-energy foods, after controlling for age and BMI	No differences were observed in brain activation depending on food proximity (i.e., available, present, or tasted)	Low

(*Continued*)

TABLE 1 (*Continued*)

Study (year, country) (ref); study design	Population (age range), *n*	Exposure	Outcome	Key primary results	Key secondary results	Quality assessment
Watson et al. (2015, The Netherlands) (52); RCT	Adolescents Study 1: (12–15 y); $n = 62$ Study 2: (12–16 y); $n = 111$	Food images: unhealthy (chocolate, potato crisps) vs. healthy (cucumber, tomato)	1) Motivation (desire to eat) to unhealthy vs. healthy food images 2) Response priming to unhealthy vs. healthy food: a) Direct (instrumental); b) Indirect (Pavlovian) response priming	- No significant difference between the reported desire (motivation) to eat high-calorie foods vs. low-calorie foods - Participants responded faster [1131 (399) ms] for high-calorie vs. low-calorie food images [1271 (640); $t(61) = 2$, $P = 0.05$] in direct and in indirect (Pavlovian) response priming	- No association was observed between self-reported impulsivity and response priming for high-calorie snacks - Females performed better on high- relative to low-calorie trials ($P = 0.004$) during the Pavlovian training; in males no differences were observed	Low
Stice et al. (2011, USA) (46); RCT; fMRI study	Adolescents of high vs. low risk of overweight (of obese vs. lean parents) $n = 60$	1) Food stimuli: images of milkshake and water glasses that signalled the delivery of a chocolate milkshake or a tasteless solution (TS) 2) Monetary reward: 3 coin images	1) Brain activation to food stimuli by: a) milkshake vs. tasteless receipt or b) unpaired milkshake vs. tasteless cue 2) Brain activation to the monetary reward	a) High- vs. low-risk adolescents showed greater activation in the right caudate, right frontal operculum, and left parietal operculum during milkshake vs. tasteless solution receipt; b) No differences emerged in response to the unpaired cue	Monetary reward paradigm: high- vs. low-risk participants showed greater activation of the right putamen, left putamen, right OFC, and left caudate boundary	Low
Social media exposure, unhealthy food intake, and dietary behaviors, by age group (observational study)						
Smit et al. (2020, The Netherlands) (55) longitudinal study	Children (8–12 y) $n = 453$	Exposure to YouTube video blogers	Consumption of: 1) unhealthy beverages (SSBs) and 2) high-ED snacks	Frequency of watching video-blogs significantly predicted unhealthy beverages consumptions at 2 y later, after adjusting for BMI and family affluence (as proxy for SES)	No association between frequency of watching video-blogs and unhealthy snack intake at 1 and 2 y later	Low

(*Continued*)

TABLE 1 (*Continued*)

Study (year, country) (ref); study design	Population (age range), *n*	Exposure	Outcome	Key primary results	Key secondary results	Quality assessment
Qutteina et al. (2021, Belgium) (61); cross-sectional study	Adolescents (11–19 y) $n = 1002$	Exposure to: 1) food messages posted by peers, influencers, celebrities on SM 2) branded food marketing	1) Frequency intake and preference for: a) high-ED foods (sweets and fast food); b) healthy foods (fruits and vegetables) 2) Food literacy	a) Exposure to SM high-ED food messages was positively associated with preference and frequency intake of those food ($Z = 3.63$, $P < 0.000$), after controlling for age, sex, BMI-for-age, self-regulated autonomy, and food literacy; b) Exposure to SM food marketing of high-ED foods was associated with higher preference for high ED foods ($Z = 3.38$, $P > 0.000$)	- Adolescents with lower exposure to high-ED food messages on SM demonstrated increased food literacy ($Z = -5.39$, $P < 0.000$) . - Food literacy mediated the association between healthy food messages/marketing exposure and increased healthy food intake, but not the relationship between exposure to high ED food posts and intake of ED foods	High
Byun et al. (2021, Republic of Korea) (68); cross-sectional study[2]	Adolescents (12–18 y) $n = 54.416$	1) Total internet duration 2) Internet use for leisure purposes 3) Internet use for study purposes	1) Single dietary behaviors: breakfast skipping, low intake of fruits and vegetables, high intake of instant noodles, fast food, chips/crackers, and SSBs 2) Composite dietary risk indicator (≥3 dietary risk factors vs. <3 factors)	- Longer total internet use (≥301 min/d) was associated with higher prevalence of frequent breakfast skipping (OR = 1.16, 95% CI = 1.08–1.24), low intake of vegetables, high intakes of instant noodles, fast food, and SSBs (1.61, 95% CI = 1.50–1.72), and the composite dietary risk indicator (OR = 1.67, 95% CI = 1.55–1.80) - Prolonged internet use during leisure time (≥241 min/d vs. 1–60 min/d) was associated	- Prolonged study time internet use (≥121 min/d vs. 1–60 min/d) was inversely associated with prevalence of low fruit and vegetable intake (OR = 0.91; 95% CI = 0.85–0.98), and positively associated with intake of instant noodles (OR = 1.10; 95% CI = 1.03–1.19), and chips/crackers (OR = 1.13; 95% CI = 1.04–1.23) . Similar results were observed in the analyses stratified by sex, school grade,	High

(*Continued*)

TABLE 1 (*Continued*)

Study (year, country) (ref); study design	Population (age range), *n*	Exposure	Outcome	Key primary results	Key secondary results	Quality assessment
				with higher prevalence of all 7 individual dietary risk factors and the composite dietary risk indicator (OR = 2.00, 95% CI = 1.85–2.15)	region, household income, physical activity, and obesity status	
Gascoyne et al. (2021, Australia) (63); cross-sectional study	Adolescents (12–17 y) $n = 8708$	1) Exposure to food marketing on SM 2) Engagement with food marketing on SM (liked or shared post)	1) Frequency intake of: a) unhealthy foods; b) unhealthy drinks (fruit juice, soft, and sports drinks) 2) Differences by SES and sex	- Exposure to food marketing on SM was not associated with unhealthy food intake, but was positively associated with frequency intake of unhealthy drinks (daily/almost daily: OR = 1.57, 95% CI = 1.30–1.90). - Stratified analyses showed that associations persisted across SES and in males (daily/almost daily: OR = 1.88, 95% CI = 1.46–2.43), but not in females ($P > 0.20$)	Engagement (liking or sharing) with food marketing posts on SM was associated with higher intake of unhealthy foods (daily/almost daily: OR = 5.26; 95% CI = 3.97–7.01) and drinks (daily/almost daily: OR = 4.14; 95% CI = 3.09–5.55), independent of age and sex, and with only slight variations by SES	High
Kim and Han (2020, Republic of Korea) (69); cross-sectional study[2]	Adolescents (12–18 y) $n = 54{,}603$	1) Total smartphone use (hours/day) 2) Smartphone use for educational vs. communication purposes	1) Breakfast skipping 2) Frequency of eating fast food	Smartphone use was associated with frequent breakfast skipping (≥5 times/wk) and higher consumption frequency of fast food (≥3 times/wk) in a dose-response manner, after adjusting for sex, school year, place of residence, parental educational level etc.	Smartphone use for communication vs. educational purposes was associated with fast-food consumption frequency for ≥3 times/wk (OR = 1.37; 95% CI = 1.25–1.50), after adjusting for covariates	High

(*Continued*)

TABLE 1 (*Continued*)

Study (year, country) (ref); study design	Population (age range), *n*	Exposure	Outcome	Key primary results	Key secondary results	Quality assessment
Bradbury et al. (2019, USA) (38); cross-sectional study	Adolescents (14–16 y) $n = 32{,}418$	Social media use (hours/day)	1) Daily intake of sugar and caffeine 2) Likelihood of exceeding the WHO recommendation on sugar and caffeine intake	- Daily sugar intake was 1.65g (95% CI = 1.13–2.14; $P < 0.001$) higher for each additional hour of SM use - Caffeine intake was 5.21 mg (95% CI = 3.51–6.99; $P < 0.001$) higher per 1 additional hour of SM, after adjusting for grade, sex, parental education, hours unattended at home	The odds of exceeding the sugar intake recommendation were 7% higher (95% CI = 1.05–1.09) with each hour of SM and 9% higher (95% CI = 1.06–1.11) for caffeine intake, independent of covariates	High
Delfino et al. (2018, Brazil) (64); cross-sectional study[2]	Children and adolescents (10–17 y) $n = 1011$	Smartphone use duration: high vs. low (cutoff: ≥2 h/d)	Food intake: fruit and vegetables, sweet foods, soft drinks, diary, fried foods, grains	- High use of smartphones was associated with high consumption frequency of sweets, independent of age, sex, and SES, but not with healthy food intake (fruits and vegetables)	High use of 3 to 4 devices was associated with higher consumption frequency of fried foods, sweets, and snacks	High
Busch et al. (2013, The Netherlands) (57); cross-sectional study[2]	Children and adolescents (11–18 y) $n = 2425$	1) Excessive internet use duration (>2 h/wk) 2) Compulsive internet use	Nutritional behavior: composite score of eating breakfast and fruits/vegetables at least 5 times/wk	Excessive internet use was associated with poor nutritional behaviors (males: OR = 1.36; 95% CI = 1.00–1.86; females: OR = 2.09; 95% CI = 1.57–2.78). When considering multi-screen use, this association remained significant only in females (OR = 1.87; 95% CI = 1.22–2.86)	Compulsive internet use was associated with poor nutritional behaviors in all children (OR = 5.35; 95% CI = 2.54–11.27)	High

(*Continued*)

TABLE 1 (*Continued*)

Study (year, country) (ref); study design	Population (age range), *n*	Exposure	Outcome	Key primary results	Key secondary results	Quality assessment
Baldwin et al. (2018, Australia) (19); cross-sectional study	Children and adolescents (10–16 y) $n = 417$	Use of Facebook and YouTube	1) Unhealthy food and beverages frequency intake 2) Exposure to unhealthy food marketing	Children who watched branded videos on YouTube had food scores 0.46 (SD = 0.18) points higher ($P = 0.01$), drink scores 0.34 (SD = 0.13) points higher ($P = 0.01$), and combined scores 0.80 (SD = 0.27) points higher ($P = 0.003$) on average than children who did not, after adjusting for age, sex, and SES	- Seeing favorite food and beverage brands on SM increased unhealthy food score with 0.63 points (SD = 0.25, $P = 0.01$), and the combined score with 0.86 points (SD = 0.35) ($P = 0.015$) - Purchasing food online was associated with higher unhealthy food score	Medium
Hansstein et al. (2017, China) (65); cross-sectional study	Children and adolescents (6–18 y) $n = 1815$	1) Watching videos and movies online (hours/week), 2) Internet use (hours/week)	1) Fast-food frequency consumption in a fast-food restaurant 2) Liked/did not like fast-food restaurants and whether liked high-ED foods (salty snack, energy drinks)	Children and adolescents in rural areas watching online videos ($P < 0.01$) and surfing the Internet ($P < 0.05$) had higher odds of eating at fast-food restaurants	- Adolescents who watched online videos were more likely to like fast food - Children living in urban areas liked fast foods, salty snacks, and sugary drinks more than the rural subsample	Medium
Sampasa-Kanyinga et al. (2015, Canada) (25); cross-sectional study	7th- to 12th-grade students (mean age = 15.2 y) $n = 9858$	Social media use (Facebook, MySpace, Instagram, Twitter) in hours/day	1) Consumption of SSBs 2) Skipping breakfast frequency	SM was positively associated with SSB intake (<1 h/d: OR = 1.67; 2 h/d: OR = 1.90 and >5 h/d: OR = 3.29), after adjusting for age, sex, ethnicity, SES, parental educational level, BMI, and tobacco, alcohol, and cannabis use	SM was associated with increased odds of skipping breakfast in a dose–response manner after adjusting for same covariates	Medium
Lwin et al. (2017, Indonesia) (66); cross-sectional study	Children (mean age = 9.4 y) $n = 394$	Online and SM use duration	1) Fast-food consumption between: a) suburban vs. urban children and b) parental mediation strategies (active vs. restrictive)	a) Children's exposure to online and SM was positively related to fast-food consumption in suburban areas ($P = 0.02$), but not in urban areas.	b) Active parental mediation significantly lowered fast-food consumption and increased nutrition knowledge for the suburban children, but not for urban children	Medium

(*Continued*)

TABLE 1 (*Continued*)

Study (year, country) (ref); study design	Population (age range), *n*	Exposure	Outcome	Key primary results	Key secondary results	Quality assessment
			2) Nutrition knowledge	Greater SM use was not associated with nutrition knowledge; instead broadcast media influenced nutrition knowledge		
Social media exposure, healthy food intake, and nutrition literacy (interventional study)						
Folkvord and de Bruijne (2020, The Netherlands) (56); RCT— between-subject study design	Adolescents (13–16 y) $n = 132$	Instagram influencer exposure: vegetables (red peppers) or ED snacks (finger foods) vs. control nonfood product (sunglasses)	1) Vegetable intake (red peppers, cherry tomatoes, cucumbers) 2) Mediators: a) Persuasion knowledge; b) Para-social interaction	- No significant effect of type of Instagram post on vegetable intake ($P > 0.05$, $\eta^2 = 0.02$) . No significant effect of type of Instagram post on the 3 individual vegetable intakes ($P > 0.05$); no adjustment for confounders was conducted	a) No interaction effect of Instagram post and persuasion knowledge on vegetable intake ($P > 0.05$, $\eta^2 = 0.20$) b) No interaction effect of Instagram post and para-social interaction on vegetable intake ($P > 0.05$, $\eta^2 = 0.19$)	Low
Cullen et al. (2013, USA) (39); RCT	Adolescents (12–17 y) $n = 291$	Intervention group: 1) Blog and website on healthy nutrition 2) Videos of peers (as role models) which address barriers on healthy eating Control group: no access to role model videos	1) Intake of fruit and vegetables, milk and less SSBs 2) Self-efficacy and home availability as mediator	- The percentage of intervention group (18% of adolescents) who reported eating ≥3 servings of vegetables/day in the past week was higher in the treatment group at postintervention compared with the control group (5%) ($P < 0.05$), independent of sex, age, SES, ethnicity, and TV availability in child's bedroom	- A significant group-by-time effect was reported for home availability for both fruit/juice ($P < 0.05$) and whole milk ($P < 0.01$) in the control group only - No significant group-by-time effect for self-efficacy for any of the groups	Low

[1]The quality rating is aggregated as low, medium, and high according to the respective appraisal tools. For RCTs, high quality refers to a low risk of bias across the 5 domains of the Cochrane risk assessment tool. For longitudinal studies, a medium quality is reached with 2 stars in the selection domain and 1 or 2 stars in the comparability domain and 2 or 3 stars in the outcome/exposure domain. For cross-sectional studies, a low quality refers to high risk of bias—if a score ≤4/8 is reached. Detailed information on the quality rating has been summarized in the **Supplementary Methods**. dlPFC, dorsolateral prefrontal cortex; dmPFC, dorsomedial prefrontal cortex; ED, energy-dense; EI, energy intake; FFM, fat-free mass; IFG, inferior frontal gyrus; mPFC, medial prefrontal cortex; NA, not applicable; OFC, orbitofrontal cortex; PPHG, parahippocampal gyri; PS, portion size; RCT, randomized controlled trial; ref, reference; SES, socioeconomic status; SM, social media; SSB, sugar-sweetened beverage; TV, television; vmPFC, ventromedial prefrontal cortex.

[2]In these studies, the main exposure was smartphone and internet use, as proxy for SM exposure in children and adolescents.

frequency of sweets (64) and fast food and increased likelihood of skipping breakfast (69). When distinguishing between patterns of smartphone use, Kim and Han (69) showed that Korean adolescents who used smartphones for communication instead of for educational purposes had higher odds of fast-food consumption (69). Prolonged use of multiple devices was associated with increased consumption frequency of fried foods, sweets, and snacks in Brazilian adolescents, independent of age, sex, and SES (64). Prolonged and compulsive internet use was associated with poor nutritional behaviors, including low frequency intake of fruits and vegetables, lower frequency of eating breakfast, and high frequency intake of SSBs, fast food, and unhealthy snacks (68), especially in girls using multiple devices (57). Similar unfavorable nutritional behaviors were also observed among Korean adolescents with prolonged internet use during leisure time, independent of age, obesity, and physical activity levels (68). Prolonged study-time internet use was positively associated with increased intake of unhealthy snacks, but inversely associated with low intake of fruits and vegetables (68). In an RCT, Marsh et al. (62) evaluated the distractive effect of multi-screening (simultaneous use of TV, iPad, smartphone) on food intake and observed that total energy intake did not differ between multi-screen compared with single-screen (TV only) users. Additionally, energy intake from and appetite for healthy relative to unhealthy foods were comparable between multi-screen compared with single-screen users.

Exposure to digital food images and patterns of brain activation.

Food vs. nonfood images. Three interventional studies investigated the neural responses to food compared with nonfood images in children and adolescents (Table 1). In children, an increased activation was observed in the visual cortex (associated with attention and visual processing) (45), the left and right posterior para-hippocampal gyri (PPHG; related to declarative memory functions), and the dorsomedial prefrontal cortex (social cognition, information processing, decision making, and response control) (45) when exposed to food compared with nonfood images. Comparing healthy children's neural responses to food stimuli after exposure to food compared with toy advertisements, Masterson et al. (44) observed reduced brain response to high- compared with low-ED food images in the left fusiform gyrus, left supramarginal gyrus, and left OFC.

In adolescents, increased activation was observed in the insula and operculum (gustation, food, and reward) (49) when exposed to food compared with nonfood images. Adolescents of parents with greater restrictive access on unhealthy foods showed greater activity in visual posterior regions—the left occipital pole, left lateral occipital cortex and right temporal occipital fusiform (49)—upon exposure to food compared with nonfood images.

Healthy food, unhealthy food vs. nonfood images. Nine interventional studies examined the neural responses to healthy food, unhealthy food, and nonfood images (Table 1).

In children, Van Meer et al. (54) observed an increased response to unhealthy compared with healthy food images in the right temporal/occipital gyri (visual attention), left precentral gyrus (reward), and left hippocampus (memory-related processes; Table 1). Exposure to high- compared with low-calorie food images in a hungry compared with the satiated state increased activation in the medial prefrontal cortex (mPFC) and the dorsomedial prefrontal cortex (dmPFC) and the right dorsolateral prefrontal cortex (dlPFC), respectively involved in reward and self-control during food choices (53) both in children and adolescents—and in the left thalamus (sensory perception and processing) among children only (42). On the other hand, high-ED food images reduced activation in the left hypothalamus (appetite regulation) even after adjusting for pre-scan fullness (i.e., satiation) in children (40), and they also increased activation in the caudate, cingulate, and precentral gyrus (regions involved in reward and taste processing) (41). A neural activation was positively associated with child's fat-free mass (FFM) index, but not fat mass, in the right substantia nigra (reward) when exposed to high- compared with low-ED food images (42).

In adolescents, Watson and colleagues (52) did not observe differences in their motivation towards unhealthy compared with healthy foods after exposure to the respective images. When evaluating the ideomotor mechanism (response priming effects), they observed that adolescents responded faster to unhealthy compared with healthy food images both in direct (instrumental) and indirect (Pavlovian) response priming, independent of impulsivity traits. Adolescents with greater appetite for palatable foods showed reduced response in the dlPFC, mPFC, and the right inferior parietal lobule (all regions associated with inhibitory control) for high- relative to low-ED foods (43). Adolescents at high compared with low risk for obesity by virtue of parental obesity showed greater activation in reward-related regions (i.e., the right caudate, right frontal operculum, and left parietal operculum) during palatable food (milkshake) receipt—following exposure to milkshake images—relative to tasteless solution receipt (46). However, no significant differences emerged in response to the unpaired cue (i.e., only viewing food images and not consuming them) and monetary reward (46). Moreover, repeated exposure to milkshake images was associated with greater response in the caudate and posterior cingulate cortex (48). A significant effect of paternal, but not maternal, obesity, was observed in the caudate response after repeated exposure to milkshake cues (48).

Food images varying in energy density and portion size vs. nonfood images and food intake.

Three interventional studies examined the neural responses to food images varying in energy density and portion size (PS), focusing on children only. In 2 different fMRI studies with the same children, English and colleagues (40) investigated neural responses to images of large- compared with small-PS food. First, activation was observed in the right inferior frontal gyrus (IFG), a region involved in inhibition and information processing. In a second study, reduced response in the bilateral IFG was observed (41). Although contradictory, these effects were no longer significant after adjustment for either pre-scan fullness or hedonic liking of foods (41). Increased activation was found in the left IFG in response to large-PS compared with scrambled images (40), while reduced activation was found in the right OFC in response to small-PS compared with scrambled images. A PS × ED interaction was observed in the superior temporal gyrus (multimodal semantic processing and functionally related to the primary gustatory cortex). Children exposed to large- compared with small-PS food images had increased activation in the left ventromedial prefrontal cortex (vmPFC; decision making) and left OFC (salience and associative learning), which was associated with increased food intake from baseline compared with children with low activation (Table 1) (47). Children exposed to large- compared with small-PS images of high-ED foods had activation in the right IFG (inhibitory control) and right caudate (reward), which was negatively associated with intake of high-ED foods with increasing PS. In contrast, activation in the left OFC was associated with increased food intake from baseline. Children's exposure to images of large- compared with small-PS of low-ED foods did not show a brain response–food intake interaction for low-ED foods in increasing portions (47).

Differences by sex.

Data on differences by sex were limited (Table 1). No significant differences in attention-related eye-tracking measures (fixation duration and count) were observed between sexes in response to unhealthy compared with healthy Facebook food advertisements (58). However, exposure to food/beverage marketing on SM was cross-sectionally associated with unhealthy beverage intake in males, but not in females (63). Watson et al. (52) reported that females responded faster to high- relative to low-calorie foods during the Pavlovian priming phase, whereas no differences were observed in males. Females with excessive internet use cross-sectionally showed 87% higher odds for poor nutritional behaviors (low frequency of eating breakfast and fruits and vegetables) when considering multi-screen use, while no significant association was observed for males, indicating a potential effect modification due to the clustering of the screen-time behaviors in males (57). When distinguishing between internet use for leisure and study purposes, Byun et al. (68) reported deteriorated dietary outcomes both in females and males, including increased intake of instant noodles and chips/crackers, and low intake of fruit and vegetables.

Discussion

This review examined the role that exposure to SM content has on healthy children's and adolescents' diets and related behaviors, and identified potential mechanisms underlying the pathway of these associations. SM exposure was associated with increased consumption frequency of unhealthy snacks, fast food and SSBs; daily caffeine and sugar intake; fast-food preference, and higher odds of skipping breakfast. These associations were observed both in children and adolescents, with those living in rural and suburban areas being at higher risk. We did not find evidence for the role of SM influencer marketing of healthy foods on the actual healthy food intake and nutrition literacy among children and adolescents. A number of mechanisms that may explain the abovementioned associations were identified.

1. Peer influence (among adolescents) and parental influence (among children) on SM

Peer influence (i.e., peers acting as role models) on SM may shape preferences and change food intake among adolescents. Although the mere exposure to images of peers with high-ED snacks and SSBs had no effect on intake of these foods (51), eye-tracking research showed that adolescents look at unhealthy food images longer when posted by peers compared with celebrities or companies (58), suggesting that food cues are processed differently depending on the source of the exposure. However, adolescents exposed to peers' videos on SM addressing barriers to healthy eating increased daily vegetable intake, indicating that peers might have a higher potential for promoting healthy eating compared with influencers (39). In fact, peers are considered the most powerful source in shaping consumption-related decision making (70) and the screen-time behaviors in early adolescence (71). Further, peers might be a more trusted source compared with celebrities and influencers, as electronic recommendations from them (eWord of Mouth) are believed to be highly trustworthy because no commercial interest is involved (72).

Parents of younger children seem to have a positive influence over their children's fast-food consumption frequency and nutrition knowledge via active parental mediation strategy such as discussing and advising (66). On the other hand, adolescents of parents who place many restrictions on unhealthy foods showed in fMRI measurements a greater activity in visual regions (e.g., left lateral occipital cortex) when exposed to food images, indicating an attentional weight (saliency) for restricted food rather than the reward per se (49). This supports previous evidence suggesting that parents are important drivers of children's eating behaviors, which diminishes in adolescence, due to adolescents' ambition for autonomy and other sociocultural factors (73). Future SM interventions should carefully consider the source of marketing of healthy foods—respectively, parents and peers—in order to motivate children and adolescents to make healthy food choices.

2. Food and influencer marketing targeting children and adolescents on SM

The child-directed marketing of branded snacks and unhealthy beverages embedded in images and videos on Instagram (26) and YouTube led to increased preference (61) and intake of those foods (60), even 2 y later (55). Food marketing may interfere with children's neural processing of food cues, as exposure to food compared with toy advertisements elicited different responses to high- relative to low-ED food images (44). In adolescents, unhealthy food brands were recalled and recognized more often than healthy foods in SM posts when coming from celebrities and companies but not peers (58). These findings reinforce the powerful use of SM influencer marketing by food companies to promote junk products on SM. These results are in line with a previous systematic review on digital advertising, which showed that exposure to advergames led to higher energy intake in children and adolescents of an age range similar to our review (74). Consumer protection acts have enacted stricter guidelines for the disclosure of paid influencer content on SM, as a "protective" tool against deceptive advertisements and to increase audience's knowledge of persuasion mechanisms (75). However, our review shows that there is no interaction between food marketing with an advertising disclosure and children's awareness of advertising on energy intake, suggesting that SM marketing negatively impacts children's and adolescents' food intake, independent of using advertising disclosures (50). A possible explanation could be that children and adolescents trust and/or feel a familiarity with SM influencers who are often also in the same age group. They may perceive an advertising disclosure as honest and/or an act of fairness, which may lead to a positive attitude towards influencers and enhanced advertising effects (70). Another explanation could be that disclosures are too small and misplaced within the SM post, underpinning hidden and misleading marketing messages as the advertising content is usually mixed with social and cultural user-generated content, hence enabling direct influences on children and adolescents (76). Nevertheless, it has been suggested that unhealthy, but not healthy, food marketing may lead to healthy food intake in children, when promoted by a sedentary compared with an athletic influencer (59). This indicates that the lifestyle of the influencer may impact children's food choice. This supports the Healthy Food Promotion Model, emphasizing the role of message and situational factors on children's susceptibility to food cues (77). Future health interventions should take into consideration the type of message and the contextual factors when using SM influencers for promoting healthy food intake in children and adolescents.

3. Ubiquitous access to SM via smartphones and food intake

Adolescents' prolonged smartphone use as the main device used to access SM and internet was associated with lower intake of fruits and vegetables but increased intake of sweets, fast food, and SSBs (68), especially among those using several screens and for leisure purposes (68, 69). This suggests that exposure to marketing via different digital channels simultaneously might have an accelerating effect on negatively impacting adolescent's dietary patterns. Although studies evaluating smartphone use and food intake were conducted only in adolescents, similar results could be expected in children as well. Sina et al. (78) observed that, in European children and adolescents, prolonged smartphone and internet use were associated with an increased preference for sweet, salty, and fatty tasting foods (taste sensations of unhealthy, highly processed foods), but were negatively associated with bitter taste preference (the taste of healthy foods). This sheds light on a further potential mechanism by which exposure to online content accessed via smartphones (i.e., SM) may affect food intake, leading to overweight and obesity. Furthermore, the capacity of smartphones to offer various services (i.e., SM, videogames, camera/pictures, texting) means a higher potential to influence children's and adolescents' attention span and act as distractors (64, 67, 79). Additionally, smartphone and SM use were associated with a lower frequency of eating breakfast in adolescents (25, 69). Shifts in circadian rhythmicity, towards a later midpoint of sleep in adolescence, may explain this relation. It is noteworthy that other types of digital media might moderate the association between SM and diets. Recent literature suggests that children and adolescents engage in media multitasking behaviors by using several devices (e.g., smartphone, TV, PC) in parallel. Media multitasking may affect children's and adolescents' self-regulation and cognitive processes, which, in turn, are also associated with unhealthy snack consumption and obesity (80, 81). In our review, only 1 study examined the role of media multitasking in adolescents' food intake and did not find any significant difference between multi-screen and single-screen users (62). More studies are needed to elucidate the long-term role of media multitasking also in combination with other non-screen activities in children's and adolescents' eating behaviors.

4. Food images on SM may elicit brain responses related to attention, memory, and reward in both children and adolescents

The fMRI-based studies evaluating the neural correlates to digital food images as a proxy to food images embedded in SM revealed that healthy children and adolescents have heightened responses towards food images (53), independent of age. The areas with increased activation included those related to gustation and reward in adolescents (insula and operculum) (49), attention and visual processing (visual cortex) (45), memory (PPHG), and information processing (dmPFC) in children . These findings suggest that, when children and adolescents view food images on SM feeds, their brain processes them differently compared with nonfood images, leading to higher attention, memory, and reward, especially when exposed to unhealthy palatable foods (54) and even after repeated exposure (48).

Appetite and brain response to unhealthy food images. The appetitive state (hungry vs. satiated) also plays a role in the manner that healthy compared with unhealthy food images are processed in the brain. Children and adolescents in the fasting state showed increased response in areas related to reward (dlPFC) (53), sensory perception and processing (the left thalamus) (42). Adolescents have reported that they use SM as soon as they wake up (i.e., in a fasting state) (82). Exposure to unhealthy food images on SM in a hungry state might lead to poor food choices for breakfast and the rest of day, including buying decisions, as motivation towards palatable foods has also been shown to reduce response in regions associated with inhibitory control (dlPFC, mPFC) after exposure to high-ED food images (43). These findings indicate that children and adolescents with high motivation (i.e., appetite) for high-ED foods available in the environment have lower executive control, which makes them vulnerable to consuming higher quantities of these foods. Furthermore, a neural activation in the right substantia nigra (reward) was positively associated with child FFM index when exposed to high- compared with low-ED food images (42), supporting the notion of FFM (i.e., lean mass) as an appetitive driver. Noteworthy, the dopamine receptors of the substantia nigra respond to signals of leptin, insulin, and ghrelin, subsequently influencing the dopamine signaling (83).

Food PS in SM images. Food PS depicted in SM images is another mechanism that might interfere with brain activation and food intake. Children exposed to large-PS food images had increased activation in areas related to decision making (left vmPFC), salience, and associative learning (left OFC), which, in turn, was associated with increased food intake (47). Previous evidence has suggested that SM influencers offering nutritional advice on healthy eating most often show food pictures of large PSs, with high-fat, -salt, and -sugar content, undermining their followers' efforts to eat a healthy diet (84). However, the appetitive state and the energy density of foods seem to lie in the pathway of how children's brains process information about PS (41). Children exposed to large- compared with small-PS images of high-ED foods had activation in inhibitory control regions (right IFG), which was negatively associated with intake of high-ED foods with increasing PS (47). These findings may indicate an increased conflict and more information processing related to social judgment and subsequently reduced food intake. Nevertheless, the role of food PS was examined only in children. Future studies are warranted to elucidate neural and developmental differences between children and adolescents in response to increasing PS of food images.

Strengths and limitations

To our best knowledge, this review is the first to identify and summarize studies examining the association between SM exposure and dietary behaviors in both children and adolescents, while identifying the underlying mechanisms. The strengths of our review include the rigorous and comprehensive search strategy applied across 3 databases, the adherence to the PRISMA guidelines (29), use of a pretested and standardized data-extraction template, as well as data extraction and quality assessment by 2 independent reviewers. Also, the wide age span we included (2–18 y) enabled us to evaluate SM use habits and their associations with dietary habits from childhood to adolescence, considering developmental differences in age and brain maturation. The inclusion of different study designs—observational studies, RCTs, and studies based on fMRI and eye-tracking methods—allowed us to better understand the possible mechanisms explaining how SM influences the diets of children and adolescents.

Limitations of the review.

This review has limitations. Due to the heterogeneity of study designs and measurements used across the included studies, a meta-analysis was not feasible. We included studies with digital food images as a proxy-variable for SM-related food images. Evidence indicates that adolescents are not able to distinguish between food images originating from traditional sources (print) compared with Instagram and they rate their advertisement features similarly (85). However, adolescents rated Instagram food images as trendier. Hence, the effect of digital food images on the neural response and the actual food intake and preference might be different in the SM context. Other factors might also influence children's and adolescents' brain response, such as influencer or peer endorsement, post engagement (liking, sharing), or SM technological features (e.g., filters, reels, animations). Similarly, the use of smartphone and internet as a proxy for SM exposure is another limitation of this review. The multitasking and other technological features of smartphones might have effects that go beyond SM alone. However, as the literature suggests, smartphones are mainly used to access SM and for communication and leisure purposes, all of which were associated with unfavorable eating behaviors. It is thus difficult to distinguish between smartphone and SM use, especially with regard to daily duration and frequency of use. Future studies should use other methods such as Ecological Momentary Assessment or log-on data from SM applications for a more comprehensive assessment of duration and context of SM exposure.

Limitations of the included studies.

Among the interventional studies, the majority assessed exposures (SM) at 1 time point only; hence, future RCTs with repeated measurements are warranted. Only 1 of the RCTs blinded the researchers from knowing the participants' allocation groups. This was also the only RCT assessed at a low risk of bias (62). The majority of the RCTs were rated low quality due to high risk of bias arising from the domains "deviations from intended interventions" and "measurement of the outcome." This is due to the fact that those delivering the interventions and assessing the outcomes were not blinded to the participants' assigned intervention. Methodological concerns were also identified in the RCT conducted by Folkvord and de Bruijne (56). First, the authors did not take into account sex differences in the exposure, as they included only a male SM influencer. Second, although evaluating the role of the influencer's marketing of healthy and unhealthy foods, at postintervention they measured only healthy food intake. The results might have differed if both healthy (vegetables) and unhealthy snack intakes were considered postintervention. Third, the authors did not report adjustments for confounders; hence, the findings should be interpreted with caution (56). Moreover, Teo et al. (67) did not consider sex differences, as they included only male adolescents in their study. Among the observational studies, the majority was cross-sectional; hence, causality cannot be inferred from the observed associations. SM exposure and diet-related outcomes were mostly self-reported; thus, results might be limited due to recall and social-desirability bias (86). Moreover, a number of these studies did not report whether the questionnaires used for measuring SM exposure were evaluated for validity and reproducibility (19, 38, 61, 63–65). Although only 5 studies reported full information on SES (19, 25, 39, 47, 57), the majority of children came from a high SES background, which might affect the generalizability of findings to children from a low SES background. Another key limitation is residual confounding in the included studies, as some of them did not adjust for ethnicity and SES, which may be key drivers of food choices (87). Future longitudinal studies with adequate follow-up of participants and with objectively measured SM exposure (e.g., log-on data from smartphones) and food intake in children from different SES backgrounds are thus needed to examine the long-term impact of SM on their diets. It is noteworthy that 5 studies were based on data from the same analytic sample (40–42, 44, 47). The type of control images presented in the fMRI studies varied, including cars, toys, and landscapes, which might have translated into different neural patterns based on their perceived arousal. Hence, use of standardized control images compared with food cues in fMRI-based studies is warranted.

Conclusions

This systematic review elucidates that SM exposure influences children's and adolescents' diets by increasing intake of unhealthy snacks and SSBs and decreasing intake of fruits/vegetables, independent of age. Exposure to unhealthy food images increased neural response in brain areas related to memory, reward, attention, and decision making, relative to healthy or nonfood images. Food PS, its energy density, and children's appetitive state play a role on how healthy and unhealthy food images are processed and the subsequent food intake. No evidence on the impact of SM on improving children's and adolescents' diet quality and nutrition literacy was found. However, peers seem to have a higher potential to improve vegetable intake among adolescents compared with influencers, while parents posed a higher influence among children. Future health interventions should take into account the identified mechanisms (e.g., food PS, peer influence) in order to yield effective outcomes. These findings suggest that further action is needed by health authorities on regulating SM exposure and SM food/beverage marketing to minimize unhealthy dietary habits in children and adolescents and subsequent adverse health outcomes.

Acknowledgments

We gratefully acknowledge the support received from Gowsiga Loganathan, Jenny Wussow, and Flora Wiegand. The authors' responsibilities were as follows—ES, WA, and AH: developed the concept and scope for this review; ES, AH, and DB: conducted the research; ES and LC: were involved in literature research; ES: wrote the manuscript; ES and AH: had primary responsibility for the final content; and all authors: read and approved the final manuscript.

Data Availability

The data described in the manuscript will be made available upon request from the corresponding author.

References

1. Abarca-Gómez L, Abdeen ZA, Hamid ZA, Abu-Rmeileh NM, Acosta-Cazares B, Acuin C, Adams RJ, Aekplakorn W, Afsana K, Aguilar-Salinas CA, et al. Worldwide trends in body-mass index, underweight, overweight, and obesity from 1975 to 2016: a pooled analysis of 2416 population-based measurement studies in 128.9 million children, adolescents, and adults. Lancet North Am Ed 2017;390(10113):2627–42.
2. Olafsdottir S, Berg C, Eiben G, Lanfer A, Reisch L, Ahrens W, Kourides Y, Molnar D, Moreno LA, Siani A, et al. Young children's screen activities, sweet drink consumption and anthropometry: results from a prospective European study. Eur J Clin Nutr 2014;68(2):223–8.
3. Bornhorst C, Wijnhoven TM, Kunesova M, Yngve A, Rito AI, Lissner L, Duleva V, Petrauskiene A, Breda J. WHO European Childhood Obesity Surveillance Initiative: associations between sleep duration, screen time and food consumption frequencies. BMC Public Health 2015;15(1):442.
4. Lissner L, Lanfer A, Gwozdz W, Olafsdottir S, Eiben G, Moreno LA, Santaliestra-Pasías AM, Kovács É, Barba G, Loit H-M, et al. Television habits in relation to overweight, diet and taste preferences in European children: the IDEFICS study. Eur J Epidemiol 2012;27(9):705–15.
5. Lipsky LM, Iannotti RJ. Associations of television viewing with eating behaviors in the 2009 health behaviour in school-aged children study. Arch Pediatr Adolesc Med 2012;166(5):465–72.
6. Reid Chassiakos Y, Radesky J, Christakis D, Moreno MA, Cross C. Children and adolescents and digital media. Pediatrics 2016;138(5):e20162593.
7. Mascheroni G, Ólafsson K. Net children go mobile: risks and opportunities. Second Edition Educatt: Milan, Italy, 2014
8. Radesky JS, Eisenberg S, Kistin CJ, Gross J, Block G, Zuckerman B, Silverstein M. Overstimulated consumers or next-generation learners? Parent tensions about child mobile technology use. Ann Fam Med 2016;14(6):503–8.
9. Robinson TN, a JA, Hale L, Lu AS, Fleming-Milici F, Calvert SL, Wartella E. Screen media exposure and obesity in children and adolescents. Pediatrics 2017;140(Suppl 2):S97–S101.
10. Livingstone S, Winther DK, Saeed M. Global kids online comparative report. 2019.
11. Rideout V, Robb MB. The common sense census: media use by kids age zero to eight, 2020. San Fransisco (CA): Commen Sense Media; 2020.
12. Anderson M, Jiang J. Teens, social media & technology 2018. Pew Research Center 2018;31(2018):1673–89.
13. Smahel D, Machackova H, Mascheroni G, Dedkova L, Staksrud E, Ólafsson K, Livingstone S, Hasebrink U. EU Kids Online 2020: survey results from 19 countries. London, UK, London School of Economics and Political Science; 2020.
14. Freeman B, Kelly B, Baur L, Chapman K, Chapman S, Gill T, King L. Digital junk: food and beverage marketing on Facebook. Am J Public Health 2014;104(12):e56–64.
15. De Veirman M, Hudders L, Nelson MR. What is influencer marketing and how does it target children? A review and direction for future research. Front Psychol 2019;10(2685). doi: 10.3389/fpsyg.2019.02685.

16. Sabbagh C, Boyland E, Hankey C, Parrett A. Analysing credibility of UK social media influencers' weight-management blogs: a pilot study. Int J Environ Res Public Health 2020;17(23). doi: 10.3390/ijerph17239022.
17. Potvin Kent M, Pauzé E, Roy EA, de Billy N, Czoli C. Children and adolescents' exposure to food and beverage marketing in social media apps. Pediatr Obesity 2019;14(6):e12508.
18. Qutteina Y, Hallez L, Mennes N, De Backer C, Smits T. What do adolescents see on social media? A diary study of food marketing images on social media. Front Psychol 2019;10(2637). doi: 10.3389/fpsyg.2019.02637.
19. Baldwin HJ, Freeman B, Kelly B. Like and share: associations between social media engagement and dietary choices in children. Public Health Nutr 2018;21(17):3210–5.
20. Rozendaal E, Buijzen M, Valkenburg P. Comparing children's and adults' cognitive advertising competences in the Netherlands. J Child Media 2010;4(1):77–89.
21. Smith R, Kelly B, Yeatman H, Boyland E. Food marketing influences children's attitudes, preferences and consumption: a systematic critical review. Nutrients 2019;11(4):875. doi: 10.3390/nu11040875.
22. Spence C, Okajima K, Cheok AD, Petit O, Michel C. Eating with our eyes: from visual hunger to digital satiation. Brain Cogn 2016;110:53–63.
23. Naderer B, Binder A, Matthes J, Spielvogel I, Forrai M. Food as an eye-catcher. An eye-tracking study on children's attention to healthy and unhealthy food presentations as well as non-edible objects in audiovisual media. Pediatr Obesity 2020;15(3):e12591.
24. Jilani HS, Pohlabeln H, Buchecker K, Gwozdz W, De Henauw S, Eiben G, Molnar D, Moreno LA, Pala V, Reisch L, et al. Association between parental consumer attitudes with their children's sensory taste preferences as well as their food choice. PLoS One 2018;13(8):e0200413.
25. Sampasa-Kanyinga H, Chaput JP, Hamilton HA. Associations between the use of social networking sites and unhealthy eating behaviours and excess body weight in adolescents. Br J Nutr 2015;114(11):1941–47.
26. Coates AE, Hardman CA, Halford JC, Christiansen P, Boyland EJ. Social media influencer marketing and children's food intake: a randomized trial. Pediatrics 2019;143(4).
27. Folkvord F, Anschutz DJ, Buijzen M, Valkenburg PM. The effect of playing advergames that promote energy-dense snacks or fruit on actual food intake among children. Am J Clin Nutr 2013;97(2):239–45.
28. Chau MM, Burgermaster M, Mamykina L. The use of social media in nutrition interventions for adolescents and young adults—a systematic review. Int J Med Informatics 2018;120:77–91.
29. Moher D, Liberati A, Tetzlaff J, Altman DG. Preferred Reporting Items for Systematic Reviews and Meta-Analyses: the PRISMA statement. PLoS Med 2009;6(7):e1000097.
30. Hamm MP, Shulhan J, Williams G, Milne A, Scott SD, Hartling L. A systematic review of the use and effectiveness of social media in child health. BMC Pediatr 2014;14(1):138.
31. Moorhead SA, Hazlett DE, Harrison L, Carroll JK, Irwin A, Hoving C. A new dimension of health care: systematic review of the uses, benefits, and limitations of social media for health communication. J Med Internet Res 2013;15(4):e85.
32. Coates AE, Hardman CA, Halford JCG, Christiansen P, Boyland EJ. Food and beverage cues featured in YouTube videos of social media influencers popular with children: an exploratory study. Front Psychol 2019;10:2142.
33. Ohla K, Toepel U, le Coutre J, Hudry J. Visual-Gustatory interaction: orbitofrontal and insular cortices mediate the effect of high-calorie visual food cues on taste pleasantness. PLoS One 2012;7(3):e32434.
34. Ouzzani M, Hammady H, Fedorowicz Z, Elmagarmid A. Rayyan—a web and mobile app for systematic reviews. Syst Rev 2016;5(1):210.
35. Wells GA, Shea B, Da O'C, Peterson J, Welch V, Losos M, Tugwell P. The Newcastle-Ottawa Scale (NOS) for assessing the quality of nonrandomised studies in meta-analyses. http://www.ohri.ca/programs/clinical_epidemiology/oxford.asp University of Ottawa Ontario, Canada; 2000.
36. Moola S, Munn Z, Tufanaru C, Aromataris E, Sears K, Sfetcu R, Currie M, Qureshi R, Mattis P, Lisy K, et al. Chapter 7: systematic reviews of etiology and risk. In: Aromataris E, Munn Z(editors). JBI Manual for Evidence Synthesis. Joanna Briggs Institute; Adelaide, South Australia, 2020.
37. Sterne JAC, Savović J, Page MJ, Elbers RG, Blencowe NS, Boutron I, Cates CJ, Cheng H-Y, Corbett MS, Eldridge SM, et al. RoB 2: a revised tool for assessing risk of bias in randomised trials. BMJ 2019;366:l4898.
38. Bradbury KM, Turel O, Morrison KM. Electronic device use and beverage related sugar and caffeine intake in US adolescents. PLoS One 2019;14(10):e0223912.
39. Cullen KW, Thompson D, Boushey C, Konzelmann K, Chen T-A. Evaluation of a web-based program promoting healthy eating and physical activity for adolescents: Teen Choice: Food and Fitness. Health Educ Res 2013;28(4):704–14.
40. English LK, Fearnbach SN, Lasschuijt M, Schlegel A, Anderson K, Harris S, Wilson SJ, Fisher JO, Savage JS, Rolls BJ, et al. Brain regions implicated in inhibitory control and appetite regulation are activated in response to food portion size and energy density in children. Int J Obes 2016;40(10):1515–22.
41. English LK, Fearnbach SN, Wilson SJ, Fisher JO, Savage JS, Rolls BJ, Keller KL. Food portion size and energy density evoke different patterns of brain activation in children. Am J Clin Nutr 2017;105(2):295–305.
42. Fearnbach SN, English LK, Lasschuijt M, Wilson SJ, Savage JS, Fisher JO, Rolls BJ, Keller KL. Brain response to images of food varying in energy density is associated with body composition in 7- to 10-year-old children: results of an exploratory study. Physiol Behav 2016;162:3–9.
43. Jensen CD, Duraccio KM, Carbine KA, Barnett KA, Kirwan CB. Motivational impact of palatable food correlates with functional brain responses to food images in adolescents. J Pediatr Psychol 2017;42(5):578–87.
44. Masterson TD, Bermudez MA, Austen M, Lundquist E, Pearce AL, Bruce AS, Keller KL. Food commercials do not affect energy intake in a laboratory meal but do alter brain responses to visual food cues in children. Appetite 2019;132:154–65.
45. Samara A, Li X, Pivik RT, Badger TM, Ou X. Brain activation to high-calorie food images in healthy normal weight and obese children: a fMRI study. BMC Obesity 2018;5(1):1–8.
46. Stice E, Yokum S, Burger KS, Epstein LH, Small DM. Youth at risk for obesity show greater activation of striatal and somatosensory regions to food. J Neurosci 2011;31(12):4360–6.
47. Keller KL, English LK, Fearnbach SN, Lasschuijt M, Anderson K, Bermudez M, Fisher JO, Rolls BJ, Wilson SJ. Brain response to food cues varying in portion size is associated with individual differences in the portion size effect in children. Appetite 2018;125:139–51.
48. Sadler JR, Shearrer GE, Papantoni A, Yokum ST, Stice E, Burger KS. Correlates of neural adaptation to food cues and taste: the role of obesity risk factors. Published online ahead of print, 2021 Mar 3 Soc Cognitive Affect Neurosci 2021. doi: 10.1093/scan/nsab018.
49. Allen HA, Chambers A, Blissett J, Chechlacz M, Barrett T, Higgs S, Nouwen A. Relationship between parental feeding practices and neural responses to food cues in adolescents. PLoS One 2016;11(8):e0157037.
50. Coates AE, Hardman CA, Halford JCG, Christiansen P, Boyl EJ. The effect of influencer marketing of food and a "protective" advertising disclosure on children's food intake. Pediatr Obesity 2019;14(10).
51. Sharps MA, Hetherington MM, Blundell-Birtill P, Rolls BJ, Evans CEL. The effectiveness of a social media intervention for reducing portion sizes in young adults and adolescents. Digital Health 2019;5:205520761987807.
52. Watson P, Wiers RW, Hommel B, Ridderinkhof KR, de Wit S. An associative account of how the obesogenic environment biases adolescents' food choices. Appetite 2016;96:560–71.
53. Charbonnier L, van Meer F, Johnstone AM, Crabtree D, Buosi W, Manios Y, Androutsos O, Giannopoulou A, Viergever MA, Smeets PAM, et al. Effects of hunger state on the brain responses to food cues across the life span. Neuroimage 2018;171:246–55.
54. Van Meer F, Van Der Laan LN, Charbonnier L, Viergever MA, Adan RAH, Smeets PAM. Developmental differences in the brain response to unhealthy food cues: an fMRI study of children and adults. Am J Clin Nutr 2016;104(6):1515–22.

55. Smit CR, Buijs L, van Woudenberg TJ, Bevel KE, Buijzen M. The impact of social media influencers on children's dietary behaviors. Front Psychol 2020;10:2975.
56. Folkvord F, de Bruijne M. The effect of the promotion of vegetables by a social influencer on adolescents' subsequent vegetable intake: a pilot study. Int J Environ Res Public Health 2020;17(7):2243. doi: 10.3390/ijerph17072243.
57. Busch V, Manders LA, de Leeuw JR. Screen time associated with health behaviors and outcomes in adolescents. Am J Health Behav 2013;37(6):819–30.
58. Murphy G, Corcoran C, Tatlow-Golden M, Boyl E, Rooney B. See, like, share, remember: adolescents' responses to unhealthy-, healthy- and non-food advertising in social media. Int J Environ Res Public Health 2181, 2020;17(7).
59. De Jans S, Spielvogel I, Naderer B, Hudders L. Digital food marketing to children: how an influencer's lifestyle can stimulate healthy food choices among children. Appetite 2021;162:105182. doi: 10.1016/j.appet.2021.105182.
60. Ngqangashe Y, Backer CJS. The differential effects of viewing short-form online culinary videos of fruits and vegetables versus sweet snacks on adolescents' appetites. Appetite 2021;166:105436.
61. Qutteina Y, Hallez L, Raedschelders M, De Backer C, Smits T. Food for teens: how social media is associated with adolescent eating outcomes. Public Health Nutr 2021:1–13.
62. Marsh S, Ni Mhurchu C, Jiang Y, Maddison R. Modern screen-use behaviors: the effects of single- and multi-screen use on energy intake. J Adolesc Health 2015;56(5):543–9.
63. Gascoyne C, Scully M, Wakefield M, Morley B. Food and drink marketing on social media and dietary intake in Australian adolescents: findings from a cross-sectional survey. Appetite 2021;166:105431. doi: 10.1016/j.appet.2021.105431.
64. Delfino LD, Dos Santos Silva DA, Tebar WR, Zanuto EF, Codogno JS, Fern, es RA, Christofaro DG. Screen time by different devices in adolescents: association with physical inactivity domains and eating habits. J Sports Med Phys Fit 2018;58(3):318–25.
65. Hansstein FV, Hong Y, Di C. The relationship between new media exposure and fast food consumption among Chinese children and adolescents in school: a rural–urban comparison. Glob Health Promot 2017;24(3):40–8.
66. Lwin MO, Malik S, Ridwan H, Sum Au CS. Media exposure and parental mediation on fast-food consumption among children in metropolitan and suburban Indonesian. Asia Pac J Clin Nutr 2017;26(5):899–905.
67. Teo E, Goh D, Vijayakumar KM, Liu JCJ. To message or browse? Exploring the impact of phone use patterns on male adolescents' consumption of palatable snacks. Front Psychol 2018;8:2298.
68. Byun D, Kim R, Oh H. Leisure-time and study-time internet use and dietary risk factors in Korean adolescents. Am J Clin Nutr 2021;114(5):1791–801.
69. Kim HR, Han MA. Associations between problematic smartphone use, unhealthy behaviors, and mental health status in Korean adolescents: based on data from the 13th Korea youth risk behavior survey (2017). Psychiatry Investigation 2020;17(12):1216–25.
70. De Jans S, Cauberghe V, Hudders L. How an advertising disclosure alerts young adolescents to sponsored vlogs: the moderating role of a peer-based advertising literacy intervention through an informational vlog. J Advertising 2018;47(4):309–25.
71. Bogl LH, Mehlig K, Ahrens W, Gwozdz W, de Henauw S, Molnár D, Moreno L, Pigeot I, Russo P, Solea A, et al. Like me, like you—relative importance of peers and siblings on children's fast food consumption and screen time but not sports club participation depends on age. Int J Behav Nutr Phys Activity 2020;17(1):50.
72. De Veirman M, Cauberghe V, Hudders L. Marketing through Instagram influencers: the impact of number of followers and product divergence on brand attitude. Int J Advertising 2017;36(5): 798–828.
73. Hebestreit A, Intemann T, Siani A, De Henauw S, Eiben G, Kourides YA, Kovacs E, Moreno LA, Veidebaum T, Krogh V, et al. Dietary patterns of European children and their parents in association with family food environment: results from the I.Family Study. Nutrients 2017;9(2):126.
74. Russell SJ, Croker H, Viner RM. The effect of screen advertising on children's dietary intake: a systematic review and meta-analysis. Obes Rev 2019;20(4):554–68.
75. Organisation for Economic Co-operation and Development (OECD). Good practice guide on online advertising: protecting consumers in e-commerce,OECD Publishing,Paris; 2019.
76. Commission TE. The Unfair Commercial Practices Directive ('the UCPD'). Brussels (Belgium); 2016.
77. Folkvord F. The psychology of food marketing and overeating. Routledge; London (UK), 2019.
78. Sina E, Buck C, Ahrens W, De Henauw S, Jilani H, Lissner L, Molnár D, Moreno LA, Pala V, Reisch L, et al. Digital media use in association with sensory taste preferences in European children and adolescents—results from the I.Family Study. Foods 2021;10(2):1–18.
79. Robinson TN, Banda JA, Hale L, Lu AS, Fleming-Milici F, Calvert SL, Wartella E. Screen media exposure and obesity in children and adolescents. Pediatrics 2017;140(Suppl 2):S97–101.
80. Lopez RB, Heatherton TF, Wagner DD. Media multitasking is associated with higher risk for obesity and increased responsiveness to rewarding food stimuli. Brain Imag Behav 2020;14(4): 1050–61.
81. Coumans JMJ, Danner UN, Ahrens W, Hebestreit A, Intemann T, Kourides YA, Lissner L, Michels N, Moreno LA, Russo P, et al. The association of emotion-driven impulsiveness, cognitive inflexibility and decision-making with weight status in European adolescents. Int J Obes 2018;42(4):655–61.
82. Toh SH, Howie EK, Coenen P, Straker LM. "From the moment I wake up I will use it…every day, very hour": a qualitative study on the patterns of adolescents' mobile touch screen device use from adolescent and parent perspectives. BMC Pediatr 2019;19(1):30.
83. Malik S, McGlone F, Bedrossian D, Dagher A. Ghrelin modulates brain activity in areas that control appetitive behavior. Cell Metab 2008;7(5):400–9.
84. Dickinson KM, Watson MS, Prichard I. Are clean eating blogs a source of healthy recipes? A comparative study of the nutrient composition of foods with and without clean eating claims. Nutrients 2018;10(10). doi: 10.3390/nu10101440.
85. Bragg M, Lutfeali S, Greene T, Osterman J, Dalton M. How food marketing on Instagram shapes adolescents' food preferences: online randomized trial. J Med Internet Res 2021;23(10):e28689. doi: 10.2196/28689.
86. Tilgner L, Wertheim EH, Paxton SJ. Effect of social desirability on adolescent girls' responses to an eating disorders prevention program. Int J Eat Disord 2004;35(2):211–6.
87. Pechey R, Monsivais P. Socioeconomic inequalities in the healthiness of food choices: exploring the contributions of food expenditures. Prev Med 2016;88:203–9.

Paper 2

Digital Media Use in Association with Sensory Taste Preferences in European Children and Adolescents—Results from the I.Family Study

Sina, Elida; Buck, Christoph; Ahrens, Wolfgang; De Henauw, Stefaan; Jilani, Hannah; Lissner, Lauren; Molnár, Dénes; Moreno, Luis A.; Pala, Valeria; Reisch, Lucia; Siani, Alfonso; Solea, Antonia; Veidebaum, Toomas; Hebestreit, Antje; on behalf of the I.Family Consortium. 2021. "Digital Media Use in Association with Sensory Taste Preferences in European Children and Adolescents—Results from the I.Family Study" *Foods* 10, no. 2: 377. https://doi.org/10.3390/foods10020377 foods

MDPI

Article

Digital Media Use in Association with Sensory Taste Preferences in European Children and Adolescents—Results from the I.Family Study

Elida Sina [1], Christoph Buck [1], Wolfgang Ahrens [1,2], Stefaan De Henauw [3], Hannah Jilani [1,4], Lauren Lissner [5], Dénes Molnár [6], Luis A. Moreno [7], Valeria Pala [8], Lucia Reisch [9], Alfonso Siani [10], Antonia Solea [11], Toomas Veidebaum [12], Antje Hebestreit [1,*] and on behalf of the I.Family Consortium †

1 Leibniz Institute for Prevention Research and Epidemiology-BIPS, 28359 Bremen, Germany; sina@leibniz-bips.de (E.S.); buck@leibniz-bips.de (C.B.); ahrens@leibniz-bips.de (W.A.); jilani@leibniz-bips.de (H.J.)
2 Institute of Statistics, Faculty of Mathematics and Computer Science, University of Bremen, 28359 Bremen, Germany
3 Department of Public Health and Primary Care, Ghent University, 9000 Ghent, Belgium; stefaan.dehenauw@ugent.be
4 Institute for Public Health and Nursing Research—IPP, University of Bremen, 28359 Bremen, Germany
5 Department of Public Health and Community Medicine, University of Gothenburg, 40530 Gothenburg, Sweden; lauren.lissner@gu.se
6 Department of Pediatrics, Medical School, University of Pécs, 7623 Pécs, Hungary; denes.molnar@aok.pte.hu
7 GENUD (Growth, Exercise, Nutrition and Development) Research Group, Instituto Agroalimentario de Aragón (IA2), Instituto de Investigación Sanitaria Aragón (IIS Aragón), Centro de Investigación Biomédica en Red Fisiopatología de la Obesidad y Nutrición (CIBERObn), University of Zaragoza, 50009 Zaragoza, Spain; lmoreno@unizar.es
8 Department of Preventive and Predictive Medicine, Fondazione IRCCS, Istituto Nazionale dei Tumori, 20133 Milan, Italy; valeria.pala@istitutotumori.mi.it
9 Department of Management, Society and Communication, Copenhagen Business School, 2000 Frederiksberg, Denmark; lre.msc@cbs.dk
10 Institute of Food Sciences, National Research Council, 83100 Avellino, Italy; asiani@isa.cnr.it
11 Research and Education Institute of Child Health, 2035 Strovolos, Cyprus; toniasolea@yahoo.com
12 Department of Chronic Diseases, National Institute for Health Development, 11619 Tallinn, Estonia; toomas.veidebaum@tai.ee
* Correspondence: hebestr@leibniz-bips.de; Tel.: +49-421-218.56849
† Reference to the I.Family Consortium is provided in the Acknowledgments.

check for updates

Citation: Sina, E.; Buck, C.; Ahrens, W.; De Henauw, S.; Jilani, H.; Lissner, L.; Molnár, D.; Moreno, L.A.; Pala, V.; Reisch, L.; et al. Digital Media Use in Association with Sensory Taste Preferences in European Children and Adolescents—Results from the I.Family Study. *Foods* **2021**, *10*, 377. https://doi.org/10.3390/foods10020377

Academic Editor: Luis Guerrero Asorey

Received: 22 December 2020
Accepted: 4 February 2021
Published: 9 February 2021

Abstract: Digital media (DM) influences children's food choice. We aim to investigate associations between DM use and taste preferences (TP) for sweet, fatty, bitter, and salty in European children and adolescents. Individuals aged 6–17 years (N = 7094) providing cross-sectional data for DM use: television (TV), computer/game console (PC), smartphone and internet, were included. Children (6 to <12 years) and adolescents (≥12 years) completed a Food and Beverage Preference Questionnaire; scores were calculated for sweet, fatty, salty and bitter preference and categorized (high vs. low). Logistic regression was used to calculate odds ratios as association measures between DM exposure and TP. On average, individuals used media for 2.4 h/day (SD = 1.7). Increasing exposures to DM were associated positively with sweet, fatty and salty TP, while inversely with bitter preference. In female adolescents, DM exposure for >2 h/day was associated with sweet (OR = 1.27, 95% CI = 1.02–1.57) and fatty preference (OR = 1.37; 95% CI = 1.10–1.70). Internet exposure was inversely associated with bitter preference, notably in male adolescents (OR = 0.65, 95% CI = 0.50–0.84), but positively associated with salty preference (OR = 1.29, 95% CI = 1.02–1.64). DM exposure was associated with sweet, fatty, salty and bitter TP in children and adolescents, serving as the basis for future longitudinal studies to shed light on the underlying mechanism by which DM exposure may determine eating habits.

Keywords: food preference; internet; smartphone; screen-time; digital marketing; I.Family study; taste preference; children

1. Introduction

The increasing prevalence of childhood obesity worldwide is mainly driven by modifiable lifestyle risk factors including unhealthy dietary intake [1] and adoption of sedentary behaviors such as use of screen media devices [2]. One of the core recommendations of the World Health Organization (WHO) to halt childhood obesity is to reduce children's intake of foods high in fat, salt and sugar (HFSS foods) [1]. It is well-documented that food intake is determined by taste preferences (TP) which are established during childhood and adolescence and are meant to track into adulthood [3]. These are influenced by genetic [4] and environmental factors, including diet quality [5], culture [6], and home and non-family-shared environment [7]. Evidence shows that children learn to prefer energy dense foods over energy-diluted versions of the same foods [8]. This behavior may promote adverse health effects in the current obesogenic environments with the omnipresence of HFSS foods, together with a high exposure to these foods in the digital environment.

Remarkably, prolonged use of screen-media devices (i.e., television (TV)) has been described as a significant contributor to poor eating habits in children and adolescents, including higher propensities to consume sweets and fatty foods [9], and reduced intake of fruits and vegetables [10], determining the development of overweight and obesity [11]. TV and video gaming can lead to unfavorable adiposity markers through prolonged bouts of sedentary behavior [12] and increased eating while viewing [13], with media distracting from or obscuring the feelings of satiety [14]. Another mechanism is the persuasive effect of food marketing targeting children increasingly on multiple digital media (DM) channels, such as computers, tablets and smartphones. These channels provide ubiquitous access to internet, social media platforms and advergames [14]. The WHO has identified digital marketing for unhealthy foods as detrimental to children's and adolescents' health [15]. Food commercials embedded in animated programs increase immediate eating of advertised food products (e.g., snacks) [16], even in brief 30-s TV commercials [17].

Highly appetizing food pictures and videos in food-related TV programs, advertisements and smartphone screens may stimulate a myriad of neural, physiological and behavioral responses [18]. Viewing pictures of food compared to non-food cues is associated with increased secretion of grehlin, the strongest orexigenic hormone increasing appetite and caloric intake [19], and higher visual attention, the latter shown via an eye-tracking study in children [20]. Furthermore, branding of foods and beverages altered young children's actual taste perceptions in side-by-side taste tests [21], especially among those watching more television. A recent study observed that eating while watching TV was associated with lower preference for bitter tasting foods and higher preference for sweet tasting foods, suggesting that TV watching could lead to a reduced attention to the sensory characteristics of food [22].

Studies indicate that merely watching TV food commercials compared to non-food ads [23] can activate taste and reward-related brain areas. Using an electro-encephalography (EEG), Ohla et al. (2012) showed that images of calorie-dense foods can enhance hedonic taste evaluation [24]. A hedonically neutral electric taste signal elicited by a small current applied to participants' tongues was rated as more pleasant after viewing high-calorie food images than after viewing low-calorie, with effects being stronger in the insula and the orbitofrontal cortex, i.e., the reward processing and decision-making brain areas.

The above evidence suggests that digital media and exposure to food images provided through them can modulate taste perceptions and preferences. However, epidemiological studies evaluating how exposure to DM in real-life settings (i.e., outside the lab) influences children's taste preferences are lacking. We aim at closing this research gap by evaluating associations between different types of DM including TV, computer/game console (PC) and smartphone use, as well as the exposure to internet content and children's and adolescents' taste preferences for sweet, fatty, salty, and bitter, in a large sample from 7 European countries.

2. Materials and Methods

2.1. Study Design and Setting

This cross-sectional study was conducted in the framework of the I.Family study, aimed at investigating determinants of eating behaviors in European children and adolescents and their parents [25]. The I.Family study was conducted in 2013–2014 using standardized instruments and protocols in Belgium, Estonia, Cyprus, Hungary, Italy, Germany, Spain and Sweden, including 7841 participants, aged 2–17 years. A sub-sample of children (7105) aged $\geq$6 years completed a Food and Beverage Preference Questionnaire across all study centers (excluding Belgium) to measure their preferences for specific food-groups. In order to correct for misreporting bias, children with extremely high DM use (>50 h/week, N = 100) and not using DM at all (or missing, N = 343) were excluded (Figure S1). A total of 7094 children and adolescents were included in the present study. Information on duration of DM use, its specific types and dietary behaviors were obtained for all participants. Questionnaires were developed in English, translated into local languages and back-translated to English to check for errors. Written informed consent was obtained from adolescents and from parents of all children. Children below the age of 12 years were orally informed by field workers before each examination and were asked for their oral assent. Ethical approval was obtained from local institutional review boards at each study center.

2.2. Data Collection

Core Questionnaire and Assessment of Media Use

Data on age, sex, country of residence and migration background were self-reported by adolescents and proxy-reported by parents of younger children (i.e., children aged <12 years), respectively using the teen and the parental version of the questionnaire, which have been tested for validity and reproducibility [26]. Parents self-reported their highest educational level, based on the International Standard Classification of Education (ISCED) [27] which was classified in three main categories: “low”, “medium” and “high”. Children’s migration background was assessed based on whether one, both or none of their parents were born outside of the respective country of residence.

Participants reported their time spent with different media types, including TV/DVD/video, computer/game consoles (PC) and use of internet on weekdays and on weekend days as: not at all, less than 30 min/day, 30 min to 1 h/day, about 1–2 h/day, about 2–3 h/day and >3 h/day” in line with the methodology used in previous studies [28]. Internet users could also choose the option of “I’m online more or less all day/night”. For PC use, we explicitly asked “How long do you usually sit at a computer/game console per day? (Please disregard the time spent on internet-use.)”, in order to obtain precise information regarding the passive use of PC and game consoles, thus preventing potential overlap with internet use. Assessment of media use did not distinguish between the time used with specific media for recreational and/or educational purposes.

Total digital media (DM) use was calculated as the weighted average of the durations reported for weekdays and for weekend days, expressed in total minutes/week and converted into total hours/day. For the present analyses, the daily duration of DM exposure was categorized as: $\leq$1 h/day, 1 to $\leq$2 h/day, 2 to $\leq$3 h/day and >3 h/day to assess trends of media exposure and to better reflect the original variable. Similarly, daily duration use of single media types was classified, hereinafter referred as TV viewing, PC use and internet exposure. Furthermore, using the question: “Thinking only about yesterday, about how much time did you spend watching TV shows, movies or music videos on a cellphone?”, children were asked to recall the time spent with cellphones (hereinafter smartphone use). On a 5-point Likert-scale, answers ranged from 0 meaning “not at all” to 5 meaning “more than 3 h/day”. Smartphone use was categorized similarly to the other media types.

2.3. Assessment of Sensory Taste Preferences

Children and adolescents (6–17 years) completed a Food and Beverage Preference Questionnaire aiming at assessing preferences for sweet, fatty, salty and bitter taste based on a list of selected food items and beverages [29]. Sour-tasting foods were not included, as we aimed to evaluate sensory taste preferences that are linked to the current obesogenic diets, characterized by foods low in fiber [30] and high in fat, sugar and salt content (HFSS foods) [31]. Hence, preferences for sweet, fatty and salty foods were measured as a proxy for unhealthy food preferences [32] and bitter preference as a proxy for healthy food preferences [33]. To ensure the availability of food items in all countries, a pre-test was conducted [34]. Photographs of 63 various food items considered appropriate for all age groups were included in the final questionnaire: single foods (e.g., spinach, banana, broccoli), condiments (e.g., mayonnaise, nougat spread), mixed foods (e.g., sausage, kebab) and drinks (e.g., lemonade). Participants indicated how much they like the taste of the foods/drinks in the photographs, using a 5 point-Likert scale, from 1 meaning "Do not like at all" to 5 meaning "I like very much". Children who had never tried (or did not know) a specific type of food indicated the respective option.

2.4. Taste Preference Scores

A sex- and age-specific factor analysis was conducted to assign specific foods and beverages to the respective taste modalities: sweet, fatty, bitter and salty, and to account for the factorial structure of food preference. Foods and beverages that were recognized/tasted by less than 75% of participants were excluded, such as: asparagus, black coffee, Brussels sprouts, grapefruit etc. Further details have been previously described [34]. The TP scores were calculated as the sum of the rating for foods/drinks assigned to each taste category and divided by the total number of food/drink items included in that specific group. Following the age and sex-specific factor analysis, taste preference scores were calculated separately for males and females of two age groups (<12 years, hereafter referred as children, vs. ≥12 years, referred as adolescents), to control for age and sex discrepancies in food preference. The age of 12 years was chosen as the median age for puberty onset, where changes in child's anatomy and psychological processes occur [35] (e.g., in the gustatory and olfactory system), and environmental factors such as peer pressure might also influence TP [36]. Additionally, children's ability to distinguish advertisements from other media content starts from the age of 12 years [37]. The four sub-groups' scores (male children, male adolescents, female children and female adolescents) were merged into one unique score for each taste modality in order to create a non-stratified taste preference score which would be used as the dependent variable in the models assessing the impact of media use on TP in all children and adolescents. Based on within-sample median values (median = 4 for sweet, fatty and salty preference; median = 3 for the bitter taste preference), each of the four TP scores was categorized as "high" vs. "low" preference. The sample size for the bitter TP was slightly lower compared to the other taste modalities, due to missing values, as a lower number of bitter foods were included, i.e., children tend to recognize bitter tasting foods less compared to sweet or salty tasting ones.

2.5. Assessment of Dietary Patterns

To assess diet quality, a healthy diet adherence score (HDAS) was developed. Using pa food frequency questionnaire (FFQ), previously tested for relative validity and reproducibility [38,39], participants indicated the frequency of consumption of 59 different foods items, beverages and mixed dishes in a typical week during the preceding four weeks. Answer options varied from 'never/less than once a week', '1–3 times/week', '4–6 times/week', '1 time/day', '2 times/day', '3 times/day' to '4 or more times/day'. The description of food items was standardized across countries; examples of country-specific foods were included for a certain food item, to account for cultural discrepancies in food intake. The score was calculated for children with ≥50% of non-missing food items. The HDAS was developed as a composite score to reflect the adherence to the healthy dietary guidelines common across all the participating countries including high consumption of fruits and vegetables (at least 400–500 g/day), limited intake of refined sugars and fat (especially saturated fats), consumption of whole meals, and of fish two–three times per week [40], as established by Waijers et al. (2007) [41]. The score ranged from 0 to 50 and was dichotomized based on median value as "high" vs. "low" adherence to assess the broad concept of healthy diet adherence and to better interpret the data. Based on the FFQ, we additionally assessed the frequency of snack food consumption (times/day), calculated from the frequencies assigned to the following food and drink items: "sweetened drinks", "chocolate or nut based spread", "crisps, corn crisps, popcorn", "chocolate, candy bars" and "candies, loose candies, marshmallows". Based on within-sample median, children's snack consumption was classified as "high" vs. "low".

2.6. Anthropometric Measurements

Each child was measured for weight and height in the morning, in light clothing and in fasting status. Weight was measured using a Tanita scale (TANITA Europe GmbH, Sindelfingen, Germany) to the nearest 0.1 kg, while height was measured using a portable stadiometer (Seca GmbH & Co. KG., Hamburg, Germany) to the nearest 0.1 cm. Body Mass Index (BMI) was calculated as weight divided by squared height and transformed into age- and sex-specific z-scores for all children and adolescents. Participant's weight status was categorized according to the cut-offs of Cole et al. (2012) [42] as thin/normal weight vs. overweight/obese.

2.7. Sweet and Fat Intake Propensity

The sweet and fat intake propensities were calculated to reflect the proportion of sweet and fatty foods in children's diets [9]. The sweet intake propensity was calculated as the proportion of consumed foods/drinks with high sugar content by dividing the sum of the weekly frequency of intake of corresponding foods (e.g., jam, nut-based spreads, chocolate, fruit juice, biscuits, as well as items with added sugar: milk, yoghurt, fresh fruits, drinks, cereal products etc.) by the total frequency of all foods/drinks items included in the FFQ and multiplied by 100. This allowed us to avoid a classification bias by misclassifying children in the high-sugar or high-fat groups only because they have a high frequency consumption of all types of food [9]. The score ranged from 0%-100%. A value of 50% for the sweet intake propensity indicates that half of the reported food consumption frequencies included foods rich in sugar content. The fat intake propensity score was similarly calculated, based on the consumption of foods high in fat including whole-fat milk and yoghurt, cheese, butter, mayonnaise, meat products, fried fish, savory snacks, etc. The scores were dichotomized as "high vs. low" intake propensity at the median value (22.5 for sweet intake propensity and 25.7 for fat intake propensity).

2.8. Statistical Analyses

The proportion of children meeting the media use guidelines, as recommended by WHO, i.e., $\leq$2 h/day of media use for children older than 5 years [2,43], was identified. Descriptive analyses were conducted to explore differences in the sample characteristics (in the number (N) and percentage meeting the DM use guidelines) and sex, including age groups (children vs. adolescents), parent's educational level, weight status (thin/normal weight vs. overweight/obese), country, migration background, diet quality (HDAS), snack consumption, sweet and fat intake propensities and specific taste preferences. Furthermore, differences in duration of single media types used (four categories: $\leq$1 h/day, 1 to $\leq$2 h/day, 2 to $\leq$3 h/day and $\geq$3 h/day) by age groups and sex were evaluated. To assess the associations of exposure to different durations of DM and its specific types with TP, odds ratios were calculated by logistic regression, adjusting for covariates: age group (children vs. adolescents), sex (males vs. females), parental educational level (low, medium and missing vs. high), country, migration background (one parent, both and missing vs. none of the parents), diet quality (low vs. high HDAS) and snack frequency intake (high vs. low). In a second step, models were further adjusted for weight status, to take into account the role of BMI. The analyses between the single media types and TP were restricted to children and adolescents actually using that specific media on a daily basis, to make better use of the available data (TV viewing: N = 7052, PC use: N = 5738, smartphone use: N = 3572; internet exposure: N = 6007).

2.9. Stratified Analyses by Sex and Age Group

To explore the mediating role of sex (males vs. females) and age (children vs. adolescents), the study population was stratified accordingly and associations were examined based on logistic regression across four strata while adjusting for the remaining covariates, including age, as a continuous variable, in order to control for residual confounding within age group strata. Due to the small sample size across different strata, the media use variables were dichotomized based on WHO recommendation for media use in children >5 years old. Consequently, for the stratified analyses only, participants were classified as "high- >2 h/day" vs. "low- ≤2 h/day" media users.

2.10. Sensitivity Analyses

Taking into account that children's propensity to consume high-fat [9] and high-sugar foods [44] is associated with children's screen habits as well as fatty and sweet taste preference [29], we considered the mediating role of sweet and fat intake propensities in sensitivity analyses. As a first step, we investigated the association of DM exposure durations (in four categories) with sweet and fatty TP by stratifying the whole sample by sweet and fat intake propensity respectively, based on logistic regressions, while adjusting for covariates. In a second step, we additionally stratified by sex and age group, to consider differences between male and female children and adolescents. Yet, due to the small sample size across strata, the media exposure was considered in two categories only (≤2 h/day vs. >2 h/day).

Odds rations (OR) and 95% Confidence Intervals (CI) were calculated and the level of statistical significance was set at $\alpha = 0.05$. The statistical software SAS, version 9.4 (Statistical Analyses System, SAS Institute Inc., Cary, NC, USA) was used to perform all statistical analyses.

3. Results

A total of 7094 children and adolescents were included in the final analyses (50.7% females). The majority (56.6%) were younger than 12 years. Detailed characteristics of the study population are described in Table 1. Overweight/obese children and adolescents made up 27.5% of the analysis population. On average, participants spent more than 2 h daily in front of screens (mean = 2.4; SD = 1.37) with 54.8% of them exceeding the guidelines (respectively, 44.2% of young children and 68.5% of adolescents). The duration of media use increased with age and differences were observed between males and females (Table S1). A quarter of all children and adolescents watched TV and 7.6% of them used PC for >2 h/day respectively (Table S1). Two out of ten children and adolescents (19%) were exposed to internet content daily for >2 h. Half of participants used a smartphone (17% of them used it for >2 h/day). Circa 60% of the study sample had high preference for sweet, fatty and bitter taste, while 52% of them had high salty taste preference. Approximately half of participants had low diet quality (HDAS) and high propensities for sweet and fatty foods, while 47.5% had high intake of snacks.

Table 1. Characteristics of the study population by sex and exposure to digital media [1].

	Total Digital Media Exposure								All	
	≤2 h/day				>2 h/day					
	Sex									
	Males		Females		Males		Females			
	n	%	n	%	n	%	n	%	N	%
All	1401	19.7	1807	25.5	2101	29.6	1785	25.2	7094	100.0
Age group										
<12 Years	1017	14.3	1221	17.2	1009	14.2	765	10.8	4012	56.6
≥12 Years	384	5.4	586	8.3	1092	15.4	1020	14.4	3082	43.4
Parental educational status										
Low	90	1.3	82	1.2	107	1.5	98	1.4	377	5.3
Medium	569	8.0	718	10.1	947	13.3	792	11.2	3026	42.7
High	685	9.7	936	13.2	985	13.9	829	11.7	3435	48.4
Missing	57	0.8	71	1.0	62	0.9	66	0.9	256	3.6
Weight status										
Thin/Normal weight	1076	15.2	1370	19.3	1435	20.2	1250	17.6	5131	72.3
Overweight/Obese	320	4.5	435	6.1	661	9.3	533	7.5	1949	27.5
Missing	5	0.1	2	0.0	5	0.1	2	0.0	14	0.2
Migration background										
None of parents	1104	15.6	1396	19.7	1652	23.3	1396	19.7	5548	78.2
Both parents	77	1.1	110	1.6	109	1.5	99	1.4	395	5.6
One parent	134	1.9	175	2.5	192	2.7	165	2.3	666	9.4
Missing	86	1.2	126	1.8	148	2.1	125	1.8	485	6.8
HDAS										
High	701	9.9	908	12.8	1087	15.3	911	12.8	3607	50.8
Low	700	9.9	899	12.7	1014	14.3	874	12.3	3487	49.2
Snack frequency intake										
Low	782	11.0	1042	14.7	1014	14.3	889	12.5	3727	52.5
High	615	8.8	756	10.8	1073	15.3	879	12.6	3323	47.5
Sweet intake propensity										
High	648	9.1	770	10.9	1118	15.8	924	13.0	3460	48.8
Low	753	10.6	1037	14.6	983	13.9	861	12.1	3634	51.2
Fat intake propensity										
High	699	9.9	872	12.3	1093	15.4	820	11.6	3484	49.1
Low	702	9.9	935	13.2	1008	14.2	965	13.6	3610	50.9
Sweet TP										
Low	521	7.3	765	10.8	805	11.3	698	9.8	2789	39.3
High	879	12.4	1038	14.6	1293	18.2	1086	15.3	4296	60.6
Missing	1	0.0	4	0.1	3	0.0	1	0.0	9	0.1
Fatty TP										
Low	430	6.1	762	10.7	698	9.8	756	10.7	2646	37.3
High	970	13.7	1043	14.7	1402	19.8	1029	14.5	4444	62.6
Missing	1	0.0	2	0.0	1	0.0			4	0.1
Bitter TP										
Low	453	6.4	662	9.3	751	10.6	703	9.9	2569	36.2
High	933	13.2	1039	14.6	1329	18.7	955	13.5	4256	60.0
Missing	15	0.2	106	1.5	21	0.3	127	1.8	269	3.8
Salty TP										
Low	617	8.7	806	11.4	1050	14.8	849	12.0	3322	46.8
High	758	10.7	977	13.8	1013	14.3	918	12.9	3666	51.7
Missing	26	0.4	24	0.3	38	0.5	18	0.3	106	1.5
Country										
Italy	287	4.0	326	4.6	391	5.5	318	4.5	1322	18.6
Estonia	125	1.8	195	2.7	377	5.3	348	4.9	1045	14.7
Cyprus	272	3.8	344	4.8	486	6.9	461	6.5	1563	22.0
Sweden	106	1.5	161	2.3	238	3.4	174	2.5	679	9.6
Germany	240	3.4	315	4.4	272	3.8	212	3.0	1039	14.6
Hungary	231	3.3	280	3.9	244	3.4	209	2.9	964	13.6
Spain	140	2.0	186	2.6	93	1.3	63	0.9	482	6.8

[1] HDAS-Healthy Dietary Adherence Score; TP—Taste preference.

3.1. Association between Media Use and Sweet Taste Preference

The adjusted logistic regression analyses showed a positive trend in the association between increasing durations of DM exposure and sweet TP (Table 3). Exposure for >3 h/day to DM was positively associated with increased sweet preference (OR = 1.23; 95% CI = 1.03–1.46). Further adjustment for weight status, did not attenuate the associations between media exposure and sweet TP (results not shown). In the stratified analyses by sex and age groups, the association remained positive in adolescents with high DM exposure (>2 h/day), for both males and females (respectively 25 and 27% higher odds), compared to those with low DM exposure (≤2 h/day) (Table 2). These associations remained after stratification by propensity to consume sweets, indicating that DM use was positively associated with sweet TP in adolescents, both in the high and low sweet intake propensity groups (Table S4). Prolonged TV viewing was positively associated with sweet TP across all strata, particularly in female children (OR = 1.31; 95% CI = 1.02–1.69). A positive trend was observed in the association between high smartphone use (>2 h/day) and high sweet TP in all participants, particularly in young children (male children: OR = 2.52; 95% CI = 0.98–6.50; female children: OR = 1.43; 95% CI = 0.73–2.79).

Table 2. Exposure to digital media in association with sweet taste preferences, stratified by sex and age group [1,2].

Media Types	Adjusted Model			
	Males		Females	
	<12 Years	≥12 Years	<12 Years	≥12 Years
	Odds Ratios (OR) and 95% Confidence Limits (95% CI)			
Total DM exposure (ref. ≤2 h/day) [3] >2 h/day	0.91 (0.74–1.10)	1.25 (0.98–1.60)	1.06 (0.86–1.29)	**1.27 (1.02–1.57)**
TV viewing (ref. ≤2 h/day) >2 h/day	1.12 (0.89–1.41)	1.20 (0.95–1.51)	**1.31 (1.02–1.69)**	1.15 (0.91–1.45)
PC use (ref. ≤2 h/day) >2 h/day	0.89 (0.59–1.35)	1.07 (0.81–1.41)	1.21 (0.48–3.04)	1.48 (0.97–2.24)
Smartphone use (ref. ≤2 h/day) >2 h/day	2.52 (0.98–6.50)	1.27 (0.93–1.74)	1.43 (0.73–2.79)	1.00 (0.78–1.28)
Internet exposure (ref. ≤2 h/day) >2 h/day	1.03 (0.70–1.50)	1.07 (0.84–1.36)	0.99 (0.61–1.60)	1.02 (0.81–1.27)

[1] Logistic regression models were adjusted for age (continuous), snack consumption, HDAS, parental educational status, migrant background and country, OR not reported. [2] DM-digital media, PC-computer/game console use. [3] 7085 participants included for total DM exposure (2023 male children, 1475 male adolescents, 1982 female children, 1605 female adolescents). For the single media types, the N varied, due to the exclusion of participants not using that specific media type at all (see Table S1). Bold significance in the adjusted models is provided via confidence limits.

3.2. Association between Media Use and Fatty Taste Preference

The adjusted regression analyses showed that exposure to DM for durations >1 h/day was associated with fatty TP (Table 3) in all children and adolescents (1–2 h/day: OR = 1.19; 95%CI = 1.01–1.41; >3 h/day: OR = 1.40, 95% CI = 1.18–1.67). Further adjustment for weight status, did not attenuate the associations between DM exposure and fatty TP (results not shown). After stratification by sex and age, the association remained positive both in male and female adolescents. In the sensitivity analyses, after stratification by fat intake propensity, high DM exposure in adolescents was associated with high fatty TP, in the low and high fat intake propensity groups (Tables S2–S4). Watching TV, using a PC and being exposed to internet content for >2 h/day was associated with high fatty TP in all participants, especially in female adolescents (TV: OR = 1.28; 95% CI = 1.02–1.61; PC: OR = 1.83; 95% CI = 1.21–2.76; internet: OR = 1.37; 95% CI = 1.10–1.71 (Table 4)). Smartphone use for >2 h/day was associated with increased fatty TP in all children and adolescents of both sexes.

Table 3. Exposure to digital media in association with taste preferences in European children and adolescents [1,2].

	Sweet TP (N = 7085) [3]		Fatty TP (N = 7090)		Bitter TP (N = 6825)		Salty TP (N = 6988)	
Media Types	**Raw Model**	**Adjusted Model**	**Raw Model**	**Adjusted Model**	**Raw Model**	**Adjusted Model**	**Raw Model**	**Adjusted Model**
	Odds Ratios (OR) and 95% Confidence Limits (95% CI)							
Total DM exposure (ref. ≤1 h/day)								
1–2 h/day	1.01 (0.87–1.19)	1.03 (0.88–1.21)	1.12 (0.96–1.31)	**1.19 (1.01–1.41)**	0.82 (0.70–0.97)	**0.83 (0.70–0.99)**	0.95 (0.81–1.11)	1.08 (0.92–1.27)
2–3 h/day	1.01 (0.86–1.18)	1.06 (0.89–1.25)	1.03 (0.87–1.21)	1.18 (0.99–1.40)	0.80 (0.67–0.94)	**0.81 (0.67–0.96)**	0.78 (0.67–0.92)	1.00 (0.84–1.19)
>3 h/day	1.13 (0.97–1.33)	**1.23 (1.03–1.46)**	1.11 (0.95–1.31)	**1.40 (1.18–1.67)**	0.75 (0.64–0.89)	**0.72 (0.60–0.87)**	0.82 (0.70–0.96)	1.15 (0.96–1.37)
TV viewing (ref. ≤1 h/day)								
1–2 h/day	1.02 (0.91–1.13)	1.02 (0.91–1.14)	0.98 (0.88–1.10)	1.00 (0.89–1.13)	**0.85 (0.75–0.95)**	**0.86 (0.77–0.97)**	0.95 (0.85–1.06)	1.01 (0.90–1.13)
2–3 h/day	1.24 (1.09–1.42)	**1.21 (1.05–1.39)**	1.12 (0.98–1.28)	1.14 (0.99–1.31)	0.87 (0.76–1.00)	0.88 (0.77–1.02)	0.92 (0.80–1.04)	1.02 (0.88–1.16)
>3 h/day	1.20 (0.94–1.23)	1.20 (0.93–1.53)	1.08 (0.85–1.37)	1.17 (0.91–1.50)	**0.70 (0.55–0.89)**	**0.74 (0.58–0.95)**	1.01 (0.79–1.27)	1.19 (0.93–1.52)
PC use (ref. ≤1 h/day)								
1–2 h/day	0.93 (0.81–1.07)	0.96 (0.82–1.11)	0.96 (0.83–1.10)	1.01 (0.87–1.18)	0.94 (0.82–1.09)	0.89 (0.77–1.04)	0.79 (0.69–0.91)	0.91 (0.79–1.06)
2–3 h/day	0.98 (0.80–1.21)	1.04 (0.83–1.29)	1.04 (0.84–1.28)	1.17 (0.94–1.47)	0.84 (0.68–1.03)	**0.77 (0.61–0.96)**	0.83 (0.68–1.02)	1.06 (0.85–1.32)
>3 h/day	1.04 (0.72–1.50)	1.15 (0.78–1.68)	1.37 (0.93–2.03)	**1.71 (1.14–2.56)**	1.18 (0.80–1.72)	1.17 (0.78–1.74)	0.74 (0.52–1.06)	0.98 (0.67–1.43)
Smartphone use (ref. ≤1 h/day)								
1–2 h/day	0.82 (0.67–0.99)	0.91 (0.74–1.11)	0.79 (0.65–0.96)	0.90 (0.73–1.10)	0.91 (0.74–1.11)	0.84 (0.68–1.03)	0.72 (0.59–0.88)	0.80 (0.65–0.98)
2–3 h/day	1.06 (0.83–1.35)	1.16 (0.90–1.50)	1.17 (0.92–1.51)	**1.36 (1.05–1.76)**	0.88 (0.68–1.13)	0.79 (0.60–1.03)	0.79 (0.62–1.01)	0.89 (0.69–1.15)
>3 h/day	0.95 (0.76–1.17)	1.10 (0.87–1.38)	1.02 (0.82–1.27)	**1.30 (1.03–1.63)**	0.87 (0.69–1.08)	0.79 (0.62–1.05)	1.00 (0.81–1.24)	1.20 (0.96–1.51)
Internet exposure (ref. ≤1 h/day)								
1–2 h/day	0.88 (0.77–1.01)	0.93 (0.81–1.08)	0.79 (0.69–0.91)	0.94 (0.81–1.09)	0.90 (0.78–1.03)	**0.85 (0.73–0.99)**	0.74 (0.64–0.84)	0.90 (0.78–1.04)
2–3 h/day	0.97 (0.82–1.15)	1.06 (0.88–1.27)	0.93 (0.78–1.10)	1.18 (0.98–1.41)	0.89 (0.75–1.06)	**0.80 (0.66–0.97)**	0.85 (0.72–1.00)	1.12 (0.93–1.34)
>3 h/day	0.90 (0.68–0.95)	0.94 (0.78–1.14)	0.78 (0.66–0.93)	1.12 (0.92–1.35)	0.87 (0.72–1.03)	**0.80 (0.65–0.97)**	0.81 (0.68–0.96)	1.13 (0.94–1.37)

[1] Logistic regression models were adjusted for age group, sex, snack consumption, HDAS, parental educational status, migrant background and country, OR not reported. [2] TP—taste preference, DM—digital media, PC-computer/game console use. [3] N reported for single taste preferences in association with DM exposure. For the single media types, the N varied, due to the exclusion of participants not using that specific media type. Bold significance in the adjusted models is provided via confidence limits.

Table 4. Exposure to digital media in association with fatty taste preference in European children and adolescents [1,2].

Media Types	Adjusted Model			
	Males		Females	
	<12 Years	≥12 Years	<12 Years	≥12 Years
	Odds Ratios (OR) and 95% Confidence Limits (95% CI)			
Total DM exposure (ref. ≤2 h/day) [3] >2 h/day	0.87 (0.71–1.06)	1.24 (0.96–1.61)	1.11 (0.90–1.36)	**1.37 (1.10–1.70)**
TV viewing (ref. ≤2 h/day) >2 h/day	0.97 (0.77–1.23)	1.09 (0.86–1.39)	1.20 (0.93–1.54)	**1.28 (1.02–1.61)**
PC use (ref. ≤2 h/day) >2 h/day	0.94 (0.62–1.42)	1.22 (0.92–1.62)	1.08 (0.45–2.60)	**1.83 (1.21–2.76)**
Smartphone use (ref. ≤2 h/day) >2 h/day	1.52 (0.63–3.68)	**1.49 (1.06–2.08)**	1.09 (0.57–2.08)	**1.36 (1.07–1.75)**
Internet exposure (Ref. ≤2 h/day) >2 h/day	1.01 (0.68–1.48)	1.26 (0.98–1.61)	0.81 (0.51–1.29)	**1.37 (1.10–1.71)**

[1] Logistic regression models were adjusted for age (continuous), snack consumption, HDAS, parental educational status, migrant background and country, OR not reported. [2] DM-digital media, PC-computer/game console use. [3] 7090 participants included for total DM exposure (2024 male children, 1476 male adolescents, 1985 female children, 1605 female adolescents). For the single media types, the N varied, due to the exclusion of participants not using that specific media type at all (see Table S1). Bold significance in the adjusted models is provided via confidence limits.

3.3. Association between Media Use and Bitter Taste Preference

Increasing durations of exposure to DM as well as its single types (TV, PC, internet and smartphone) were inversely associated with bitter TP (Table 3), after adjusting for covariates. Exposures of 1–2 h/day to DM and internet in our cross-sectional sample were respectively associated with 17% and 15% lower odds for preferring bitter tasting foods, compared to ≤1 h/day DM use. The odds for bitter TP in all children reduced to 30% for exposures to DM longer than 3 h/day (OR = 0.72, 95% CI = 0.60–0.87). TV viewing for >2 h daily (Table 5), was inversely associated with preference for bitter taste in male children and adolescents, but not in females. Additionally, in adolescent males, negative associations with bitter TP were observed when they used PC (OR = 0.65; 95% CI = 0.48–0.87), smartphone (OR = 0.68, 95% CI = 0.49–0.94) and internet (OR = 0.65; 95% CI = 0.50–0.84) for >2 h/day. The associations between media types and bitter TP did not attenuate after further adjustment for weight status (results not shown).

Table 5. Association of media use with bitter taste preference in European children and adolescents [1,2].

Media Types	Adjusted Model			
	Males		Females	
	<12 Years	≥12 Years	<12 Years	≥12 Years
	Odds Ratios (OR) and 95% Confidence Limits (95%CI)			
Total DM exposure (ref. ≤2 h/day) [3] >2 h/day	0.82 (0.67–1.00)	0.79 (0.60–1.05)	1.07 (0.87–1.31)	0.82 (0.65–1.03)
TV viewing (ref. ≤2 h/day) >2 h/day	0.84 (0.68–1.06)	0.84 (0.65–1.07)	1.07 (0.84–1.38)	0.98 (0.77–1.25)
PC use (ref. ≤2 h/day) >2 h/day	1.31 (0.86–1.98)	**0.65 (0.48–0.87)**	0.91 (0.36–2.32)	0.86 (0.56–1.31)
Smartphone use (ref. ≤2 h/day) >2 h/day	0.92 (0.42–2.03)	**0.68 (0.49–0.94)**	0.80 (0.40–1.57)	0.98 (0.75–1.27)
Internet exposure (ref. ≤2 h/day) >2 h/day	0.94 (0.66–1.36)	**0.65 (0.50–0.84)**	0.87 (0.53–1.43)	0.92 (0.73–1.16)

[1] Logistic regression models were adjusted for age (continuous), snack consumption, HDAS, parental educational status, migrant background and country, OR not reported. [2] DM-digital media, PC-computer/game console use. [3] 6825 participants were included for total DM exposure (1995 male children, 1471 male adolescents, 1830 female children, 1529 female adolescents). For the single media types, the N varied, due to the exclusion of participants not using that specific media type at all (see Table S1). Bold significance in the adjusted models is provided via confidence limits.

3.4. Association between Media Use and Salty Taste Preference

Exposure of children and adolescents to DM and TV content for longer than 3 h/day (Table 3) showed a positive trend in association with salty TP (respectively: OR = 1.15, 95% CI = 0.96–1.37; OR = 1.19, 95% CI = 0.93–1.52), compared to low DM exposure (≤1 h/day). Further adjustment for weight status, did not attenuate the associations between media exposure and salty TP (results not shown). After stratification by sex and age, associations remained positive in female children only (Table 6). PC and smartphone use for longer than 2 h/day in female children was positively associated with high salty TP. Additionally, we observed positive associations between increasing durations of internet exposure and salty TP in all participants (Table 3) and in adolescent males in particular (OR = 1.29, 95% CI = 1.02–1.64).

Table 6. Association of media use with salty taste preference in European children and adolescents [1,2].

Media Types	Adjusted Model			
	Males		Females	
	<12 Years	≥12 Years	<12 Years	≥12 Years
	Odds Ratios (OR) and 95% Confidence Limits (95% CI)			
Total DM exposure (ref. ≤2 h/day) [3] >2 h/day	0.86 (0.71–1.04)	1.07 (0.84–1.38)	1.12 (0.92–1.37)	1.02 (0.82–1.27)
TV viewing (ref. ≤2 h/day) >2 h/day	0.92 (0.73–1.15)	1.05 (0.83–1.32)	1.16 (0.91–1.48)	1.06 (0.84–1.34)
PC use (ref. ≤2 h/day) >2 h/day	0.73 (0.49–1.10)	1.16 (0.88–1.53)	**3.85 (1.26–11.72)**	1.14 (0.75–1.71)
Smartphone use (ref. ≤2 h/day) >2 h/day	0.99 [3](0.44–2.24)	1.21 (0.89–1.66)	1.62 (0.81–3.21)	1.00 (0.78–1.29)
Internet exposure (ref. ≤2 h/day) >2 h/day	1.14 (0.79–1.66)	**1.29 (1.02–1.64)**	1.25 (0.77–2.02)	1.09 (0.87–1.36)

[1] Logistic regression models were adjusted for age (continuous), snack consumption, HDAS, parental educational status, migrant background and country, OR not reported. [2] DM-digital media, PC-computer/game console use. [3] 6988 participants included for total DM exposure (1977 male children, 1461 male adolescents, 1953 female children, 1597 female adolescents). For the single media types, the N varied, due to the exclusion of participants not using that specific media type at all (see Table S1). Bold significance in the adjusted models is provided via confidence limits.

4. Discussion

To our best knowledge, this is the first epidemiological study investigating the association of media use patterns with sensory taste preferences in children and adolescents. Our results indicated that European children and adolescents spent 2.4 h/day on average in front of screens, with 54.8% of them exceeding the WHO guidelines. Our cross-sectional study showed that exposure to increasing durations of DM was positively associated with sweet, fatty and salty taste preference in all participants, while inverse associations were observed for bitter TP, independently of diet quality and weight status. Differences by sex and age groups were observed.

4.1. Media Use in Association with Sweet Taste Preference

Our results showed that prolonged DM use was positively associated with high sweet TP in adolescents. These associations were also observed in the sensitivity analyses, where prolonged DM use in adolescents was associated with high sweet TP, regardless of their consumption frequency of sugary foods. This could be explained by the increase of media use with age [45] and, as a consequence, the higher exposure to food-related advertisements. Branding and TV marketing of high-sugar foods is associated with higher preference [21] and intake of those foods in children and adolescents [46]. Data from the same group of children included in our study, but at younger age (IDEFICS study-Identification and prevention of Dietary- and lifestyle-induced health EFfects In Children and infantS), have shown that children with high TV and commercial exposures had a higher consumption of sugar sweetened beverages (SSB) [11,44] independently of parental norms. In our study, use of PC/game console was positively associated with females' sweet TP, regardless of age. Similarly, in a longitudinal study conducted by Falbe et al. (2014), longer duration of electronic gaming in females was associated with increased frequency consumption of foods low in nutritional quality (e.g., sugar-rich foods), but not in males [47]. However, other individual differences might explain the female's higher preference for sweet taste. Although no differences have been observed in the number of fungiform papillae between female and male children [48], it has been shown that females of older age can recognize taste intensity better than males, which could lead them to a heightened preference for sweet tasting foods [49].

4.2. Media Use in Association with Fatty Taste Preference

Positive associations were observed between exposure to DM (and the single media types) and fatty taste preference. High DM exposure in adolescents (especially females) was positively associated with high fatty TP. These associations remained in the sensitivity analyses, both in the high and low fat intake propensity groups, suggesting that DM use and exposure to its content could influence teens' fatty TP, regardless of their actual intake of high-fat foods. Our results built on previous findings from earlier investigations when the IDEFICS participants were younger, which showed that high TV was associated with a higher propensity to consume fatty foods [9]. Children may also contribute to grocery shopping decisions (i.e. pester power), which in turn is associated with a high consumption of high-fat and high-sugar foods [50]. Moreover, those children who frequently asked for food/drink items seen on TV had a higher likelihood of later becoming overweight. Our results give evidence regarding a further hypothetical underlying pathway by which DM exposure could lead to poor eating habits and obesity, stressing the important role of taste preferences. This predisposition could be explained by neuropsychological factors, related to the sensory appeal of high-fat foods [51]. Studies have shown that unhealthy food cues (notably rich in fat content) attract children's attention more than healthy ones [20]. Previous findings from the I.Family study showed that children watching unhealthy food images vs. healthy ones had increased activation in brain areas involved in reward, motivation and memory [52]. Literature suggests that personality traits related to urgency, lower levels of consciousness and higher levels of extraversion have been associated with preference for unhealthy foods [53] as well as with excessive screen time use in children [54]. Hence, it may be possible that children's personality traits played a role in their preference for fatty foods.

4.3. Media Use in Association with Bitter Taste Preference

Our results showed an inverse relationship between high DM use (TV, PC, smartphone and internet) and bitter taste preference. These findings, although cross-sectional, built on previous longitudinal studies indicating that extended screen viewing predicts lower intake of fruits and vegetables, with the latter being the responsible source for the bitter tasting molecules perceived by the taste receptors located on the tongue and other parts of the oropharynx [55]. TV food advertising was shown to lead to unhealthy dietary changes, including low intake of fruits and vegetables, which, despite their potential to promote health, receive little airtime [56]. In our study, prolonged exposure to PC, smartphone and internet was negatively associated with bitter TP, in adolescent males in particular, but not in females. One explanation could be that food marketing is more likely to influence males' food preferences rather than that of females [57]. Furthermore, other factors related to family-environment might play a role in shaping children's food preferences and eating patterns [58] as well as their screen time habits. Literature suggests that male children whose parents did not limit internet usage time, were at higher risk of developing internet addiction [59]. Another study based on I.Family participants observed that children with prolonged media use were more likely to come from non-traditional families with no rules set for screen time use [60]. On the other hand, parenting feeding practices and mother's education can influence females' eating habits [61], but not those of males [62]. Remarkably, other underlying social factors such as peer pressure and perception of body weight influence female adolescents to make healthier food choices compared to males [36].

4.4. Media Use in Association with Salty Taste Preference

Our study showed a positive trend in the association between high internet exposure and salty TP, especially in male adolescents. Studies have shown that male adolescents tend to play more advergames in a multiplayer gaming environment compared to younger males [63], hence being more exposed to digital advertising of HFSS food [64]. Coates et al. (2019) have shown that influencer marketing of unhealthy snacks in online social networking platforms is associated with increased intake of the promoted snacks [65]. Our results showed that female children who used PC for >2 h/day, cross-sectionally, had three times higher odds for preferring salty tasting foods compared to those using PC for $\leq$2 h daily. The broad confidence intervals suggest that these results should be interpreted cautiously. However, evidence has shown that female children are actually heavier users of PC games than female adolescents, hence they might also indulge more in snacking while gaming [66] including snacks with high salt content (e.g., potato chips and popcorn) [10].

4.5. Strengths and Limitations

This is the first epidemiological study evaluating associations between exposure to DM and its specific types in real-life setting and sensory taste preferences in European children and adolescents. We included information on TV, computer, game console, internet and smartphone use, thus having a broad picture of the media use patterns of the participants. One of the main strengths of our study is the large sample size of 7094 children and adolescents and the large age range (6 to 17 years) which enabled us to obtain reliable results. Including participants from seven European countries allowed us to have a clear understanding of the different types of media used across the continent and their potential influence on TP. As taste preferences were self-reported by adolescents, as well as by younger children (6 to 12 years), and not proxy-reported by parents, we could exclude parental social-desirability bias and recall bias in both age groups. Literature suggests that, when parents report food preferences for their children, they may report preferences similar to their own food preference [67]. The standardized protocol and the pre-test conducted in a subsample of children make the FBPQ an established and feasible instrument for evaluating preferences of food and drinks in children and adolescents [29]. Furthermore, using information on various covariates, such as country, sex, age, parental education status, migration background, diet quality and snack frequency consumption allowed us to adjust for potential confounders.

There are methodological limits to our investigation. We could not totally exclude a social-desirability bias as adolescents, who self-reported taste preferences tend to report less their liking of foods/beverages with high energy content, such as fat- and sugar-rich foods [68]. We could not obtain information on social media use and its specific platforms including Facebook, Instagram, Snapchat, TikTok and YouTube. The social networking sites are becoming ubiquitously present in children's and adolescents' everyday life and they represent a powerful gateway for food companies to advertise their unhealthy/junk products. Thus, we suggest that further research should tackle the influence of social media on children's taste preferences. We did not distinguish between internet use for academic work and entertainment. This could explain the lack of significant association of internet use and sweet (and fat) taste preference in the overall sample. We acknowledge the limitation that mean media use in our children (2.4 h/day), is relatively low compared to current reports—U.S. children spend 5 h/day with screens while adolescents spend up to 7 h/day with recreational screen use [69]. However, as our data was collected during 2013–2014, the mean media use of our study is similar to that of earlier studies [70]. Newer studies with up-to-date information on media use in children and adolescents are warranted. Lastly, our research was conducted using cross-sectional data and we were unable to assess the temporal sequence in which dependent and independent factors occurred. Hence, future longitudinal studies with objectively-measured taste preferences are recommended to provide insights on the potential underlying mechanism by which exposure to DM content could influence poor eating habits and obesity in children and adolescents.

5. Conclusions

Exposure to DM was positively associated with increased preference for sweet, fatty, and salty taste while inversely associated with bitter TP in European children and adolescents. These results provide a starting point for future longitudinal research to shed light on further mechanisms by which exposure to DM might lead to poor eating behaviors and childhood obesity. Our findings could serve as an incentive for parents, pediatricians and policy makers alike in their battle to limit children's and adolescents' exposure to digital media content, to improve their eating habits and to prevent childhood obesity-related comorbidities.

Supplementary Materials: The following are available online at https://www.mdpi.com/2304-8158/10/2/377/s1 as an Online Supplementary Material: Figure S1: Participant flow chart from I.Family study included in current analyses, Table S1: Duration of media use in European children and adolescents, by sex and age group, Table S2: Association of total digital media exposure with sweet taste preference in European children and adolescents, by sweet intake propensity, Table S3: Association of total media exposure with fatty taste preference in European children and adolescents, by fat intake propensity, Table S4: Association of total media exposure with sweet and fatty taste preference in European children and adolescents, by sex and age group.

Author Contributions: The authors' contributions were as follows: Conceptualization, E.S.; Formal analysis, E.S.; Funding acquisition, W.A.; Methodology, E.S., C.B., W.A. and A.H.; Project administration and data collection, W.A., S.D.H., H.J., L.L., D.M., L.A.M., VP., L.R., A.S. (Alfonso Siani), A.S. (Antonia Solea), T.V. and A.H.; Supervision, A.H.; Visualization, E.S.; Writing—Original draft, E.S.; Writing—Review & editing, E.S., C.B., W.A., S.D.H., H.J., L.L., D.M., L.A.M., V.P., L.R., A.S. (Alfonso Siani), A.S. (Antonia Solea), T.V. and A.H., E.S., C.B. and A.H. had primary responsibility for the final content; All authors were responsible for critical revisions and final approval of the manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the European Community within the Seventh RTD Framework Programme Contract No. 266044.

Institutional Review Board Statement: Ethical approval was obtained for each study center from its local institutional review board as follows: Tallinn Medical Research Ethics Committee, Tallinn, Estonia; Egészségügyi Tudományos Tanács, Pécs, Hungary; Ethics Committee of the University of Bremen, Bremen, Germany; Cyprus National Bioethics Committee, Nicosia, Cyprus; Azienda Sanitaria Locale Avellino Comitato Etico, Avellino, Italy; Comité Ético de Investigación Clínica de Aragón, Zaragoza, Spain; Regionala Etikprövningsnämnden i Göteborg, Gothenburg, Sweden).

Informed Consent Statement: Written informed consent was obtained from adolescents and from parents of all children. Children below the age of 12 years were orally informed by field workers before each examination and were asked for their oral assent.

Data Availability Statement: Data described in this study will be made available upon request from the corresponding author.

Acknowledgments: This research was done in the framework of the I.Family study (http://www.ifamilystudy.eu/). We are grateful for the participation of European children and their parents in this examination. We acknowledge the support received from school boards, headmasters, and communities. The publication of this article was funded by the Open Access Fund of the Leibniz Association.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

References

1. World Health Organization. *Report of the Commission on Ending Childhood Obesity*; World Health Organization: Geneva, Switzerland, 2016.
2. World Health Organization. *Guidelines on Physical Activity, Sedentary Behaviour and Sleep for Children under 5 Years of Age*; World Health Organization: Geneva, Switzerland, 2019.
3. Drewnowski, A. Taste preferences and food intake. *Annu. Rev. Nutr.* **1997**, *17*, 237–253. [CrossRef]
4. Birch, L.L. Development of food preferences. *Annu. Rev. Nutr.* **1999**, *19*, 41–62. [CrossRef]
5. Sina, E.; Buck, C.; Jilani, H.; Tornaritis, M.; Veidebaum, T.; Russo, P.; Moreno, L.A.; Molnar, D.; Eiben, G.; Marild, S.; et al. Association of Infant Feeding Patterns with Taste Preferences in European Children and Adolescents: A Retrospective Latent Profile Analysis. *Nutrients* **2019**, *11*, 1040. [CrossRef]
6. Ahrens, W. Sensory taste preferences and taste sensitivity and the association of unhealthy food patterns with overweight and obesity in primary school children in Europe—A synthesis of data from the IDEFICS study. *Flavour* **2015**, *4*, 8. [CrossRef]
7. Fildes, A.; van Jaarsveld, C.H.; Llewellyn, C.H.; Fisher, A.; Cooke, L.; Wardle, J. Nature and nurture in children's food preferences. *Am. J. Clin. Nutr.* **2014**, *99*, 911–917. [CrossRef] [PubMed]
8. Johnson, S.L.; McPhee, L.; Birch, L.L. Conditioned preferences: Young children prefer flavors associated with high dietary fat. *Physiol. Behav.* **1991**, *50*, 1245–1251. [CrossRef]
9. Lissner, L.; Lanfer, A.; Gwozdz, W.; Olafsdottir, S.; Eiben, G.; Moreno, L.A.; Santaliestra-Pasías, A.M.; Kovács, É.; Barba, G.; Loit, H.-M.; et al. Television habits in relation to overweight, diet and taste preferences in European children: The IDEFICS study. *Eur. J. Epidemiol.* **2012**, *27*, 705–715. [CrossRef] [PubMed]
10. Börnhorst, C.; Wijnhoven, T.M.; Kunešová, M.; Yngve, A.; Rito, A.I.; Lissner, L.; Duleva, V.; Petrauskiene, A.; Breda, J. WHO European Childhood Obesity Surveillance Initiative: Associations between sleep duration, screen time and food consumption frequencies. *BMC Public Health* **2015**, *15*, 442. [CrossRef]
11. Olafsdottir, S.; Berg, C.; Eiben, G.; Lanfer, A.; Reisch, L.; Ahrens, W.; Kourides, Y.; Molnar, D.; Moreno, L.A.; Siani, A.; et al. Young children's screen activities, sweet drink consumption and anthropometry: Results from a prospective European study. *Eur. J. Clin. Nutr.* **2014**, *68*, 223–228. [CrossRef] [PubMed]
12. Shakir, R.N.; Coates, A.M.; Olds, T.; Rowlands, A.; Tsiros, M.D. Not all sedentary behaviour is equal: Children′s adiposity and sedentary behaviour volumes, patterns and types. *Obes. Res. Clin. Pract.* **2018**, *12*, 506–512. [CrossRef]
13. Avery, A.; Anderson, C.; McCullough, F. Associations between children's diet quality and watching television during meal or snack consumption: A systematic review. *Matern. Child Nutr.* **2017**, *13*, e12428. [CrossRef] [PubMed]
14. Robinson, T.N.; Banda, J.A.; Hale, L.; Lu, A.S.; Fleming-Milici, F.; Calvert, S.L.; Wartella, E. Screen Media Exposure and Obesity in Children and Adolescents. *Pediatrics* **2017**, *140*, S97–S101. [CrossRef]
15. Tatlow-Golden, M.; Boyland, E.; Jewell, J.; Zalnieriute, M.; Handsley, E.; Breda, J. *Tackling Food Marketing to Children in a Digital World: Trans-Disciplinary Perspectives. Children′s Rights, Evidence of Impact, Methodological Challenges, Regulatory Options and Policy Implications for the WHO European Region*; World Health Organization: Geneva, Switzerland, 2016.
16. Halford, J.C.; Gillespie, J.; Brown, V.; Pontin, E.E.; Dovey, T.M. Effect of television advertisements for foods on food consumption in children. *Appetite* **2004**, *42*, 221–225. [CrossRef] [PubMed]
17. Borzekowski, D.L.; Robinson, T.N. The 30-second effect: An experiment revealing the impact of television commercials on food preferences of preschoolers. *J. Am. Diet. Assoc.* **2001**, *101*, 42–46. [CrossRef]
18. Spence, C.; Okajima, K.; Cheok, A.D.; Petit, O.; Michel, C. Eating with our eyes: From visual hunger to digital satiation. *Brain Cogn.* **2016**, *110*, 53–63. [CrossRef]
19. Schüssler, P.; Kluge, M.; Yassouridis, A.; Dresler, M.; Uhr, M.; Steiger, A. Ghrelin Levels Increase After Pictures Showing Food. *Obesity* **2012**, *20*, 1212–1217. [CrossRef]
20. Spielvogel, I.; Matthes, J.; Naderer, B.; Karsay, K. A treat for the eyes. An eye-tracking study on children's attention to unhealthy and healthy food cues in media content. *Appetite* **2018**, *125*, 63–71. [CrossRef]
21. Robinson, T.N.; Borzekowski, D.L.; Matheson, D.M.; Kraemer, H.C. Effects of fast food branding on young children′s taste preferences. *Arch. Pediatr. Adolesc. Med.* **2007**, *161*, 792–797. [CrossRef]
22. Rodrigues, L.; Silverio, R.; Costa, A.R.; Antunes, C.; Pomar, C.; Infante, P.; Cristina, C.; Amado, F.; Lamy, E. Taste sensitivity and lifestyle are associated with food preferences and BMI in children. *Int. J. Food Sci. Nutr.* **2020**, *71*, 875–883. [CrossRef]
23. Bruce, A.S.; Pruitt, S.W.; Ha, O.-R.; Cherry, J.B.C.; Smith, T.R.; Bruce, J.M.; Lim, S.-L. The Influence of Televised Food Commercials on Children's Food Choices: Evidence from Ventromedial Prefrontal Cortex Activations. *J. Pediatr.* **2016**, *177*, 27–32.e21. [CrossRef]
24. Ohla, K.; Toepel, U.; le Coutre, J.; Hudry, J. Visual-Gustatory Interaction: Orbitofrontal and Insular Cortices Mediate the Effect of High-Calorie Visual Food Cues on Taste Pleasantness. *PLoS ONE* **2012**, *7*, e32434. [CrossRef]
25. Ahrens, W.; Siani, A.; Adan, R.; De Henauw, S.; Eiben, G.; Gwozdz, W.; Hebestreit, A.; Hunsberger, M.; Kaprio, J.; Krogh, V.; et al. Cohort Profile: The transition from childhood to adolescence in European children-how I.Family extends the IDEFICS cohort. *Int. J. Epidemiol.* **2017**, *46*, 1394–1395j. [CrossRef]
26. Suling, M.; Hebestreit, A.; Peplies, J.; Bammann, K.; Nappo, A.; Eiben, G.; Alvira, J.M.F.; Verbestel, V.; Kovács, É.; Pitsiladis, Y.P.; et al. Design and results of the pretest of the IDEFICS study. *Int. J. Obes.* **2011**, *35*, S30–S44. [CrossRef]
27. UNESCO. International Standard Classification of Education ISCED 2011. Available online: http://uis.unesco.org/sites/default/files/documents/international-standard-classification-of-education-isced-2011-en.pdf (accessed on 3 July 2020).

28. Rideout, V.J.; Foehr, U.G.; Roberts, D.F. Generation M2: Media in the Lives of 8- to 18-Year-Olds. Available online: https://www.kff.org/other/poll-finding/report-generation-m2-media-in-the-lives/ (accessed on 16 December 2020).
29. Jilani, H.; Pohlabeln, H.; De Henauw, S.; Eiben, G.; Hunsberger, M.; Molnar, D.; Moreno, L.A.; Pala, V.; Russo, P.; Solea, A.; et al. Relative Validity of a Food and Beverage Preference Questionnaire to Characterize Taste Phenotypes in Children Adolescents and Adults. *Nutrients* **2019**, *11*, 1453. [CrossRef]
30. Rauber, F.; Da Costa Louzada, M.L.; Steele, E.M.; Millett, C.; Monteiro, C.A.; Levy, R.B. Ultra-Processed Food Consumption and Chronic Non-Communicable Diseases-Related Dietary Nutrient Profile in the UK (2008–2014). *Nutrients* **2018**, *10*, 587. [CrossRef]
31. Ambrosini, G.L.; Johns, D.J.; Northstone, K.; Emmett, P.M.; Jebb, S.A. Free Sugars and Total Fat Are Important Characteristics of a Dietary Pattern Associated with Adiposity across Childhood and Adolescence. *J. Nutr.* **2016**, *146*, 778–784. [CrossRef] [PubMed]
32. Liem, D.G.; Russell, C.G. The Influence of Taste Liking on the Consumption of Nutrient Rich and Nutrient Poor Foods. *Front. Nutr.* **2019**, *6*, 174. [CrossRef] [PubMed]
33. Mennella, J.A.; Bobowski, N.K. The sweetness and bitterness of childhood: Insights from basic research on taste preferences. *Physiol. Behav.* **2015**, *152*, 502–507. [CrossRef] [PubMed]
34. Jilani, H.S.; Intemann, T.; Bogl, L.H.; Eiben, G.; Molnar, D.; Moreno, L.A.; Pala, V.; Russo, P.; Siani, A.; Solea, A.; et al. Familial aggregation and socio-demographic correlates of taste preferences in European children. *BMC Nutr.* **2017**, *3*, 87. [CrossRef]
35. Juraska, J.M.; Willing, J. Pubertal onset as a critical transition for neural development and cognition. *Brain Res.* **2017**, *1654*, 87–94. [CrossRef] [PubMed]
36. Salvy, S.-J.; Elmo, A.; Nitecki, L.A.; Kluczynski, M.A.; Roemmich, J.N. Influence of parents and friends on children′s and adolescents′ food intake and food selection. *Am. J. Clin. Nutr.* **2010**, *93*, 87–92. [CrossRef]
37. De Veirman, M.; Hudders, L.; Nelson, M.R. What Is Influencer Marketing and How Does It Target Children? A Review and Direction for Future Research. *Front. Psychol.* **2019**, *10*, 2685. [CrossRef] [PubMed]
38. Bel-Serrat, S.; Mouratidou, T.; Pala, V.; Huybrechts, I.; Bornhorst, C.; Fernandez-Alvira, J.M.; Hadjigeorgiou, C.; Eiben, G.; Hebestreit, A.; Lissner, L.; et al. Relative validity of the Children's Eating Habits Questionnaire-food frequency section among young European children: The IDEFICS Study. *Public Health Nutr.* **2014**, *17*, 266–276. [CrossRef] [PubMed]
39. Lanfer, A.; Hebestreit, A.; Ahrens, W.; Krogh, V.; Sieri, S.; Lissner, L.; Eiben, G.; Siani, A.; Huybrechts, I.; Loit, H.M.; et al. Reproducibility of food consumption frequencies derived from the Children's Eating Habits Questionnaire used in the IDEFICS study. *Int. J. Obes.* **2011**, *35*, S61–68. [CrossRef] [PubMed]
40. Arvidsson, L.; Eiben, G.; Hunsberger, M.; De Bourdeaudhuij, I.; Molnar, D.; Jilani, H.; Thumann, B.; Veidebaum, T.; Russo, P.; Tornatitis, M.; et al. Bidirectional associations between psychosocial well-being and adherence to healthy dietary guidelines in European children: Prospective findings from the IDEFICS study. *BMC Public Health* **2017**, *17*, 926. [CrossRef]
41. Waijers, P.M.C.M.; Feskens, E.J.M.; Ocké, M.C. A critical review of predefined diet quality scores. *Br. J. Nutr.* **2007**, *97*, 219–231. [CrossRef]
42. Cole, T.J.; Lobstein, T. Extended international (IOTF) body mass index cut-offs for thinness, overweight and obesity. *Pediatr. Obes.* **2012**, *7*, 284–294. [CrossRef]
43. World Health Organization. *Global Recommendations on Physical Activity for Health*; World Health Organization: Geneva, Switzerland, 2010; p. 58.
44. Olafsdottir, S.; Eiben, G.; Prell, H.; Hense, S.; Lissner, L.; Marild, S.; Reisch, L.; Berg, C. Young children′s screen habits are associated with consumption of sweetened beverages independently of parental norms. *Int. J. Public Health* **2014**, *59*, 67–75. [CrossRef]
45. Trinh, M.H.; Sundaram, R.; Robinson, S.L.; Lin, T.C.; Bell, E.M.; Ghassabian, A.; Yeung, E.H. Association of Trajectory and Covariates of Children's Screen Media Time. *JAMA Pediatr.* **2019**, *174*, 71–78. [CrossRef]
46. Emond, J.A.; Longacre, M.R.; Drake, K.M.; Titus, L.J.; Hendricks, K.; MacKenzie, T.; Harris, J.L.; Carroll, J.E.; Cleveland, L.P.; Langeloh, G.; et al. Exposure to Child-Directed TV Advertising and Preschoolers′ Intake of Advertised Cereals. *Am. J. Prev. Med.* **2019**, *56*, e35–e43. [CrossRef]
47. Falbe, J.; Willett, W.C.; Rosner, B.; Gortmaker, S.L.; Sonneville, K.R.; Field, A.E. Longitudinal relations of television, electronic games, and digital versatile discs with changes in diet in adolescents. *Am. J. Clin. Nutr.* **2014**, *100*, 1173–1181. [CrossRef]
48. Jilani, H.; Ahrens, W.; Buchecker, K.; Russo, P.; Hebestreit, A. Association between the number of fungiform papillae on the tip of the tongue and sensory taste perception in children. *Food Nutr. Res.* **2017**, *61*, 1348865. [CrossRef]
49. Overberg, J.; Hummel, T.; Krude, H.; Wiegand, S. Differences in taste sensitivity between obese and non-obese children and adolescents. *Arch. Dis. Child.* **2012**, *97*, 1048–1052. [CrossRef]
50. Huang, C.Y.; Reisch, L.A.; Gwozdz, W.; Molnár, D.; Konstabel, K.; Michels, N.; Tornaritis, M.; Eiben, G.; Siani, A.; Fernández-Alvira, J.M.; et al. Pester power and its consequences: Do European children's food purchasing requests relate to diet and weight outcomes? *Public Health Nutr.* **2016**, *19*, 2393–2403. [CrossRef] [PubMed]
51. Drewnowski, A. Energy intake and sensory properties of food. *Am. J. Clin. Nutr.* **1995**, *62*, 1081s–1085s. [CrossRef] [PubMed]
52. van Meer, F.; van der Laan, L.N.; Charbonnier, L.; Viergever, M.A.; Adan, R.A.; Smeets, P.A. Developmental differences in the brain response to unhealthy food cues: An fMRI study of children and adults. *Am. J. Clin. Nutr.* **2016**, *104*, 1515–1522. [CrossRef]
53. Zhou, Z.; SooHoo, M.; Zhou, Q.; Perez, M.; Liew, J. Temperament as Risk and Protective Factors in Obesogenic Eating: Relations Among Parent Temperament, Child Temperament, and Child Food Preference and Eating. *J. Genet. Psychol.* **2019**, *180*, 75–79. [CrossRef] [PubMed]

54. Yañez, A.M.; Bennasar-Veny, M.; Leiva, A.; García-Toro, M. Implications of personality and parental education on healthy lifestyles among adolescents. *Sci. Rep.* **2020**, *10*, 7911. [CrossRef]
55. Barr-Anderson, D.J.; Larson, N.I.; Nelson, M.C.; Neumark-Sztainer, D.; Story, M. Does television viewing predict dietary intake five years later in high school students and young adults? *Int. J. Behav. Nutr. Phys. Act.* **2009**, *6*, 7. [CrossRef]
56. Wiecha, J.L.; Peterson, K.E.; Ludwig, D.S.; Kim, J.; Sobol, A.; Gortmaker, S.L. When Children Eat What They Watch: Impact of Television Viewing on Dietary Intake in Youth. *Arch. Pediatrics Adolesc. Med.* **2006**, *160*, 436–442. [CrossRef] [PubMed]
57. Chernin, A. The Effects of Food Marketing on Children's Preferences: Testing the Moderating Roles of Age and Gender. *ANNALS Am. Acad. Political Soc. Sci.* **2008**, *615*, 101–118. [CrossRef]
58. Hebestreit, A.; Intemann, T.; Siani, A.; De Henauw, S.; Eiben, G.; Kourides, Y.A.; Kovacs, E.; Moreno, L.A.; Veidebaum, T.; Krogh, V.; et al. Dietary Patterns of European Children and Their Parents in Association with Family Food Environment: Results from the I.Family Study. *Nutrients* **2017**, *9*, 126. [CrossRef] [PubMed]
59. Chen, H.C.; Wang, J.Y.; Lin, Y.L.; Yang, S.Y. Association of Internet Addiction with Family Functionality, Depression, Self-Efficacy and Self-Esteem among Early Adolescents. *Int. J. Environ. Res. Public Health* **2020**, *17*, 8820. [CrossRef] [PubMed]
60. Stahlmann, K.; Hebestreit, A.; DeHenauw, S.; Hunsberger, M.; Kaprio, J.; Lissner, L.; Molnár, D.; Ayala-Marín, A.M.; Reisch, L.A.; Russo, P.; et al. A cross-sectional study of obesogenic behaviours and family rules according to family structure in European children. *Int. J. Behav. Nutr. Phys. Act.* **2020**, *17*, 32. [CrossRef]
61. Orlet Fisher, J.; Mitchell, D.C.; Wright, H.S.; Birch, L.L. Parental influences on young girls' fruit and vegetable, micronutrient, and fat intakes. *J. Am. Diet. Assoc.* **2002**, *102*, 58–64. [CrossRef]
62. Rey-López, J.P.; Vicente-Rodríguez, G.; Répásy, J.; Mesana, M.I.; Ruiz, J.R.; Ortega, F.B.; Kafatos, A.; Huybrechts, I.; Cuenca-García, M.; León, J.F.; et al. Food and drink intake during television viewing in adolescents: The Healthy Lifestyle in Europe by Nutrition in Adolescence (HELENA) study. *Public Health Nutr.* **2011**, *14*, 1563–1569. [CrossRef]
63. Mascheroni, G.; Ólafsson, K. *Net Children Go Mobile: Risks and Opportunities*; Educatt: Milan, Italy, 2014.
64. Folkvord, F.; Anschutz, D.J.; Buijzen, M.; Valkenburg, P.M. The effect of playing advergames that promote energy-dense snacks or fruit on actual food intake among children. *Am. J. Clin. Nutr.* **2013**, *97*, 239–245. [CrossRef]
65. Coates, A.E.; Hardman, C.A.; Halford, J.C.G.; Christiansen, P.; Boyland, E.J. Social Media Influencer Marketing and Children's Food Intake: A Randomized Trial. *Pediatrics* **2019**, *143*, e20182554. [CrossRef] [PubMed]
66. Delfino, L.D.; Dos Santos Silva, D.A.; Tebar, W.R.; Zanuto, E.F.; Codogno, J.S.; Fernandes, R.A.; Christofaro, D.G. Screen time by different devices in adolescents: Association with physical inactivity domains and eating habits. *J. Sports Med. Phys. Fit.* **2018**, *58*, 318–325. [CrossRef]
67. Skinner, J.D.; Carruth, B.R.; Wendy, B.; Ziegler, P.J. Children's food preferences: A longitudinal analysis. *J. Am. Diet. Assoc.* **2002**, *102*, 1638–1647. [CrossRef]
68. Perl, M.A.; Mandić, M.L.; Primorac, L.; Klapec, T.; Perl, A. Adolescent acceptance of different foods by obesity status and by sex. *Physiol. Behav.* **1998**, *65*, 241–245. [CrossRef]
69. Rideout, V.J.; Robb, M.B. *The Common Sense Census: Media Use by Tweens and Teens*; Common Sense Media: San Francisco, CA, USA, 2019.
70. Guram, S.; Heinz, P. Media use in children: American Academy of Pediatrics recommendations 2016. *Arch. Dis. Child. Educ. Pract. Ed.* **2018**, *103*, 99–101. [CrossRef] [PubMed]

Paper 3

Digital media exposure and cognitive functioning in European children and adolescents of the I.Family study

Sina, Elida, Buck, Christoph, Ahrens, Wolfgang, Coumans, Juul, Eiben, Gabriele, Formisano, Annarita, Krogh, Vittorio, Lissner, Lauren, Mazur, Artur, Michels, Nathalie, Molnar, Dénes, Moreno, Luis, Pohlabeln, Hermann, Reisch, Lucia, Tornaritis, Michael, Veidebaum, Toomas, Hebestreit, Antje, & on behalf of the I.Family consortium. Digital media exposure and cognitive functioning in European children and adolescents of the I.Family study. *Sci Rep* **13**, 18855 (2023). https://doi.org/10.1038/s41598-023-45944-0 scientific reports

Check for updates

OPEN

Digital media exposure and cognitive functioning in European children and adolescents of the I.Family study

Elida Sina[1], Christoph Buck[1], Wolfgang Ahrens[2], Juul M. J. Coumans[3], Gabriele Eiben[4], Annarita Formisano[5], Lauren Lissner[6], Artur Mazur[7], Nathalie Michels[8], Dénes Molnar[9], Luis A. Moreno[10], Valeria Pala[11], Hermann Pohlabeln[1], Lucia Reisch[1,12], Michael Tornaritis[13], Toomas Veidebaum[14], Antje Hebestreit[1]✉ & I. Family consortium*

The digital environment can pose health risks through exposure to unhealthy content. Yet, little is known about its relation to children's cognitive functioning. This study investigates the association between digital media (DM) exposure and children's cognitive functioning. This cross-sectional study is based on examinations of children aged 8–18 years (N = 8673) of the I.Family cohort (2013–2014). Exposure to television, computer, smartphone and internet was self-reported (hours/day). Media multitasking (MMT) was defined as simultaneous use of computers with other digital or non-screen-based activities. Standard instruments were used to assess cognitive inflexibility (score: 0–39), decision-making ability (− 100 to + 100) and impulsivity (12–48). Adjusted regression coefficients and 99.9%CIs were calculated by generalized linear mixed-effects models. In total, 3261 participants provided data for impulsivity, 3441 for cognitive inflexibility and 4046 for decision-making. Exposure to smartphones and media multitasking were positively associated with impulsivity ($\beta_{smartphone} = 0.74$; 99.9%CI = 0.42–1.07; $\beta_{MMT} = 0.73$; 99.9%CI = 0.35–1.12) and cognitive inflexibility ($\beta_{smartphone} = 0.32$; 99.9%CI = -0.02–0.66; $\beta_{MMT} = 0.39$; 99.9%CI = 0.01–0.77) while being inversely associated with decision-making ability. Extensive smartphone/internet exposure combined with low computer/medium TV exposure was associated with higher impulsivity and cognitive inflexibility scores, especially in girls. DM exposure is adversely associated with cognitive functioning in children and adolescents. Children require protection against the likely adverse impact of digital environment.

[1]Leibniz Institute for Prevention Research and Epidemiology - BIPS, Bremen, Germany. [2]Faculty of Mathematics and Computer Science, Institute of Statistics, University of Bremen, Bremen, Germany. [3]Teaching and Learning Centre, Open University of the Netherlands, Heerlen, The Netherlands. [4]Department of Public Health, School of Health Sciences, University of Skövde, Skövde, Sweden. [5]Institute of Food Sciences, National Research Council, Avellino, Italy. [6]School of Public Health and Community Medicine, Institute of Medicine, Sahlgrenska Academy, University of Gothenburg, Gothenburg, Sweden. [7]Faculty of Medicine, University of Rzeszów, Rzeszów, Poland. [8]Department of Public Health and Primary Care, Ghent University, Ghent, Belgium. [9]Department of Pediatrics, Medical School, University of Pécs, Pécs, Hungary. [10]GENUD (Growth, Exercise, Nutrition and Development) Research Group, Centro de Investigación Biomédica en Red Fisiopatología de La Obesidad y Nutrición (CIBERObn), Instituto Agroalimentario de Aragón (IA2), Instituto de Investigación Sanitaria Aragón (IIS Aragón), University of Zaragoza, Zaragoza, Spain. [11]Department of Epidemiology and Data Science, Fondazione IRCCS, Istituto Nazionale Dei Tumori, Milan, Italy. [12]Cambridge Judge Business School, University of Cambridge, Cambridge, UK. [13]Research and Education Institute of Child Health, Strovolos, Cyprus. [14]Department of Chronic Diseases, National Institute for Health Development, Tallinn, Estonia. *A list of authors and their affiliations appears at the end of the paper. ✉email: sec-epi@leibniz-bips.de

Today's children and adolescents are growing up in a digital media (DM) saturated environment, and they increasingly spend time with televisions, computers, video-games and smartphones. In the US, children and adolescents use DM for entertainment for five and eight hours daily, respectively, more than any other waking activity[1]. European children aged 9–16 years use online media for almost three hours/day[2]. Hence, DM represents a fundamental part of the environment in which children grow up. Therefore, it is crucial to investigate the role of DM exposure on children's health.

It is well-documented that DM exposure is positively associated with unhealthy dietary patterns during childhood and adolescence[3–5], and obesity in adulthood[6–9]. Moreover, studies have shed light on the deleterious role of DM exposure on children's and adolescents' psychosocial well-being[10,11] and body image[12]. The impact of DM exposure seems to extend beyond obesity and well-being, by influencing children's cognitive development as well[13]. In fact, children's brain and neural structure and their cognitive functioning are shaped through interactions with the external environment, including the digital environment[14]. Nowadays, DM is intertwined with children's lives, and an excessive exposure to DM during childhood, when the brain is highly plastic, might deteriorate the healthy development of brain structures. Studies conducted in laboratory conditions using functional magnetic resonance imaging (fMRI) have shown that prolonged exposure to screen-based media is associated with reduced microstructural integrity of the brain white matter in areas related to language, attention, and executive functioning in children[15] and adolescents[16]. Sound cognitive functioning is important for making healthy lifestyle choices, known as neuro-selection. Children with poor cognitive functioning are more likely to engage in unhealthy behaviours, such as consumption of unhealthy foods[17], but also smoking and alcohol drinking later in adulthood[18].

Non-educational television viewing (TV) has been associated with reduced language skills and executive functioning among pre-schoolers due to exposure to adult-directed programmes and reduced parent–child interactions[19]. A recent meta-analysis showed that DM exposure (TV and video-gaming) negatively impacted the academic performance of children aged 4–18 years[20]. This impact is also observed for smartphones[21], which facilitate the ubiquitous access to internet, messaging applications and social media (SM). The prolific information provided by DM, the urge to constantly check notifications and online content, may lead to over-stimulation and impact children's emotion regulation, distract them during routine tasks, limiting their cognitive processing capacities[22,23]. Furthermore, laboratory based studies have shown that excessive smartphone use among adolescents is associated with lower connectivity in the prefrontal cortex and the anterior cingulate region of the brain, which are specialized in inhibition control (i.e., impulsivity) and cognitive flexibility, respectively[24]. These latter constructs were previously positively associated with unhealthy snack consumption[25] and unfavourable weight status among adolescents[26]. Media multitasking (MMT) is a common behaviour among today's youth and refers to using multiple media devices simultaneously (e.g., PC used while watching TV) or using DM while engaged in non-media activities (e.g., PC used while reading a book). MMT has been associated with cognitive outcomes, including long-term attention problems[27], poor memory and reduced volume in anterior cingulate cortex, a region implicated in cognitive and socio-emotional control[28].

Given the limited empirical evidence on the role of digital environment on children's cognitive functioning, further research outside laboratory conditions is required. Therefore, this study investigates the association between DM exposure, including smartphone, PC, TV and internet use as well as MMT, on several measures of cognition – namely emotion-driven impulsiveness, decision-making ability and cognitive inflexibility – in a sample of European children and adolescents aged 8 to 18 years, in free-living conditions. We consider differences in the family environment, such as parental education [13] and family structure in the abovementioned associations. Moreover, we use a latent class analysis to identify underlying patterns of DM use based on the examined single media exposures to better understand the impact of DM exposure on children's cognitive functioning.

Methods

Study design and setting

This cross-sectional study exploits data from the I.Family study (2013—2014) conducted across nine countries, i.e., Belgium, Estonia, Cyprus, Hungary, Italy, Germany, Poland, Spain and Sweden, following standardized instruments and protocols[29]. Across study centres, we included children aged ≥ 8 years who provided information on three distinct measures of cognitive functioning: (i) emotion-driven impulsiveness, (ii) decision-making ability, and (iii) cognitive inflexibility. Besides age, primary exclusion criteria were implausible self-reports on DM use or a self-reported medical ADHD-diagnosis (Supplementary Fig. S1, Supplementary Methods). Adolescents and parents of all children provided written informed consent. Children (< 12 years) provided their oral assent. All procedures followed were in accordance with the ethical standards of the Helsinki Declaration of 1975, and its later amendments. Ethical approval was obtained from local institutional review boards at each study centre: (1) Belgium: Ethics Committee of the Gent University Hospital, 15/10/2007, ref: no. EC UZG 2007/243 and 19/02/2013, No. B670201316342; (2) Cyprus: Cyprus National Bioethics Committee, 12/07/2007, ref: no. EEBK/EM/2007/16 and 21/Feb/2013, No. EEBK/ETI/2012/33; (3) Estonia: Tallinn Medical Research Ethics Committee (TMREC), 14/06/2007, ref: no. 1093 and 17/January 2013, No. 128; (4) Germany: Ethic Commission of the University of Bremen, 16/01/2007 and 11/12/2012; (5) Hungary: Medical Research Council, 21/Jun/2007, ref: 22-156/2007-1018EKU and 18/12/2012, 4536/2013/EKU; (6) Italy: Ethics Committee of the Local Health Authority (ASL) in Avellino, 19/06/2007, ref: no. 2/CE and 18/Sep/2012, No. 12/12; (7) Spain: Ethics Committee for Clinical Research of Aragon (CEICA), 20/06/2007, ref:no. PI07/13 and 13/Feb/2013, No. PI13/0012; (8) Sweden: Regional Ethics Research Board in Gothenburg, 30/07/2007, ref: no. 264–07 and 10/Jan/2013, No. 927–12; (9) Poland: Bioethical Committee of the University of Rzeszów, 05/06/2013 and 01/12/2015.

Data collection

Core questionnaire and assessment of media use

Age, sex, and country of residence were self-reported by adolescents (≥ 12 years) and proxy-reported by parents of younger children (< 12 years). Information on DM use duration, MMT, and confounding variables were measured using standardized questionnaires, previously tested for relative validity and reproducibility[30]. Participants reported the DM use duration separately for weekdays and weekend days, including TV/DVD/video, computer/game console (PC), and internet use (Supplementary Methods). In order to prevent a potential overlap with internet use, for PC use participants were asked "How long do you usually sit at a computer/game console per day? (Please disregard the time spent on internet use.)", which enabled the assessment of off-line use of PC and game consoles. Total duration of TV, PC and internet use was respectively calculated as the sum of the weighted durations during weekdays and weekend days (hours/week), and quantified as hours/day. We measured smartphone use asking: "Thinking only about yesterday, about how much time did you spend watching TV shows, movies or music videos on a cell phone?". On a 5-point Likert-scale, answers ranged from 0 (not at all) to 5 (> 3 h/day). An attributed time was assigned to each category to calculate the duration (hours/day) of smartphone use. Moreover, we measured MMT asking whether children engaged in other activities while using PCs, including TV, sending text messages, playing video-games, listening to music and reading. Based on dichotomized answers ("yes" or "no), a composite score of media multitasking behaviour ranging from 0 to 5 was calculated.

Emotion-driven impulsiveness

To assess emotion-driven impulsiveness (EDI), 3400 children aged ≥ 8 years self-completed the 12-item negative urgency subscale from the Urgency, Premeditation, Perseverance, Sensation seeking, and Positive urgency (UPPS-P) questionnaire[31]. Participants rated items on a 4-point Likert scale ranging from 1 (agree strongly) to 4 (disagree strongly). All items were recoded except for one item, to make sure that all items ran in the same direction. For participants who completed all items (those with incomplete items were excluded), a sum score for EDI was calculated ranging from 12 to 48 [31]. A higher score indicated higher impulsivity. After all exclusion criteria (incomplete items of the subscale in addition to primary exclusion criteria, Supplementary Fig. S1) were applied, 3261 children aged 9.9–17.9 years remained for the final analyses on impulsivity.

Cognitive inflexibility

To measure cognitive inflexibility (CIF), 4034 children and adolescents performed a computerised version of the Berg Card Sorting test[32,33]. Four cards of different colours and shapes, and a deck consisting of 64 stimulus cards were shown to the participant. Participants had to sort cards according to a particular rule (by symbol, number or colour) that was unknown to them, by choosing one of the key cards (e.g., if 'by colour' is the correct rule, the colour of symbols on the stimulus card should match the colour of symbols on the key card). A feedback message ('correct' or 'incorrect') was provided to the participants after sorting each card. The rule was changed without notice after 10 consecutive correct trials, and the participant had to find out the new rule. The number of perseverative errors after the rule had changed, i.e., the number of cards sorted according to the previous rule, was used as the measure of CIF. A higher number of errors indicates higher CIF. After all exclusion criteria were applied (Supplementary Fig. S1), 3441 children aged 8–17.9 years remained in the final analysis group.

Decision-making ability

Decision-making ability (DMA) was measured in 4169 children aged 8–18 years, using a computerised version of the Hungry Donkey Test[34], the child-friendly version of the Iowa Gambling Task[35], consisting of 100 trials. In each trial, participants should help a hungry donkey to collect apples by choosing one of the four doors presented on the screen. Each choice resulted in reward (apples) or in punishment (loss of apples). Doors 1&2 were disadvantageous doors because they yielded larger immediate reward but led to losing more apples in the long-term, resulting in net loss. Doors 3&4 were advantageous doors because they yielded smaller immediate rewards but led to winning more apples in the long-term, resulting in net gain[34]. DMA was calculated by subtracting the number of advantageous choices (doors 3&4) from the number of disadvantageous choices (doors 1&2), resulting in a score ranging from − 100 to + 100. A higher DMA is characterised by more advantageous choices than disadvantageous ones. After all exclusion criteria were applied (Supplementary Fig. S1), 4046 children aged 8–17.9 years remained for the final analyses on DMA.

Potential confounders

A vast array of confounders was self- or proxy-reported via questionnaires. Besides age, sex and country of residence, we also included information on parental highest education attainment[36], the number of media rules at home[37], pubertal status[38,39], weight status (objectively-measured)[40], total daily sleep duration and psychosocial well-being[41]. Moreover, via a kinship and household interview[42], parents reported on family structure, including whether the participating child was an only child in the household and whether he/she lived in a one-parent or a two-parent family. Detailed explanation on measurements, operationalization and the rationale of including the confounding variables is provided in Supplementary Methods.

Statistical analyses

Response proportions differed for the cognitive tests and UPPS-P questionnaire resulting in three overlapping analysis groups (Supplementary Fig. S1), thus descriptive analyses were conducted separately for each cognitive outcome. Characteristics of age, sex, parental education attainment, weight status, pubertal status, family structure, country, MMT and media rules at home were tabulated for each analysis group. Children's performance on the cognitive tests was also calculated. To account for missing values, standard fully conditional specification multiple imputation (MI) was performed with 10 replications. This procedure has demonstrated unbiased handling of missing values, and enables the inclusion of both continuous and categorical variables in the imputation model[43]. All exposures and covariates used in the analyses were included in the MI, except the outcomes due to high percentage of missing values (> 50%). The relative efficiency of imputation (i.e., how well the true population parameters are estimated) for all variables was ≥ 98%, indicating good imputation quality. The proportion of missing information ranged from 0.5% for weight status to 26% for puberty based on Tanner stages. The characteristics of imputed and non-imputed analysis groups are shown in Supplementary Table S1. To examine the role of DM exposure on cognitive outcomes, a two-step analysis approach was conducted:

Step 1: Association of single DM exposures with cognitive outcomes

The associations between duration of using single DM and single outcomes were examined using generalized linear mixed regressions, adjusting for confounders. To assess potential multicollinearity of DM variables, we included TV, PC, internet, smartphone, MMT and media rules in the same regression model (step two) and calculated the tolerance and variance inflation factor (our limit: < 10)[44], which indicated lack of multicollinearity (data not shown).

Step 2: Latent profiles of DM use in association with cognitive outcomes

To identify underlying latent profiles of DM use, latent class analyses (LCA) were conducted[45] with three categories of duration for each DM variable (low duration: < 1 h/day; medium duration: 1–2 h/day; high duration: > 2 h/day). LCA was performed using two to six latent profiles of four variables (TV, PC, smartphone and internet), clustered by country, as we previously observed country-differences on DM use[46]. Models were then compared based on the Bayesian Information Criterium (BIC) and a clear distinction of latent profiles in terms of conditional probabilities (Supplementary Table S2). The chosen profiles (Supplementary Table S3) were then used in generalized linear mixed-effect models as predictors for each outcome, adjusting for covariates, including MMT (categorized as "no MMT", "1–2 MMT", " > 2 MMT").

To adjust for multiple testing (56 regressions in total: crude and adjusted models for three outcomes and five exposures; the latent class analyses for each outcome, and the stratified analyses), the statistical significance level was set at $\alpha = 0.001$, using the Sidak method[47]. Non-standardized regression coefficients (β) and 99.9% confidence intervals (99.9%CI) were estimated and then combined for the multiple imputed datasets. All analyses were performed with the statistical software SAS version 9.4 (Statistical Analyses System, SAS Institute Inc., Cary, NC, USA).

Sensitivity analyses

In post-hoc analyses, the associations in step two were stratified by sex, family structure (one- vs. two-parent) and parental education attainment, adjusted for remaining covariates, in order to explore underlying differences. To account for self- and proxy-reported data by adolescents and parents, we stratified the impulsivity analysis group by age group (< 12 years vs. ≥ 12 years) and further adjusted for continuous age.

Informed consent

All procedures followed were in accordance with the ethical standards of the Helsinki Declaration of 1975, and its later amendments. Ethical approval was obtained from local institutional review boards at each study centre. Informed consent was obtained from all participants included in the study.

Results

Characteristics of the analysis groups are provided in Table 1 and Supplementary Table S4. Information on emotion-driven impulsiveness was provided by 3261 children aged 9.9–17.9 years (mean/SD = 13.6/1.1). The impulsivity score ranged from 12 to 48 (mean/SD = 25.1/7.6). Data on decision-making ability was provided by 4046 children aged 8–17.9 years (mean/SD = 11.6/1.9). The DMA score ranged from − 100 to + 100 (median = − 6.0, IQR = -18/0). Information on CIF was provided by 3441 children aged 8–17.9 years (mean/SD = 11.7/2.0). The CIF score ranged from 0 to 39 (median = 11.0, IQR = 7/15). Across all children, about half of them were females and 26% of them had overweight/obesity. Additionally, half of children had parents with high educational background. Characteristics of children not completing the cognitive tests are depicted in Supplementary Table S5.

Digital media exposure in association with cognitive functioning

The results of the adjusted associations between individual DM use and measures of cognitive functioning are shown in Table 2**.** One additional hour of smartphone and internet exposure daily were associated with higher impulsivity score ($\beta_{smartphone}$, 0.74; 99.9%CI 0.42–1.07; $\beta_{internet}$, 0.57; 99.9%CI 0.28–0.85), after correcting for multiple testing. Smartphone exposure was positively associated with CIF (β, 0.32; 99.9%CI -0.02–0.66), although not statistically significant after correcting for multiple testing. Positive associations between MMT and impulsivity (β, 0.73; 99.9%CI 0.35–1.12) and CIF (β, 0.39; 99.9%CI 0.01–0.77) were also observed. Although not statistically significant, smartphone exposure (β, -0.47; 99.9%CI − 1.50–0.55) and MMT (β, − 0.70; 99.9%CI − 1.82–0.41) were inversely associated with DMA, while PC (β, 0.52; 99.9%CI − 0.72–1.77) and internet exposure were positively associated with DMA.

Latent profiles of DM use in association with cognitive functioning

The LCA of four latent DM profiles showed the lowest BIC and a clear interpretable distinction of conditional probabilities for the respective variables (Supplementary Table S3). Profile names were chosen based on the highest conditional probabilities. The majority of participants (57%) had low usage of all media types, i.e., < 1 h/day for each media. This was considered the most favorable DM profile and was thus used as reference category in regression models of step two. Circa 13% of participants had high DM use except smartphone, while 10% had

Covariables	Cognitive outcomes					
	Impulsivity		Decision-making ability		Cognitive inflexibility	
	N	%[a]	N	%	N	%
All	32,610	100.0	40,460	100.0	34,410	100.0
Sex						
Boys	15,500	47.5	20,280	50.1	17,230	50.1
Girls	17,110	52.5	20,180	49.9	17,180	49.9
Parental education attainment						
Low	1834	5.6	2492	6.2	2034	5.9
Medium	14,128	43.3	18,022	44.5	15,191	44.1
High	16,648	51.1	19,946	49.3	17,185	49.9
Weight status						
Underweight	2393	7.3	3043	7.5	2634	7.7
Normal weight	21,589	66.2	26,531	65.6	22,763	66.2
Overweight/obese	8628	26.5	10,886	26.9	9013	26.2
Pubertal status						
Pre-pubertal or early pubertal	7369	22.6	24,094	59.6	19,883	57.8
Pubertal	25,241	77.4	16,366	40.4	14,527	42.2
Being an only child						
Yes	7307	22.4	8438	20.9	7202	20.9
No	25,303	77.6	32,022	79.1	27,208	79.1
Family structure						
One-parent	4009	12.3	5331	13.2	4610	13.4
Two-parent	28,601	87.7	35,129	86.8	29,800	86.6
Country						
Italy	5630	17.3	8210	20.3	6300	18.3
Estonia	4900	15.0	9780	24.2	8760	25.5
Cyprus	7810	23.9	1110	2.7	870	2.5
Belgium	710	2.2	1560	3.9	1400	4.1
Poland[b]	760	2.3	–	–	–	–
Sweden	2420	7.4	3300	8.2	2400	7.0
Germany	4570	14.0	6470	16.0	5960	17.3
Hungary	4210	12.9	7850	19.4	6840	19.9
Spain	1600	4.9	2180	5.4	1880	5.5
Age, range (mean, SD)	9.9–17.9 (13.6, 1.1)		8.0–17.9 (11.6, 1.9)		8.0–17.9 (11.7, 2.0)	
Media rules, range (median, IQR)[c]	0–9 (6.0, 5/7)		0–9 (7.0, 5/7)		0–9 (7.0, 5/7)	
Impulsivity score, range (mean, SD)	12–48 (25.1, 7.6)					
Decision making score, range (median, IQR)[d]			− 100–+ 100 (− 6.0, − 18/0)			
Cognitive inflexibility score, range (median, IQR)					0–39 (11.0, 7/15)	

Table 1. Characteristics of European children and adolescents who took part in the cognitive tests for assessing impulsivity, cognitive inflexibility and decision-making ability. [a] Results are based on imputed samples (10 replications). Due to rounding of decimals, percentages may not add up to 100%. [b] Polish children and adolescents reported information only on impulsivity, as the computerized tests were not performed in this sample. [c] Abbreviations: IQR- interquartile range. [d] For DMA and CIF, the median and IQR are reported because the scores were skewed. However, the values of skewness (0.8 and -0.14 respectively) did not exceed the threshold (-1, + 1), hence transformation was not necessary[75].

high smartphone and internet use, but medium TV and low PC use. Roughly 20% of participants had medium TV/internet, but low smartphone/PC use.

The adjusted regression models in step two showed that participants with "high DM use, except smartphone", had an almost 2-point higher impulsivity score (β, 1.81; 99.9%CI 0.67–2.96) compared to those with low use of all media, independent of MMT (Table 3). This association remained significant among girls (β, 2.32; 99.9%CI 0.66–3.99), adolescents (β, 1.80; 99.9%CI 0.65–2.95) and those living in two-parent family (β, 1.79; 99.9%CI 0.54–3.04). The stratified analyses by parental education level (Supplementary Table S6) showed positive associations across all strata. Statistically significant associations were observed in participants from families with a medium educational background (β, 2.21; 99.9%CI 0.41–4.01). Children and adolescents with "high smartphone/internet, medium TV/low PC use" also showed higher impulsivity scores (β, 1.67, 99.9%CI 0.47–2.87), especially

	Digital media exposure [a]									
	TV use		PC use		Smartphone use		Internet use		Media multitasking	
	Crude β (99.9%CI)	Adjusted β (99.9%CI)[b]	Crude β (99.9% CI)	Adjusted β (99.9%CI)[b]	Crude β (99.9% CI)	Adjusted β (99.9%CI)[b]	Crude β (99.9% CI)	Adjusted β (99.9%CI)[b]	Crude β (99.9% CI)	Adjusted β (99.9%CI)[b]
Impulsivity (N = 3260) [c]	0.42 (− 0.03,0.86)	0.22 (− 0.20,0.64)	0.22 (− 0.22, 0.66)	0.33 (− 0.11, 0.77)	**1.00 (0.66, 1.33)** [d]	**0.74 (0.42, 1.07)**	**0.68 (0.39, 0.97)**	**0.57 (0.28, 0.85)**	**1.11 (0.71, 1.51)**	**0.73 (0.35, 1.12)**
Cognitive inflexibility (N = 3441)	− 0.08 (− 0.46, 0.28)	− 0.03 (− 0.40, 0.34)	− 0.24 (− 0.62, 0.14)	0.07 (− 0.33, 0.48)	0.11 (− 0.20, 0.43)	0.32 (− 0.02, 0.66)	**− 0.35 (− 0.60, − 0.10)**	0.001 (− 0.28, 0.29)	0.20 (− 0.15, 0.55)	**0.39 (0.01, 0.77)**
Decision-making ability N = 4046)	− 0.32 (− 1.40, 0.76)	− 0.16 (− 1.28, 0.96)	− 0.15 (− 1.27, 0.96)	0.52 (− 0.72, 1.77)	− 0.83 (− 1.75, 0.09)	− 0.47 (− 1.50, 0.55)	− 0.37 (− 1.10, 0.36)	0.23 (− 0.66, 1.14)	**− 1.05 (− 2.06, − 0.05)**	-0.70 (-1.82, 0.41)

Table 2. The association of digital media exposure with impulsivity, cognitive inflexibility and decision-making ability in European children and adolescents. [a] Models are based on regressing single DM exposures on each of the outcomes. [b] All models are adjusted for basic confounders including sex, continuous age, parental education level (low, medium, high), country of residence, total sleep duration (continuous), pubertal status (pre- or early pubertal vs. pubertal), well-being score (continuous), in addition to media rules at home (continuous), being an only child (yes vs. no) and family structure (one-parent vs. two-parent family). In all models, a random effect for family-id was included, to consider family influences, thus to partially account for genetic factors. [c] Due to missing value for the family id, one participant was not included in the analysis. [d] Bold numbers indicate statistical significance based on 99.9% confidence intervals.

	Media use profiles [a] (Ref: Low DM use)			Media multitasking (Ref: No MMT)	
	High DM use, except smartphone	High smartphone/internet, medium TV/low PC	Medium TV/internet, low smartphone/PC	1–2 MMT	> 2 MMT
	Adjusted β (99.9% CI)	Adjusted β (99.9% CI)	Adjusted β (99.9% CI)	Adjusted β (99.9% CI)	Adjusted β (99.9% CI)
Analysis group (N = 3260) [b]	**1.81 (0.67, 2.96)** [c]	**1.67 (0.47, 2.87)**	0.55 (− 0.55, 1.66)	0.97 (− 0.07, 2.02)	**1.61 (0.2, 3.03)**
Boys (N = 1549)	1.35 (− 0.26, 2.96)	1.80 (− 0.19, 3.80)	− 0.16 (− 1.66, 1.33)	0.74 (− 0.71, 2.20)	0.96 (− 1.01, 2.94)
Girls (N = 1711)	**2.32 (0.66, 3.99)**	**1.73 (0.21, 3.24)**	1.31 (− 0.33, 2.96)	1.21 (− 0.29, 2.71)	**2.30 (0.27, 4.34)**
Children (N = 38)	1.22 (− 9.57, 12.02)	− 4.19 (− 22.2, 13.9)	1.52 (− 7.97, 11.3)	1.04 (− 6.81, 8.91)	10.15 (− 6.75, 27.0)
Adolescents (N = 3222)	**1.80 (0.65, 2.95)**	**1.62 (0.42, 2.82)**	0.53 (− 0.58, 1.64)	1.00 (− 0.04, 2.06)	**1.62 (0.20, 3.04)**
One parent family (N = 397)	1.94 (− 1.34, 5.23)	− 0.04 (− 3.81, 3.71)	− 0.02 (− 3.18, 3.14)	1.34 (− 1.89, 4.58)	2.32 (− 1.98, 6.63)
Two parent family (N = 2863)	**1.79 (0.54, 3.04)**	**1.88 (0.60, 3.17)**	0.62 (− 0.58, 1.82)	0.91 (− 0.21, 2.05)	**1.54 (0.02, 3.05)**

Table 3. Association of latent profiles of digital media use with impulsivity in European children and adolescents. [a] Models are based on regressing the latent profiles of DM exposure on impulsivity, adjusting for basic confounders, including sex (not in the models stratified by sex), continuous age, parental education level (low, medium vs. high), country of residence, total sleep duration (continuous), pubertal status (pre- or early pubertal vs. pubertal), well-being score (continuous), in addition to media rules at home (continuous), being an only child (yes vs. no), family structure (one- vs. two-parent family; not in the models stratified by family structure) and media multitasking (no MMT, 1–2 MMT vs. > 2 MMT). In all models, a random effect for family id was included, to consider family influences and to partially account for genetic factors influencing the cognitive functioning. [b] Due to missing value for the family id, one participant was not included in the analyses. [c] Bold numbers indicate statistical significance based on 99.9% confidence intervals.

among girls (β, 1.73, 99.9%CI 0.21, 3.24), adolescents (β, 1.62, 99.9%CI 0.42, 2.82), and participants from two-parent families (β, 1.88, 99.9%CI 0.60, 3.17) (Table 3).

Table 4 shows the association between latent profiles of DM use and cognitive inflexibility in children and adolescents. Although not statistically significant, the results indicate a negative association between the profile "high DM use, except smartphone" and CIF. In contrast, a positive association between "high smartphone/internet, medium TV/low PC use" profile and CIF was observed in the overall sample and across strata, except for boys (Table 4) and for participants from families with low educational level (Supplementary Table S7).

The adjusted associations between latent DM profiles and DMA, depicted in Table 5 and Supplementary Table S8, showed a positive, but not statistically significant association for the profile of "high DM use, except smartphone" and DMA. Children with high smartphone/internet, but medium TV/low PC use" showed lower DMA scores across all strata. Although not statistically significant, participants living in one-parent households (Table 5) showed more than 4-point lower DMA score when exposed to smartphones/internet for > 2 h/day (β, − 4.36; 99.9%CI, -16.1–7.43) compared to low use of all media (< 1 h/day).

	Media use profiles [a] (Ref: Low DM use)			Media multitasking (Ref: No MMT)	
	High DM use, except smartphone	High smartphone/internet, medium TV/low PC	Medium TV/internet, low smartphone/PC	1–2 MMT	> 2 MMT
	Adjusted β (99.9% CI)	Adjusted β (99.9% CI)	Adjusted β (99.9% CI)	Adjusted β (99.9% CI)	Adjusted β (99.9% CI)
Analysis group (N = 3441)	− 0.37 (− 1.49, 0.75)	0.47 (− 0.79, 1.74)	− 0.06 (− 0.97, 0.84)	0.45 (− 0.34, 1.24)	1.13 (− 0.29, 2.56)
Boys (N = 1723)	− 0.62 (− 2.09, 0.85)	− 0.12 (− 2.19, 1.84)	− 0.21 (− 1.39, 0.96)	0.66 (− 0.37, 1.70)	1.23 (− 0.68, 3.16)
Girls (N = 1718)	− 0.15 (− 1.94, 1.63)	0.95 (− 0.81, 2.72)	0.14 (− 1.33, 1.62)	0.23 (− 0.92, 1.40)	0.97 (− 1.13, 3.08)
One-parent family (N = 459)	− 0.53 (− 3.86, 2.78)	0.56 (− 3.04, 4.16)	− 0.004 (− 3.16, 3.15)	0.40 (− 1.95, 2.75)	1.07 (− 2.88, 5.03)
Two-parent family (N = 2982)	− 0.34 (− 1.56, 0.88)	0.49 (− 0.90, 1.88)	− 0.08 (− 1.08, 0.90)	0.45 (− 0.38, 1.29)	1.18 (− 0.37, 2.74)

Table 4. Association of latent profiles of digital media use with cognitive inflexibility in European children and adolescents. [a] Models are based on regressing the latent profiles of DM exposure on cognitive inflexibility on the same model, adjusting for basic confounders, including sex (not in the models stratified by sex), continuous age, parental education level (low, medium vs. high), country of residence, total sleep duration (hours/day), pubertal status (pre- or early pubertal vs. pubertal status), well-being score (continuous), in addition to media rules at home (continuous), being an only child (yes vs. no), family structure (one- vs. two parent family; not in the models stratified by family structure) and media multitasking (no MMT, 1–2 MMT, > 2 MMT). In all models, a random effect for family id was included, to consider family influences and to partially account for genetic factors influencing the cognitive functioning. None of the associations were statistically significant after adjustment for multiple testing.

	Media use profiles [a] (Ref: Low DM use)			Media multitasking (Ref: No MMT)	
	High DM use, except smartphone	High smartphone/internet, medium TV/low PC	Medium TV/internet, low smartphone/PC	1–2 MMT	> 2 MMT
	Adjusted β (99.9% CI)	Adjusted β (99.9% CI)	Adjusted β (99.9% CI)	Adjusted β (99.9% CI)	Adjusted β (99.9% CI)
Analysis group (N = 4046)	1.32 (− 2.14, 4.79)	− 1.40 (− 5.12, 2.32)	− 0.82 (− 3.54, 1.90)	− 1.24 (− 3.50, 1.00)	− 1.46 (− 5.80, 2.86)
Boys (N = 2028)	1.71 (− 3.17, 6.6)	− 3.05 (− 9.73, 3.62)	− 0.78 (− 4.59, 3.03)	− 2.02 (− 5.37, 1.33)	− 1.58 (− 8.1, 4.94)
Girls (N = 2018)	− 0.16 (− 5.02, 4.7)	− 0.82 (− 5.44, 3.79)	− 1.17 (− 5.13, 2.78)	− 0.22 (− 3.25, 2.80)	− 1.07 (− 6.72, 4.58)
One-parent family (N = 528)	− 0.10 (− 11.0, 10.8)	− 4.37 (− 16.1, 7.43)	− 0.46 (− 8.72, 7.79)	− 0.64 (− 7.73, 6.45)	− 1.84 (− 13.8, 10.1)
Two-parent family (N = 3518)	1.54 (− 2.37, 5.56)	− 0.89 (− 5.0, 3.21)	− 1.03 (− 4.0, 1.93)	− 1.25 (− 3.65, 1.13)	− 1.24 (− 5.95, 3.47)

Table 5. Association of latent profiles of digital media use with decision-making ability in European children and adolescents. [a] Models are based on regressing the latent profiles of DM exposure on the decision-making ability on the same model, adjusting for covariates including sex (not in the models stratified by sex), continuous age, parental education level (low, medium vs. high), country of residence, total sleep duration (hours/day), pubertal status (pre- or early pubertal vs. pubertal status), well-being score (continuous), in addition to media rules at home (continuous), being an only child (yes vs. no), family structure (one- vs. two parent family; not in the models stratified by family structure) and media multitasking (no MMT, 1–2 MMT, > 2 MMT). In all models, a random effect for family id was included, to consider family influences and to partially account for genetic factors influencing the cognitive function. None of the associations were statistically significant after adjustment for multiple testing.

Discussion

This cross-sectional study using data from European children and adolescents shows that the duration of exposure to contemporary DM, including smartphones and internet as well as media multitasking, are positively associated with emotion-driven impulsiveness and cognitive inflexibility, independent of well-being, sleep duration and weight status. The strength of these associations differed by sex and family structure.

Longer exposure to smartphones, internet and MMT was associated with a higher impulsivity score among children and adolescents in the present study, while no association was observed for non-internet-based media including TV and PC use. These findings suggest that the perpetual flow of information and input received simultaneously from the online environment such as emails, notifications and SM posts, may act as stressors. It is hypothesized that these exposures exceed the cognitive capacity of youth to handle and process that information, thus leading to "digital stress"[48]. Children and adolescents may be particularly vulnerable to digital stress because the neuronal myelination and synaptic pruning within the parietal and prefrontal cortex (areas related to attention control and delayed reinforcement) are not fully developed, leading to compromised emotional-regulation[49] and reduced control of impulses[50]. These findings are worrisome considering the obesogenic (digital) food environment. The impact of smartphones and internet on EDI might lie in the pathway of mindless eating in front of screens, especially in reward-seeking contexts. Moreover, the prolific content accessible via internet-based DM (smartphones, SM platforms) which provides short and continuous gratifications that may activate the reward system (caudate, insula) and subsequent emotional and behavioural responses, such as snacking[24].

Another potential explanation may lie in the fact that DM displaces (real-life) social interactions such as parent–child, sibling- or peer relationships, often known as technoference. Social interactions are crucial for a healthy development because they built the foundation of processes related with personality and cognitive development, such as emotion regulation[51]. The interference of DM with parent–child interactions may compete with children's ability to concentrate and regulate their emotions, leading to internalizing and externalizing problems like reduced ability to control impulses[52].

Children and adolescents who used all DM except smartphone for > 2 h/day, had almost 2-point higher impulsivity score compared to children with low use of all media. Although the sole exposure to TV and PC was not associated with impulsivity, using them for prolonged duration in addition to constantly checking internet content seems to have a higher negative impact on children's capabilities to regulate emotions. The association between "high smartphone/internet use, medium TV/low PC" and impulsivity was stronger among girls compared to boys, potentially because girls use smartphones and internet mainly for socializing and navigating SM, while boys mainly use them to play games[2]. Previous evidence shows that SM exposure impacts girls' and adolescents' psycho-emotional well-being[53] and body-image[54] via social comparisons over images posted on these platforms. This may lead to emotional overeating or restrained eating, as maladaptive coping strategies for relieving negative emotions[55]. Remarkably, neuro-developmental differences between children and adolescents might explain the stronger association between DM exposure and impulsivity in adolescents. The limbic subcortical system (affective/hot system) matures early on and the control system (cold) matures later in adolescence[56], hence adolescents are more prone to engage in risky habits, also under digital stress.

Our results show that smartphone exposure and MMT were associated with higher cognitive inflexibility, suggesting that the digital environment may adversely impact youth's ability to smoothly shift between tasks. Smartphones and MMT encourage high levels of flicking between information sources at the expense of brain circuitry needed to sustain concentration[57]. This may explain why smartphone use and MMT lead to poor academic performance in youth[27,28]. Additionally, repeated exposure to fast-paced content, like short-edited video segments in SM (e.g., Instagram reels) or online game applications might trigger individuals into seeking higher arousal levels, which in turn hamper engagement in activities that require sustained attention (e.g., homework)[58]. The frequency of checking smartphones and internet might also lie in the pathway of the aforementioned associations. One longitudinal study conducted among Japanese children of a similar age range observed that increasing internet use frequency was associated with reduced increases of the grey and white brain matter volume, which are responsible for attention control and executive functioning[16]. Although not significant, the negative association between prolonged exposure to all DM, except smartphone, and CIF suggests that children may be using those media for educational purposes and this could positively influence their mental multitasking abilities. Prolonged exposure to smartphones/internet but medium TV/low PC use was associated with higher CIF, indicating that smartphones particularly may disrupt children's cognitive multitasking compared to other DM, as they are mostly used for entertainment purposes[59,60], rather than for education[12].

The adjusted associations between DM exposure and decision-making ability in a reward-related context were not statistically significant, but suggested a negative association of smartphone exposure and MMT with DMA. This aligns with a previous study where excessive smartphone use was related to reduced connectivity in the orbitofrontal cortex, a brain region related to DMA in reward-seeking behaviours[61]. One potential explanation could be that DM may interfere with children's capacities to weigh short-term rewards against long-term negative outcomes, especially in a highly rewarding (digital) food environment (e.g., by consuming energy-dense foods). This is supported by previous research, which showed that children exposed to multiple DM tend to make unhealthy food choices[62]. Nevertheless, to our best knowledge, no other study has investigated the role of DM exposure on decision-making ability using the Hungry Donkey Test. Given the limited research in this area, our non-significant results should be interpreted with caution. Studies conducted in children of a similar age range using both the Hungry Donkey Test[63] and Iowa Gambling Test[64] have shown that DMA varies with age in a U-shaped curve. Younger children perform better in the task compared to early-adolescents, with performance becoming again better in late adolescents. This indicates that although DM use increases with age[46,65], other mechanisms impact the development of DMA. The ventromedial prefrontal cortex, for instance, which is specialized in decision-making, functionally matures during adolescence and continues until young adulthood[66]. In our study, we measured the self-reported DM use duration, while previous studies that found significant association between DM exposure and activation of decision-making related brain areas, used the Smartphone[61] and Internet Addiction Scale[67,68]. Thus, more longitudinal research is warranted to understand the extent and the underlying mechanisms (e.g., structural changes in the brain) via which DM exposure may impact DMA, using more detailed measures of DM, including SM exposure.

Strengths and limitations

This is the first observational study to investigate the role of DM exposure on several measures of cognition in European children and adolescents. In contrast to most other studies focusing only on TV and video-gaming, we examined various DM exposures including contemporary DM like smartphone and internet, as well as MMT. Although all the single media (TV, PC, internet and smartphones) are digital media, we aimed at examining the association of each media with measures of cognitive functioning, because the patterns of use and the content children and adolescents are exposed to differs from one media to another. Using LCA to identify underlying patterns of DM exposure represents an advantage. We accounted for various important confounders of the associations between DM use and cognition, including sleep, well-being, pubertal and weight status, and family structure. All analyses were corrected for multiple testing, strengthening the reliability of the reported associations.

The cross-sectional nature of our study limits our ability to draw causal conclusions. Hence, we cannot exclude that certain psychological characteristics and personality traits predispose certain forms of DM use. Applying the reverse causality hypothesis, it can be assumed that prior delays in cognitive functioning may have led to a prolonged DM use among children and adolescents. Recent evidence also suggests that genetic variants and neuro-biological mechanisms commonly observed in behavioural addictions (i.e., dopamine release) are related to the excessive use of smartphones, internet, and video-games[69–71]. On the other side, an increasing number of studies have suggested various potential mechanisms through which DM may lead to poor cognitive functioning in children (as already discussed in this paper: digital stress, technoference, overstimulation, reduced attention control or impact on brain structures). Given that research on this topic is still at its infancy, future longitudinal studies are warranted to investigate how DM exposure over time impacts cognitive functioning while accounting for genetic and psychological characteristics, including the cognitive abilities in early childhood. Of note, when we controlled for factors like psychosocial well-being and partially accounted for family influences, the observed associations between DM exposure and cognitive functioning remained robust. When comparing the characteristics of participants completing the cognitive tests vs. those who did not, we observed no differences (expect for age and subsequently for pubertal status). Hence, it is unlikely that results are affected by selection bias, although the external validity may be limited given the non-representative sampling frame for each included country. Recall bias may have led to an underreported EDI, as the impulsivity sub-scale was self-reported. DM exposure was measured based on self-reports, thus a recall and social-desirability bias may have resulted to over- and under-estimation of DM use[72]. However, previous studies have shown that self-reported DM usage (e.g., smartphones) adequately distinguished between high and low use among adolescents[73]. The recency of the data is a limitation, as the digital environment and media skills of children have dramatically changed since 2013/2014. Our assessment of smartphone duration included the exposure to content such as TV shows, music videos or movies. Smartphones can be used for various purposes both offline and online, including playing games (offline) or social interactions (e.g., video-calling, texting etc.), which we could not account for with the available data. MMT was defined as the simultaneous use of a computer with other media, without considering smartphone and SM use, which are also significant contributors to MMT behaviour[74]. Therefore, the observed associations between MMT and cognitive functioning could be much more prominent in real life. We urge future studies to consider all sources of screen time and MMT to capture the complete picture of DM exposure during childhood. Moreover, we did not distinguish between smartphone and internet use for academic and entertainment purposes, which might lead to different results, and future studies should examine this hypothesis. We also lacked information on ease of access to DM at home, although we partly accounted for this by using information on media rules at home and MMT. Finally, we could not obtain information on SM exposure (Instagram, TikTok)[60] and we urge further research to investigate the role of SM on children's cognitive functioning, by considering the patterns of use (duration or problematic/addictive use of SM) and type of content provided.

Conclusions

Smartphone, internet and media multitasking were found to be positively associated with emotion-driven impulsiveness and cognitive inflexibility, independent of psychosocial well-being and family structure. Our study provides evidence on a potential underlying mechanism by which DM exposure affects cognitive development and related health behaviours. These findings ask for parents, paediatricians and policy makers to help youth implement sound media use habits, in order to build the foundation for developing healthy psycho-physiological resilience against the likely adverse impact of digital environment.

Data availability

Due to the sensitive nature of data collected, ethical restrictions prohibit the authors from making the minimal data set publicly available. Each cohort centre received approval of the corresponding local Ethical Commission and participants did not provide consent for data sharing. Data are available on request and all requests need approval by the Steering Committee of the study. Interested researchers can contact the study co-ordinator (ahrens@leibniz-bips.de) to request data access. All requests for accessing data of the I.Family cohort are discussed on a case-by-case basis by the Steering Committee.

Received: 2 June 2023; Accepted: 26 October 2023
Published online: 01 November 2023

References

1. The Common Sense Media. *The Common Sense Census: Media Use by Tweens and Teens, 2019*, <https://www.commonsensemedia.org/research/the-common-sense-census-media-use-by-tweens-and-teens-2019> (2019).
2. Smahel, D. *et al.* EU Kids Online 2020: Survey results from 19 countries. (2020).
3. Lissner, L. *et al.* Television habits in relation to overweight, diet and taste preferences in European children: The IDEFICS study. *Eur. J. Epidemiol.* **27**, 705–715. https://doi.org/10.1007/s10654-012-9718-2 (2012).
4. Olafsdottir, S. *et al.* Young children's screen habits are associated with consumption of sweetened beverages independently of parental norms. *Int. J. Public Health* **59**, 67–75. https://doi.org/10.1007/s00038-013-0473-2 (2014).
5. Sina, E. *et al.* Digital media use in association with sensory taste preferences in European children and adolescents—results from the I. Family study. *Foods* **10**, 377 (2021).
6. Viner, R. M. & Cole, T. J. Television viewing in early childhood predicts adult body mass index. *J. Pediatr.* **147**, 429–435. https://doi.org/10.1016/j.jpeds.2005.05.005 (2005).
7. Robinson, T. N. Reducing children's television viewing to prevent obesity–a randomized controlled trial. *JAMA* **282**, 1561–1567. https://doi.org/10.1001/jama.282.16.1561 (1999).
8. Robinson, T. N. *et al.* Screen media exposure and obesity in children and adolescents. *Pediatrics* **140**, S97-s101. https://doi.org/10.1542/peds.2016-1758K (2017).
9. Hancox, R. J., Milne, B. J. & Poulton, R. Association between child and adolescent television viewing and adult health: a longitudinal birth cohort study. *Lancet* **364**, 257–262. https://doi.org/10.1016/S0140-6736(04)16675-0 (2004).

10. Hinkley, T. *et al.* Early childhood electronic media use as a predictor of poorer well-being: A prospective cohort study. *JAMA Pediatr.* **168**, 485–492. https://doi.org/10.1001/jamapediatrics.2014.94 (2014).
11. Twenge, J. M. & Martin, G. N. Gender differences in associations between digital media use and psychological well-being: Evidence from three large datasets. *J. Adolesc.* **79**, 91–102. https://doi.org/10.1016/j.adolescence.2019.12.018 (2020).
12. Kwon, S. *et al.* Association of smartphone use with body image distortion and weight loss behaviors in korean adolescents. *JAMA Netw. Open* **5**, e2213237–e2213237. https://doi.org/10.1001/jamanetworkopen.2022.13237 (2022).
13. Anderson, D. R. & Subrahmanyam, K. Digital screen media and cognitive development. *Pediatrics* **140**, S57-s61. https://doi.org/10.1542/peds.2016-1758C (2017).
14. Christakis, D. A., Ramirez, J. S. B., Ferguson, S. M., Ravinder, S. & Ramirez, J.-M. How early media exposure may affect cognitive function: A review of results from observations in humans and experiments in mice. *Proc. Natl. Acad. Sci.* **115**, 9851–9858. https://doi.org/10.1073/pnas.1711548115 (2018).
15. Hutton, J. S., Dudley, J., Horowitz-Kraus, T., DeWitt, T. & Holland, S. K. Associations between screen-based media use and brain white matter integrity in preschool-aged children. *JAMA Pediatr.* **174**, e193869–e193869. https://doi.org/10.1001/jamapediatrics.2019.3869 (2020).
16. Takeuchi, H. *et al.* Impact of frequency of internet use on development of brain structures and verbal intelligence: Longitudinal analyses. *Hum. Brain Map.* **39**, 4471–4479. https://doi.org/10.1002/hbm.24286 (2018).
17. Batty, G. D., Deary, I. J., Schoon, I. & Gale, C. R. Childhood mental ability in relation to food intake and physical activity in adulthood: The 1970 British cohort study. *Pediatrics* **119**, e38–e45. https://doi.org/10.1542/peds.2006-1831 (2007).
18. Batty, G. D., Deary, I. J., Schoon, I. & Gale, C. R. Mental ability across childhood in relation to risk factors for premature mortality in adult life: The 1970 British cohort study. *J. Epidemiol. Commun. Health* **61**, 997–1003. https://doi.org/10.1136/jech.2006.054494 (2007).
19. Zimmerman, F. J. & Christakis, D. A. Children's television viewing and cognitive outcomes: A longitudinal analysis of national data. *Arch. Pediatr. Adolesc. Med.* **159**, 619–625. https://doi.org/10.1001/archpedi.159.7.619 (2005).
20. Adelantado-Renau, M. *et al.* Association between screen media use and academic performance among children and adolescents: A systematic review and meta-analysis. *JAMA Pediatr.* https://doi.org/10.1001/jamapediatrics.2019.3176 (2019).
21. Kliesener, T., Meigen, C., Kiess, W. & Poulain, T. Associations between problematic smartphone use and behavioural difficulties, quality of life, and school performance among children and adolescents. *BMC Psychiatr.* **22**, 195. https://doi.org/10.1186/s12888-022-03815-4 (2022).
22. Camerini, A.-L. & Marciano, L. Media Use and Academic Achievement. In *The International Encyclopedia of Media Psychology* 1–12 (ed. Bulck, J.). https://doi.org/10.1002/9781119011071.iemp0223 (2020).
23. van der Schuur, W. A., Baumgartner, S. E., Sumter, S. R. & Valkenburg, P. M. The consequences of media multitasking for youth: A review. *Comput. Hum. Behav.* **53**, 204–215. https://doi.org/10.1016/j.chb.2015.06.035 (2015).
24. Marciano, L., Camerini, A.-L. & Morese, R. The developing brain in the digital era: A scoping review of structural and functional correlates of screen time in adolescence. *Front. Psychol.* **12**, 671817. https://doi.org/10.3389/fpsyg.2021.671817 (2021).
25. Coumans, J. M. J. *et al.* Emotion-driven impulsiveness and snack food consumption of European adolescents: results from the I. Family study. *Appetite* **123**, 152–159. https://doi.org/10.1016/j.appet.2017.12.018 (2018).
26. Coumans, J. M. J. *et al.* The association of emotion-driven impulsiveness, cognitive inflexibility and decision-making with weight status in European adolescents. *Int. J. Obes. (Lond.)* **42**, 655–661. https://doi.org/10.1038/ijo.2017.270 (2018).
27. Baumgartner, S. E., van der Schuur, W. A., Lemmens, J. S. & te Poel, F. The relationship between media multitasking and attention problems in adolescents: Results of two longitudinal studies. *Hum. Commun. Res.* **44**, 3–30. https://doi.org/10.1111/hcre.12111 (2018).
28. Uncapher, M. R. *et al.* Media multitasking and cognitive, psychological, neural, and learning differences. *Pediatrics* **140**, S62-s66. https://doi.org/10.1542/peds.2016-1758D (2017).
29. Ahrens, W. *et al.* Cohort profile: The transition from childhood to adolescence in European children-how I. Family extends the IDEFICS cohort. *Int. J. Epidemiol.* **46**, 1394–1395j. https://doi.org/10.1093/ije/dyw317 (2017).
30. Suling, M. *et al.* Design and results of the pretest of the IDEFICS study. *Int. J. Obes.* **35**, S30–S44. https://doi.org/10.1038/ijo.2011.33 (2011).
31. Whiteside, S. P. & Lynam, D. R. The five factor model and impulsivity: Using a structural model of personality to understand impulsivity. *Pers. Individ. Differ.* **30**, 669–689. https://doi.org/10.1016/S0191-8869(00)00064-7 (2001).
32. Berg, E. A. A simple objective technique for measuring flexibility in thinking. *J. Gen. Psychol.* **39**, 15–22. https://doi.org/10.1080/00221309.1948.9918159 (1948).
33. Mueller, S. T. & Piper, B. J. The psychology experiment building language (PEBL) and pebl test battery. *J. Neurosci. Methods* **222**, 250–259. https://doi.org/10.1016/j.jneumeth.2013.10.024 (2014).
34. Crone, E. A. & van der Molen, M. W. Developmental changes in real life decision making: Performance on a gambling task previously shown to depend on the ventromedial prefrontal cortex. *Devel. Neuropsychol.* **25**, 251–279. https://doi.org/10.1207/s15326942dn2503_2 (2004).
35. Bechara, A., Damasio, A. R., Damasio, H. & Anderson, S. W. Insensitivity to future consequences following damage to human prefrontal cortex. *Cognition* **50**, 7–15. https://doi.org/10.1016/0010-0277(94)90018-3 (1994).
36. UNESCO. International Standard Classification of Education. 2012 [cited 27.02.2023]; Available from: http://uis.unesco.org/sites/default/files/documents/international-standard-classification-of-education-isced-2011-en.pdf.
37. Stahlmann, K. *et al.* A cross-sectional study of obesogenic behaviours and family rules according to family structure in European children. *Int. J. Behav. Nutr. Phys. Act.* **17**, 32. https://doi.org/10.1186/s12966-020-00939-2 (2020).
38. Carskadon, M. A. & Acebo, C. A self-administered rating scale for pubertal development. *J. Adolesc. Health* **14**, 190–195. https://doi.org/10.1016/1054-139X(93)90004-9 (1993).
39. Tanner, J. M. Growth and maturation during adolescence. *Nutr. Rev.* **39**, 43–55. https://doi.org/10.1111/j.1753-4887.1981.tb06734.x (1981).
40. Cole, T. J. & Lobstein, T. Extended international (IOTF) body mass index cut-offs for thinness, overweight and obesity. *Pediatr. Obes.* **7**, 284–294. https://doi.org/10.1111/j.2047-6310.2012.00064.x (2012).
41. Bullinger, M., Brütt, A. L., Erhart, M. & Ravens-Sieberer, U. Psychometric properties of the KINDL-R questionnaire: Results of the BELLA study. *Eur. Child. Adolesc. Psychiatr.* **17**(Suppl 1), 125–132. https://doi.org/10.1007/s00787-008-1014-z (2008).
42. Bogl, L.-H., Kaprio, J., Brünings-Kuppe, C., Lissner, L. & Ahrens, W. *Instruments for Health Surveys in Children and Adolescents 291–301* (Springer, 2019).
43. Liu, Y. & De, A. Multiple imputation by fully conditional specification for dealing with missing data in a large epidemiologic study. *Int. J. Stat. Med. Res.* **4**, 287–295. https://doi.org/10.6000/1929-6029.2015.04.03.7 (2015).
44. Schreiber-Gregory, D. N. & Jackson, H. M. in *Proc. of the SAS R global forum 2017 conference paper.*
45. Lanza, S. T., Collins, L. M., Lemmon, D. R. & Schafer, J. L. PROC LCA: A SAS procedure for latent class analysis. *Struct. Equ. Model. Multidiscip. J.* **14**, 671–694 (2007).
46. Sina, E. *et al.* Media use trajectories and risk of metabolic syndrome in European children and adolescents: The IDEFICS/IFamily cohort. *Int. J. Behav. Nutr. Phys. Act.* **18**, 1–14 (2021).
47. Šidák, Z. Rectangular confidence regions for the means of multivariate normal distributions. *J. Am. Stat. Assoc.* **62**, 626–633. https://doi.org/10.1080/01621459.1967.10482935 (1967).

48. Hefner, D. & Vorderer, P. Permanent Connectedness and Multitasking. In *The Routledge handbook of media use and well-being: International perspectives on theory and research on positive media effects* 237–249 (Routledge, 2016).
49. Steele, R. G., Hall, J. A. & Christofferson, J. L. Conceptualizing digital stress in adolescents and young adults: Toward the development of an empirically based model. *Clin. Child. Fam. Psychol. Rev.* **23**, 15–26. https://doi.org/10.1007/s10567-019-00300-5 (2020).
50. Defoe, I. N., Dubas, J. S., Figner, B. & van Aken, M. A. A meta-analysis on age differences in risky decision making: Adolescents versus children and adults. *Psychol. Bull.* **141**, 48–84. https://doi.org/10.1037/a0038088 (2015).
51. Pempek, T. A. & Lauricella, A. R. in *Cognitive Development in Digital Contexts* (eds Fran C. Blumberg & Patricia J. Brooks) 53–74 (Academic Press, 2017).
52. McDaniel, B. T. & Radesky, J. S. Technoference: Parent distraction with technology and associations with child behavior problems. *Child. Dev.* **89**, 100–109. https://doi.org/10.1111/cdev.12822 (2018).
53. Svensson, R., Johnson, B. & Olsson, A. Does gender matter? The association between different digital media activities and adolescent well-being. *BMC Public Health* **22**, 273. https://doi.org/10.1186/s12889-022-12670-7 (2022).
54. McLean, S. A., Jarman, H. K. & Rodgers, R. F. How do "selfies" impact adolescents' well-being and body confidence? A narrative review. *Psychol. Res. Behav. Manag.* **12**, 513–521. https://doi.org/10.2147/PRBM.S177834 (2019).
55. Shriver, L. H. *et al.* Emotional eating in adolescence: Effects of emotion regulation, weight status and negative body image. *Nutrients* **13**, 79 (2021).
56. Schweizer, S., Gotlib, I. H. & Blakemore, S. J. The role of affective control in emotion regulation during adolescence. *Emotion* **20**, 80–86. https://doi.org/10.1037/emo0000695 (2020).
57. Firth, J. A., Torous, J. & Firth, J. Exploring the impact of internet use on memory and attention processes. *Int. J. Environ. Res. Public Health* **17**, 9481. https://doi.org/10.3390/ijerph17249481 (2020).
58. Lissak, G. Adverse physiological and psychological effects of screen time on children and adolescents: Literature review and case study. *Environ. Res.* **164**, 149–157. https://doi.org/10.1016/j.envres.2018.01.015 (2018).
59. Rideout, V. & Robb, M. *The Common Sense census: Media use by kids age zero to eight, 2020* (Common Sense Media, 2020).
60. Rideout, V. J. & Robb, M. B. *The Common Sense Census: Media Use by Tweens and Teens* (Common Sense Media, 2019).
61. Chun, J.-W. *et al.* Role of frontostriatal connectivity in adolescents with excessive smartphone use. *Front. Psychiat.* **9**, 437. https://doi.org/10.3389/fpsyt.2018.00437 (2018).
62. Sina, E., Boakye, D., Christianson, L., Ahrens, W. & Hebestreit, A. Social media and children's and adolescents' diets: A systematic review of the underlying social and physiological mechanisms. *Adv. Nutr.* **13**, 913–937. https://doi.org/10.1093/advances/nmac018 (2022).
63. Smith, D. G., Xiao, L. & Bechara, A. Decision making in children and adolescents: Impaired iowa gambling task performance in early adolescence. *Dev. Psychol.* **48**, 1180–1187. https://doi.org/10.1037/a0026342 (2012).
64. Cortes-Patino, D. M., Soares-Filho, P. S. D. & Acosta-Barreto, M. R. Decision-making in children in the Hungry donkey test: A behavioral analysis. *Dev. Neuropsychol.* **42**, 521–533. https://doi.org/10.1080/87565641.2017.1404065 (2017).
65. Trinh, M. H. *et al.* Association of trajectory and covariates of children's screen media time. *JAMA Pediatr.* **174**, 71–78. https://doi.org/10.1001/jamapediatrics.2019.4488 (2019).
66. Hooper, C. J., Luciana, M., Conklin, H. M. & Yarger, R. S. Adolescents' performance on the iowa gambling task: Implications for the development of decision making and ventromedial prefrontal Cortex. *Dev. Psychol.* **40**, 1148–1158. https://doi.org/10.1037/0012-1649.40.6.1148 (2004).
67. Hong, S.-B. *et al.* Reduced orbitofrontal cortical thickness in male adolescents with internet addiction. *Behav. Brain Funct.* **9**, 11. https://doi.org/10.1186/1744-9081-9-11 (2013).
68. Lin, F. *et al.* Abnormal white matter integrity in adolescents with internet addiction disorder: A tract-based spatial statistics study. *PLOS ONE* **7**, e30253. https://doi.org/10.1371/journal.pone.0030253 (2012).
69. Kuss, D. J. & Griffiths, M. D. Internet and gaming addiction: a systematic literature review of neuroimaging studies. *Brain Sci.* **2**, 347–374 (2012).
70. Weinstein, A. & Lejoyeux, M. New developments on the neurobiological and pharmaco-genetic mechanisms underlying internet and videogame addiction. *Am. J. Addict.* **24**, 117–125. https://doi.org/10.1111/ajad.12110 (2015).
71. Montag, C. & Reuter, M. *Internet Addiction* (Springer, 2017).
72. Scharkow, M. The accuracy of self-reported internet use—a validation study using client log data. *Commun. Methods Meas.* **10**, 13–27. https://doi.org/10.1080/19312458.2015.1118446 (2016).
73. Mireku, M. O. *et al.* Total recall in the SCAMP cohort: Validation of self-reported mobile phone use in the smartphone era. *Environ. Res.* **161**, 1–8. https://doi.org/10.1016/j.envres.2017.10.034 (2018).
74. Voorveld, H. A., Segijn, C. M., Ketelaar, P. E. & Smit, E. G. Investigating the prevalence and predictors of media multitasking across countries. *Int. J. Commun.* **8**, 2755–2777 (2014).
75. West, S. G., Finch, J. F. & Curran, P. J. Structural equation models with nonnormal variables: Problems and remedies. In *Structural Equation Modeling: Concepts, Issues, and Applications* (ed. Hoyle, R. H.) 56–75 (Sage Publications, Inc. 1995).

Acknowledgements
The research was done in the framework of the I.Family study (http://www.ifamilystudy.eu). We are thankful for the participation of European children and adolescents and their parents in our study as well as the support received from school boards, headmasters, and communities.

Author contributions
The authors' contributions were: E.S. wrote the paper and performed the data analysis; E.S., A.H., C.B., and W.A. designed the research; G.E., A.F., V.P., L.L., A.M., N.M., D.M., L.M., H.P., M.T., T.V., and W.A. participated in the coordination of data collection and the project administration; J.C. supported the interpretation of the findings; E.S., C.B., and A.H. had primary responsibility for the final content; E.S. and C.B. had full access to all the data of the study and take responsibility for the integrity of the data and accuracy of the data analysis. All authors were responsible for critical revisions and final approval of the manuscript.

Funding
Open Access funding enabled and organized by Projekt DEAL. This research was funded by the European Community within the Seventh RTD Framework Programme Contract No. 266044. The funding sources had no role in the design and conduct of the study; collection, management, analysis, and interpretation of the data; preparation, review, or approval of the manuscript; and decision to submit the manuscript for publication.

Competing interests
The authors declare no competing interests.

Additional information

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1038/s41598-023-45944-0.

Correspondence and requests for materials should be addressed to A.H.

I. Family consortium

Elida Sina[1], Gabriele Eiben[4], Annarita Formisano[5], Lauren Lissner[6], Artur Mazur[7], Nathalie Michels[8], Dénes Molnar[9], Valeria Pala[11] & Lucia Reisch[1,12]

Paper 4

Media use trajectories and risk of metabolic syndrome in European children and adolescents: the IDEFICS/I.Family cohort

Sina, Elida, Buck, Christoph, Veidebaum, Thomas, Siani, Alfonso, Reisch, Lucia, Pohlabeln, Hermann, Pala, Valeria, Moreno, Luis A., Molnar, Dénes, Lissner, Lauren, Kourides, Yannis, De Henauw, Stefaan, Eiben, Gabriele, Ahrens, Wolfgang, Hebestreit, Antje, & IDEFICS, I.Family consortia (2021). Media use trajectories and risk of metabolic syndrome in European children and adolescents: the IDEFICS/I.Family cohort. *The international journal of behavioral nutrition and physical activity*, *18*(1), 134. https://doi.org/10.1186/s12966-021-01186-9

Sina et al. Int J Behav Nutr Phys Act (2021) 18:134
https://doi.org/10.1186/s12966-021-01186-9

International Journal of Behavioral
Nutrition and Physical Activity

RESEARCH

Open Access

Media use trajectories and risk of metabolic syndrome in European children and adolescents: the IDEFICS/I.Family cohort

Elida Sina[1], Christoph Buck[1], Toomas Veidebaum[2], Alfonso Siani[3], Lucia Reisch[4], Hermann Pohlabeln[1], Valeria Pala[5], Luis A. Moreno[6], Dénes Molnar[7], Lauren Lissner[8], Yiannis Kourides[9], Stefaan De Henauw[10], Gabriele Eiben[11], Wolfgang Ahrens[1,12] and Antje Hebestreit[1*] on behalf of the IDEFICS, I.Family consortia

Abstract

Background: Media use may influence metabolic syndrome (MetS) in children. Yet, longitudinal studies are scarce. This study aims to evaluate the longitudinal association of childhood digital media (DM) use trajectories with MetS and its components.

Methods: Children from Belgium, Cyprus, Estonia, Germany, Hungary, Italy, Spain and Sweden participating in the IDEFICS/I.Family cohort were examined at baseline (W1: 2007/2008) and then followed-up at two examination waves (W2: 2009/2010 and W3: 2013/2014). DM use (hours/day) was calculated as sum of television viewing, computer/game console and internet use. MetS z-score was calculated as sum of age- and sex-specific z-scores of four components: waist circumference, blood pressure, dyslipidemia (mean of triglycerides and HDL-cholesterol^{-1}) and homeostasis model assessment for insulin resistance (HOMA-IR). Unfavorable monitoring levels of MetS and its components were identified (cut-off: ≥ 90th percentile of each score). Children aged 2–16 years with ≥ 2 observations (W1/W2; W1/W3; W2/W3; W1/W2/W3) were eligible for the analysis. A two-step procedure was conducted: first, individual age-dependent DM trajectories were calculated using linear mixed regressions based on random intercept (hours/day) and linear slopes (hours/day/year) and used as exposure measures in association with MetS at a second step. Trajectories were further dichotomized if children increased their DM duration over time above or below the mean.

Results: 10,359 children and adolescents (20,075 total observations, 50.3% females, mean age = 7.9, SD = 2.7) were included. DM exposure increased as children grew older (from 2.2 h/day at 2 years to 4.2 h/day at 16 years). Estonian children showed the steepest DM increase; Spanish children the lowest. The prevalence of MetS at last follow-up was 5.5%. Increasing media use trajectories were positively associated with z-scores of MetS (slope: β = 0.54, 95%CI = 0.20–0.88; intercept: β = 0.07, 95%CI = 0.02–0.13), and its components after adjustment for puberty, diet and other confounders. Children with increasing DM trajectories above mean had a 30% higher risk of developing MetS (slope: OR = 1.30, 95%CI = 1.04–1.62). Boys developed steeper DM use trajectories and higher risk for MetS compared to girls.

Conclusions: Digital media use appears to be a risk factor for the development of MetS in children and adolescents. These results are of utmost importance for pediatricians and the development of health policies to prevent cardio-metabolic disorders later in life.

*Correspondence: sec-epi@leibniz-bips.de
[1] Leibniz Institute for Prevention Research and Epidemiology-BIPS, Achterstraße 30, 28359 Bremen, Germany
Full list of author information is available at the end of the article

Trial registration: ISRCTN, ISRCTN62310987. Registered 23 February 2018- retrospectively registered.

Keywords: Longitudinal study, Digital media, Screen-time, Metabolic disorders, Sedentary behavior, Physical activity, Diet quality, Children, Adolescents

Background

Non-communicable diseases have reached alarming proportions worldwide [1]. Cardiovascular diseases in adults are associated with cardio-metabolic factors including hypertension, dyslipidaemia, abdominal obesity and abnormal glucose regulation- the combination of which is known as metabolic syndrome (MetS) [2]. These associations are observed in children as well [3]. Cohort studies have shown that childhood MetS is associated with a 2.4 fold risk of MetS in adulthood [4].

Unhealthy eating, low levels of physical activity and sedentary behaviours (SB), the latter characterized by activities that require low energy expenditure performed in reclining or lying position such as sitting in front of screens, substantially contribute to the development of MetS [5]. World Health Organisation (WHO) has recognized the adverse role of prolonged exposure to digital media (DM) in childhood obesity and recommends that children and adolescents should limit recreational screen-time [6]. Remarkably, current evidence suggests that average screen-time (excluding school-related work) stands at 5 h/day in children and 8 h/day in adolescents [7]. This underlines the displacement of physical activity in favour of screen-based activities which may associate with adverse health outcomes.

Cross-sectional studies have reported a positive relationship between screen-media exposure and metabolic disorders in obese children [8–11]. Prolonged television viewing (TV) has been associated with obesity throughout the life course [12], but represents only one component of screen-time. With increasing age, TV is displaced by other digital media (e.g. computer use) which provide access to internet platforms [13]. Thus, it is important to evaluate the combined impact of these media types on the development of MetS, particularly in youth.

Evidence on the longitudinal associations between DM use and MetS in children and adolescents is currently lacking. Hence, based on the definition of childhood MetS developed by Ahrens et al. (2014) [14], we aim to investigate the longitudinal association of DM use during childhood with incident MetS and its components, including abdominal obesity, dyslipidaemia, insulin resistance (IR) and high blood pressure (BP) at two to six years after baseline examination in European children and adolescents. We use a trajectory analysis approach while taking into account sex and country discrepancies. Moreover, in a sample with available accelerometer data, we investigate the confounding role of objectively-measured sedentary time (SED) and moderate to vigorous physical activity (MVPA) in the association between DM use and MetS.

Methods

Design

The IDEFICS/I.Family cohort includes children and adolescents from 8 European countries: Belgium, Cyprus, Estonia, Germany, Hungary, Italy, Spain and Sweden. During 2007–2008, 16,229 children aged 2–9 years, meeting the basic inclusion criteria (complete information on age, sex, weight and height; attending kindergartens or grade 1 and 2 of primary schools and residing in the respective regions) participated in baseline (W1) [15]. In the second wave (W2: 2009–2010), 13,596 children were re-examined (68% of W1 (11,041); 2555 children were newly recruited from new families)). The I.Family study (2013–2014) represents the third wave (W3), where 9,617 children and (meanwhile) adolescents aged 2–17 years were re-examined: 73.8% of them already participated at W2 (7105) while 2512 were new children (siblings from the same families) [15, 16]. Informed consent was obtained from adolescents (≥ 12 years), and the assent was given from younger children, in addition to parental informed consent, at all study waves. Ethical approval was obtained from local ethic committees of each study center.

Participants

The cohort includes 21,272 children and adolescents who participated at baseline and/or at one or two follow-up examinations (W1/W2; W1/W3; W2/W3; W1/W2/W3), accounting for 39,433 observations in total. Observations excluded were those with implausible age at follow up ($N=6$), implausibly high DM use (>50 h/week, $N=137$), missing information on DM ($N=3{,}240$) and all metabolic risk-factors ($N=1{,}031$); aged > 16 years or being non-fasting during blood sampling ($N=1{,}745$); suffering from chronic diseases (e.g. MetS, Type 2 Diabetes) at baseline or taking related medications (W1: $N=131$; W2: $N=204$; W3: $N=15$). The analysis group was restricted to children participating in ≥ 2 examination waves, leading to a final analysis population of 10,359 children (24,075 observations in total; 41.8% contributed three observations (i.e. 10,071 observations of 3357 children). The observation period ranged between 2 to 6 years (median = 5 years) as children could enter the cohort at W1 in 2007/08 or at W2 in 2009/10 (median age = 6.3 years, (IQR = 4.5–7.6 years)) and were then followed up until W3 in 2013/14. The median age at last follow-up was 10 years (IQR = 8.6–12.2 years).

Media use

DM use was proxy-reported by parents of children aged < 12 years and self-reported by adolescents, using respectively a parental and a teen version of the core questionnaire, pre-tested for reliability and acceptability [17]. Information on TV and computer/game console use was separately reported for weekdays and weekend days in all waves as: "Not at all, < 30 min/day, < 1 h/day, 1–2 h/day, 2–3 h/day, > 3 h/day". At W3, duration of internet use was additionally provided as a proxy for the exposure to online games and online advertisements for unhealthy foods. Total DM use was calculated as sum of the weighted average of durations reported for weekdays and weekend days (minutes/week) at all waves for all screen-time behaviors (TV, PC and internet use for W3), and quantified as hours/day. Hereinafter, the terms DM use and screen-time will be interchangeably used.

Clinical and laboratory evaluations

Blood pressure (BP) was measured in children after resting for 5 min in a sitting position using an automated oscillometric device (Welch Allyn 4200B-E2, Welch Allyn Inc., New York, NY, USA) [18]. The average of two measurements [19] was calculated for the analysis. Waist circumference (WC) was measured according to the international standards of kinanthropometry [20]. Fasting blood samples were collected and levels of glucose, insulin, high-density lipoprotein cholesterol (HDL-c) and triglycerides were measured [14]. The Homeostasis Model Assessment for Insulin Resistance (HOMA-IR) was calculated as (fasting insulin*fasting glucose)/405 [21]. Age and sex-specific z-scores were derived for children and adolescents aged 2–16 years for WC [22], HDL-c, triglycerides [23], diastolic and systolic BP (and height-specific) [19] and HOMA-IR [21].

Metabolic syndrome

A continuous score for cardio-metabolic risk has been proposed by Ahrens et al. (2014) [14], to combine the four components of MetS. The additive MetS score was calculated as sum of z-scores of HOMA-IR, WC, BP (mean of age-, sex- and height-specific z-scores of diastolic and systolic BP), and dyslipidemia (mean of z-scores of triglycerides and HDL-c, the latter multiplied with -1 due to the inverse relationship with the metabolic risk).

A monitoring level for MetS [14] was defined if at least three of the four MetS components exceeded the 90^{th} percentile of the respective age- and sex-specific distributions. Unfavorable levels of the four components were identified (monitoring level: $\geq 90^{th}$ percentile): abdominal obesity measured via WC, IR measured via HOMA-IR or fasting insulin; hypertension via diastolic or systolic BP and dyslipidemia via triglycerides or HDL-c ($\leq 10^{th}$ percentile). Subsequently, children being at the monitoring level for MetS and its components were considered as requiring closer monitoring by the clinician. For clarity, the terms MetS, abdominal obesity, elevated BP, dyslipidemia and IR will be respectively used to refer to the monitoring level for each metabolic outcome.

Potential confounders

Using a food frequency questionnaire—previously tested for relative validity and reproducibility [24, 25], participants reported the consumption frequency of unhealthy snacks (times/week) during the past four weeks (self-reported by adolescents or proxy reported by parents of younger children), including sugar-sweetened drinks, chocolate/nut-based spread, crisps, corn crisps and popcorn, chocolate/candy bars, candies, loose candies and marshmallows. The median of daily consumption frequency was calculated and categorized as high vs. low snack intake. In addition, a healthy diet adherence score (HDAS) was derived, as indicator of adherence to dietary recommendations [26] on fruits and vegetables intake, whole-meal foods, fish, refined sugars and fat intakes. The HDAS ranged from 0 to 50 and dichotomized as high (median ≥ 20) vs. low (median < 20) diet quality. These variables were considered due to the close relationship with metabolic health and screen-time in children [5]. For participants with available accelerometer data (W1: N = 4640, W2: N = 4344, W3 = 3238), daily moderate-to-vigorous physical activity (MVPA) and sedentary-time (SED) was measured using Actigraph accelerometers (Actigraph, LLC, Pensacola, FL, USA). The valid accelerometer wear-time (≥ 6 h/day) and total time spent in ≥ 30 min SED-bouts (derived allowing 2 min. of accumulated activities within 30 min. of sedentary time according to Evenson et al. cut-point [27]) and ≥ 10 min MVPA-bouts was calculated. These cut-offs were selected because: i) ≥ 10 min MVPA-bouts have been shown to confer benefits in children's cardio-metabolic health [28]; ii) ≥ 30 min SED-bouts facilitates comparison with previous studies conducted in the same age range [29, 30]. The SED-time in bouts was categorized at median = 798 min/day as high vs. low SED-time. Regarding MVPA-time in bouts (median of any MVPA = 34 min/day), children were classified as: physically inactive (MVPA = 0 min/day), low MVPA (0 < MVPA ≤ 34 min/day) and high MVPA duration (> 34 min/day) in order to observe underlying differences between groups. As puberty influences physiological (e.g. hormonal changes), psychosocial and behavioral processes (e.g. sedentary patterns) [31], children aged ≥ 8 years (at W3) provided information on puberty status as: changes in voice (boys) and onset of menarche (girls) [32]. In a smaller sample (N = 2999), information on pubertal Tanner stage: pubic hair (boys) and breast development (girls) was obtained to complement the information on puberty [33]. Highest parental educational attainment was self-reported and classified according to the International Standard Classification of Education (ISCED) [34] as high, medium and low ISCED. Further details on covariates are given in the Supplementary file.

Statistical analyses

Descriptive characteristics of the analysis population were generated (number and percentage) by sex and study wave at the most recent measurement point (W2 or W3). Missing values for HDAS, snacking frequency, pubertal status and ISCED were treated as an additional category (i.e. included in the analyses as missing category) to make better use of data provided on outcomes and exposure. Characteristics of participants excluded were compared to those included in the analysis population (eTable 1).

To investigate the role of DM use over time on MetS (and its components), a two-step trajectory analysis approach was used. This approach allows comparisons of individuals' DM use over the age-span of the cohort, thus evaluating changes in DM duration (hours/day) with increasing age such that each child has its individual DM trajectory. This approach handles DM assessments at different time points and unbalanced data with different number of repeated measures per child as well as subjects measured at different ages [35–37].

First step: Linear DM trajectories over the age-span of the cohort

Trajectories of DM duration over age (2 to 16 years, centred at age 8) were estimated using linear mixed models including two levels (repeated measurements nested within individuals) to reduce data dimensionality and to derive exposure measures that are comparable between children. Models considered a random intercept and random linear slope over age per each child. To account for repeated measurements, the subject-specific DM intercepts and slopes were estimated from fixed and random effects. The random DM intercept (hours/day) and slope (hours/day/year) indicate the deviations for child i from the average DM use across childhood (2–16 years) and from the average velocities (slopes) of DM increase over the age span (between 2–16 years), respectively. A detailed description of the mixed models is provided in the Supplementary material. Further, to investigate a fanning pattern and possible multicollinearity of random intercept and random slope, we calculated the covariance of both subject-specific parameters and further considered the tolerance and variance inflation factor (VIF) in regression models of step 2. Covariance was almost zero and did not indicate any fanning pattern as well as tolerance and VIF did not show any multicollinearity in regression models of step 2, particularly for random intercept and random slopes (results not shown). Age-dependent trajectories were additionally calculated by sex and country of residence (i.e. model was respectively stratified on sex and country, thus considering sex- and country-specific population intercept and slope), in order to take into account country- and sex-specific DM habits.

Second step: DM trajectories in association with MetS

The estimated individual DM intercepts and slopes were used as exposure variables in the longitudinal association with z-scores of MetS, WC, BP, HOMA-IR, HDL-c and triglycerides, at the most recent examination (W2 or W3, i.e. the highest age of each individual within the cohort). Generalized linear mixed regressions without a random effect were used to estimate regression coefficients (β) and 95% confidence intervals (95%CI), adjusting for confounders from the most recent examination: continuous age, sex, puberty status (ref. pre-pubertal), ISCED (ref. high), snack intake (high vs. low), HDAS (high vs. low); country as well as observation period (the difference between age at last follow-up and age at baseline), and baseline z-score of the respective outcome. When adiposity was not part of the outcome (i.e. BP, HOMA-IR, triglycerides, HDL-c), models were further adjusted for current WC z-score. Due to missing values for different components, sample size varied. These analyses were repeated in the sample with accelerometer data to observe if the association between DM trajectories and MetS attenuates in these children. At a later step, the role of physical activity was considered by further adjusting for MVPA- and SED-time in bouts (and accelerometer wear time).

The role of DM exposure over time on the risk of developing MetS (monitoring level) and its components was further investigated. The slopes of DM trajectories were dichotomized at the population mean (random slope = 0), to identify children with increasing DM above or below the average. Logistic regressions were used to estimate odds ratios (OR) and 95% CI adjusting for individual continuous intercept and confounders, except PA. Children being at monitoring level (≥ 90th percentile) for MetS, abdominal obesity, BP, IR, and dyslipidaemia at baseline, were excluded from the respective analyses, in order to evaluate the long-term role of DM trajectories in the incident MetS and its components. The sample size varied due to missing values on single components.

Additional analyses

The association of DM slope (categorized) with MetS was further investigated stratifying by sex, to observe sex-specific differences, and by country, to account for cross-country discrepancies. In a sensitivity analysis, we stratified the analysis group by parental ISCED to evaluate a potential interaction in the relationship between DM trajectories and MetS, as observed previously [38, 39]. Level of significance was set to $\alpha \leq 0.05$, without adjusting for multiple testing. Statistical analyses were conducted using SAS 9.4 (Statistical Analyses System, SAS Institute Inc., Cary, NC, USA).

Results

A total of 10,359 children (50.3% girls), aged 2–16 years (mean = 7.9, SD = 2.7), with at least two observations were eligible (in total: 24,075 observations- described in eTable 2 by sex and examination wave). The excluded participants (eTable 1) were mostly boys, less than 12 years of age and pre-pubertal, with missing information on parental ISCED, diet quality and unhealthy snack intake frequency. A quarter (25%) of the excluded children and adolescents were from Cyprus. The characteristics of the analysis group at the last follow-up are described in Table 1. Overall, DM exposure increased as children grew older (Fig. 1), from 2.2 h/day at age 2 to 4.3 h/day at age 16 (mean intercept = 1.95 h/day, mean slope = 0.14 h/day/year). Boys developed a steeper DM increase compared to girls (Fig. 2). Estonian children showed the steepest increase (2.7 h/day at age 2 to 5.2 h/day at age 16), followed by Swedish and Cypriot children which were all above the average. Spanish children showed the lowest DM increase (1.8 h/day at age 2 to 3.2 h/day at age 16). Of all children, 28.7% suffered from abdominal obesity, 13.5% from dyslipidemia, 15.6% from IR, 17.4% showed elevated BP, and 5.5% were classified with MetS (monitoring level) (Table 1).

The regression results (Table 2) showed positive association between DM intercept (h/day) and slope (h/day/year) and WC z-score (intercept: $\beta = 0.15$, 95%CI = 0.11, 0.19; slope: $\beta = 0.19$; 95%CI = -0.04, 0.43). DM trajectories were positively associated with the later MetS z-score (intercept: $\beta = 0.07$, 95%CI = 0.02, 0.13; slope: $\beta = 0.54$, 95%CI = 0.20, 0.88), indicating that one hour increase in DM over time increased the MetS-score with 0.54. The repeated analysis in children with accelerometer data showed similar results. Further adjustment for MVPA and SED-time did not attenuate the associations, indicating positive associations between both DM intercept and slope and the later MetS z-score. However, larger confidence intervals were observed, due to the lower sample size. Positive associations were also observed between DM intercept and slopes and z-scores of BP, HOMA-IR and triglycerides, while inverse associations were observed with HDL-c z-score.

The logistic regression based on DM slope categories (Table 3) showed that children with increasing DM use above average had 30% higher risk of developing MetS (OR = 1.30, 95%CI = 1.04–1.62). This risk was higher in children with more educated parents (high ISCED: OR = 1.56, 95%CI = 1.07–2.26; medium: OR = 1.22, 95%CI = 0.90–1.66, low: OR = 0.92, 95%CI = 0.45–1.86) (eTable 3). Boys with increased DM above average had higher risk for elevated BP and IR, and 62% higher risk for MetS (OR = 1.62, 95%CI = 1.17–2.24). One hour increase in DM intercept was positively associated with MetS, abdominal obesity and IR in both sexes; stronger associations were observed for elevated BP and dyslipidemia in boys, compared to girls.

The country-stratified analyses are presented in Table 4. In Cyprus, children with increased DM use above average had two-fold higher risk of developing MetS (OR = 2.66, 95%CI = 1.38–5.14); while positive associations were observed for dyslipidemia (OR = 1.66, 95%CI = 1.05–2.63) and IR (OR = 1.45, 95%CI = 0.96–2.16). In Estonia and Sweden- also countries with above average DM trajectories- children had increased risk of developing abdominal obesity and MetS; Belgian children showed almost two-fold higher risk of developing elevated BP (OR = 1.87; 95%CI = 1.16–3.02) and MetS (OR = 2.08, 95%CI = 0.37–11.58). In Hungary, children with increased slope had higher risk for MetS, elevated BP and abdominal obesity. Remarkably, increasing DM intercept showed higher risk for MetS and its components across all countries, except Italy.

Discussion

Key findings

In children of the IDEFICS/I.Family cohort, DM exposure increased with age, from 2.2 h/day at age 2 to 4.3 h/day at age 16. Estonian children showed the strongest DM increase while Spanish children showed the weakest. The average DM exposure across childhood (intercept) and increase of DM over time (slope- i.e. DM trajectory) were independently associated with the later z-scores of MetS and its components. Children with increased DM trajectories showed higher risk of developing MetS later in life.

These findings build upon previous cross-sectional studies where screen-time was positively associated with MetS [11, 40, 41]. Earlier investigations on IDEFICS children showed that DM use increased the risk for IR after two years [42], and having a

Table 1 Metabolic risk profiles and characteristics of analysis population at the most recent examination point

	Most recent examination point				All
	W2		W3		
	Sex				
	Boys	Girls	Boys	Girls	
	N (%)	N (%)	N (%)	N (%)	N (%)
All	2550 (24.6)	2543 (24.5)	2594 (25.0)	2672 (25.8)	10,359 (100.0)
DM trajectory					
Below mean	1274 (12.3)	1249 (12.1)	1312 (12.7)	1546 (14.9)	5381 (51.9)
Above mean	1276 (12.3)	1294 (12.5)	1282 (12.4)	1126 (10.9)	4978 (48.1)
Age group					
< 12 years	2550 (24.6)	2543 (24.5)	1410 (13.6)	1428 (13.8)	7931 (76.6)
≥ 12 years	0 (0)	0 (0)	1184 (11.4)	1244 (12.0)	2428 (23.4)
ISCED[a]					
Low	143 (1.4)	121 (1.2)	147 (1.4)	139 (1.3)	550 (5.3)
Medium	1088 (10.5)	1089 (10.5)	1104 (10.7)	1160 (11.2)	4441 (42.9)
High	1297 (12.5)	1309 (12.6)	1323 (12.8)	1353 (13.1)	5282 (51.0)
Missing	22 (0.2)	24 (0.2)	20 (0.2)	20 (0.2)	86 (0.8)
HDAS					
High	1336 (12.9)	1395 (13.5)	1085 (10.5)	1114 (10.8)	4930 (47.6)
Low	1097 (10.6)	1013 (9.8)	1426 (13.8)	1469 (14.2)	5005 (48.3)
Missing	117 (1.1)	135 (1.3)	83 (0.8)	89 (0.9)	424 (4.1)
Snack intake					
High	1012 (9.8)	967 (9.3)	1643 (15.9)	1610 (15.5)	5232 (50.5)
Low	1263 (12.2)	1261 (12.2)	723 (7.0)	858 (8.3)	4105 (39.6)
Missing	275 (2.7)	315 (3.0)	228 (2.2)	204 (2.0)	1022 (9.9)
Puberty status					
Pre-pubertal	1123 (10.8)	999 (9.6)	1387 (13.4)	1514 (14.6)	5023 (48.5)
Pubertal	0 (0.0)	0 (0.0)	1040 (10.0)	1035 (10.0)	2075 (20.0)
Missing	1427 (13.8)	1544 (14.9)	167 (1.6)	123 (1.2)	3261 (31.5)
Country					
Italy	326 (3.1)	297 (2.9)	530 (5.1)	514 (5.0)	1667 (16.1)
Estonia	269 (2.6)	301 (2.9)	403 (3.9)	444 (4.3)	1417 (13.7)
Cyprus	327 (3.2)	333 (3.2)	524 (5.1)	509 (4.9)	1693 (16.3)
Belgium	311 (3.0)	303 (2.9)	103 (1.0)	126 (1.2)	843 (8.1)
Sweden	366 (3.5)	361 (3.5)	295 (2.8)	307 (3.0)	1329 (12.8)
Germany	209 (2.0)	215 (2.1)	354 (3.4)	358 (3.5)	1136 (11.0)
Hungary	359 (3.5)	380 (3.7)	205 (2.0)	220 (2.1)	1164 (11.2)
Spain	383 (3.7)	353 (3.4)	180 (1.7)	194 (1.9)	1110 (10.7)
Abdominal adiposity					
No	1875 (18.1)	1831 (17.7)	1754 (16.9)	1867 (18.0)	7327 (70.7)
Yes	664 (6.4)	708 (6.8)	821 (7.9)	781 (7.5)	2974 (28.7)
Missing	11 (0.1)	4	19 (0.2)	24 (0.2)	58 (0.6)
Elevated BP					
No	1944 (18.8)	2037 (19.7)	2109 (20.4)	2209 (21.3)	8299 (80.1)
Yes	548 (5.3)	443 (4.3)	419 (4.0)	390 (3.8)	1800 (17.4)
Missing	58 (0.6)	63 (0.6)	66 (0.6)	73 (0.7)	260 (2.5)
Dyslipidaemia					
No	1425 (13.8)	1406 (13.6)	1542 (14.9)	1599 (15.4)	5972 (57.7)
Yes	385 (3.7)	408 (3.9)	315 (3.0)	292 (2.8)	1400 (13.5)

Table 1 (continued)

	Most recent examination point				All
	W2		W3		
	Sex				
	Boys	Girls	Boys	Girls	
	N (%)	N (%)	N (%)	N (%)	N (%)
Missing	740 (7.1)	729 (7.0)	737 (7.1)	781 (7.5)	2987 (28.8)
Insulin resistance					
No	1599 (15.4)	1520 (14.7)	1480 (14.3)	1504 (14.5)	6103 (58.9)
Yes	442 (4.3)	496 (4.8)	332 (3.2)	342 (3.3)	1612 (15.6)
Missing	509 (4.9)	527 (5.1)	782 (7.5)	826 (8.0)	2644 (25.5)
MetS					
No	1607 (15.5)	1605 (15.5)	1627 (15.7)	1668 (16.1)	6507 (62.8)
Yes	159 (1.5)	165 (1.6)	127 (1.2)	117 (1.1)	568 (5.5)
Missing	784 (7.6)	773 (7.5)	840 (8.1)	887 (8.6)	3284 (31.7)

[a] *W2* second wave of follow-up, *W3* third examination wave, *DM* digital media, *ISCED* parental educational status, *HDAS* healthy diet adherence score (diet quality), *BP* blood pressure, *MetS* metabolic syndrome

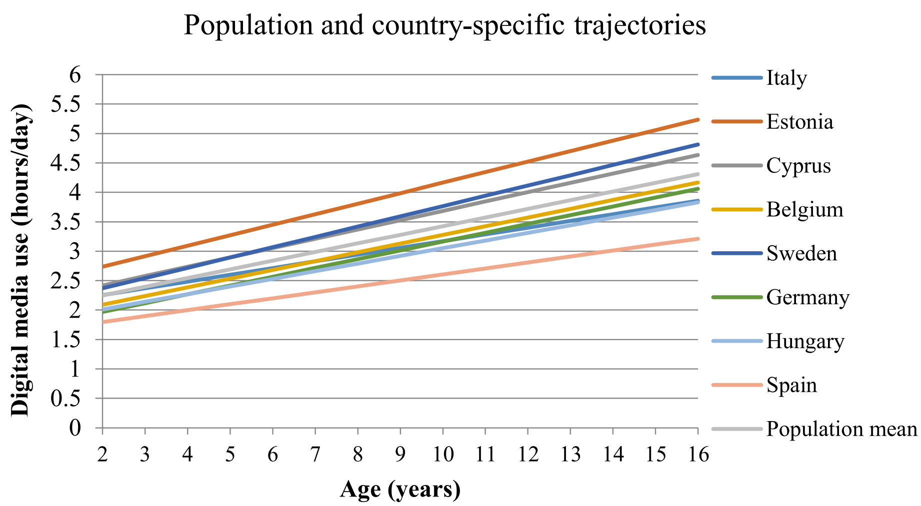

Fig. 1 Country-specific digital media use trajectories in European children and adolescents

media device in child's bedroom increased the odds for abdominal obesity and MetS [43]. In our analysis, the associations of DM trajectories with z-scores of MetS, WC, BP, HOMA-IR and HDL^{-1} remained after adjustment for MVPA and SED-time, supporting previous findings [44]. One underlying explanation could be that sedentary screen-time in children is associated with lower metabolic rate (i.e. energy expenditure) compared to rest condition [45]. Further, children might engage with screen-based and MVPA-based activities simultaneously (e.g. exposure to age inappropriate advertisements such as those with violent content or for unhealthy foods while dancing to a music video on the internet) [46], thus undermining the positive effects of MVPA on metabolic health. These findings also shed light on a methodological aspect whereby digital media exposure is associated with metabolic syndrome independently of total sedentary time, thus they should not be interchangeably used, supporting previous concerns on examining different types of sedentary behaviors in relation with health outcomes [47].

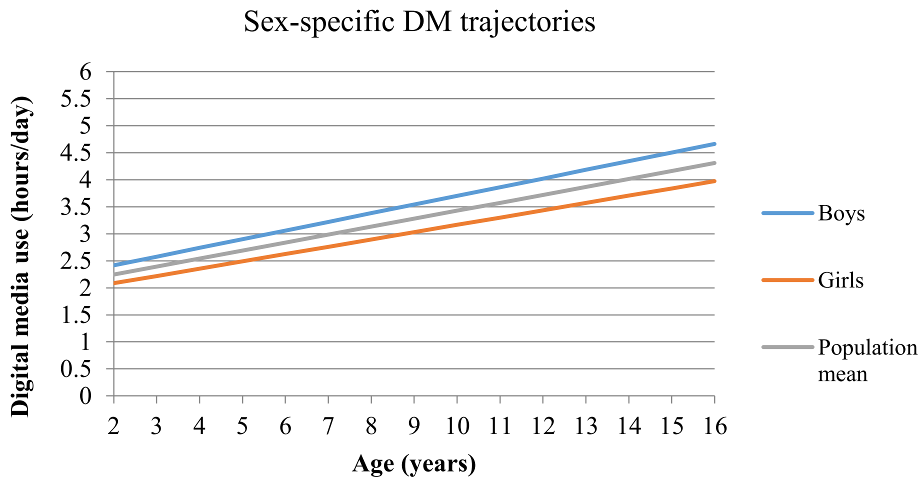

Fig. 2 Sex-specific digital media use trajectories in European children and adolescents

Table 2 Association of average DM across childhood (intercept) and increase of DM over time (slope) with metabolic syndrome score and its components in children and adolescents

Metabolic outcomes	DM use			Analysis population[a]		Accelerometer –sample [b]		
		N	Crude β (95%CI)	N	Adjusted β (95%CI) [a]	N	Adjusted β (95% CI) [b]	Adjusted β (95% CI) [c]
z_WC [d]	Intercept	10,301	**0.33 (0.28, 0.39)**	10,153	**0.15 (0.11, 0.19)**	4258	**0.19 (0.13, 0.26)**	**0.19 (0.12, 0.25)**
	Slope		-0.05 (-0.40, 0.29)		0.19 (-0.04, 0.43)		0.26 (-0.10, 0.63)	0.26 (-0.10, 0.63)
z_BP [e]	Intercept	10,099	**0.04 (0.01, 0.08)**	9409	**0.04 (0.00, 0.07)**	4073	0.02 (-0.03, 0.08)	0.02 (-0.03, 0.07)
	Slope		-0.05 (-0.27, 0.16)		0.09 (-0.10, 0.30)		0.18 (-0.13, 0.49)	0.16 (-0.14, 0.47)
z_TRG	Intercept	7398	**0.11 (0.07, 0.15)**	6193	**0.08 (0.03, 0.12)**	2683	0.06 (-0.01, 0.13)	0.06 (-0.01, 0.13)
	Slope		0.17 (-0.08, 0.44)		0.02 (-0.24, 0.30)		0.01 (-0.40, 0.42)	0.00 (-0.41, 0.41)
z_HDL-c	Intercept	7766	**-0.10 (-0.14, -0.06)**	6506	**-0.08 (-0.12, -0.04)**	2857	**-0.07 (-0.14, -0.002)**	**-0.07 (-0.14, -0.00)**
	Slope		**-0.35 (-0.63, -0.06)**		**-0.28 (-0.54, -0.02)**		-0.32 (-0.72, 0.07)	-0.33 (-0.73, 0.06)
z_HOMA	Intercept	6293	**0.16 (0.11, 0.22)**	3435	**0.12 (0.05, 0.19)**	1688	**0.15 (0.05, 0.26)**	**0.15 (0.04, 0.25)**
	Slope		0.19 (-0.13, 0.51)		0.64 (0.21, 1.08)		0.58 (-0.01, 1.18)	0.59 (0.00, 1.19)
z_MetS	Intercept	5770	**0.16 (0.11, 0.21)**	2973	**0.07 (0.02, 0.13)**	1476	0.07 (-0.01, 0.15)	0.06 (-0.02, 0.14)
	Slope		0.14 (-0.15, 0.44)		**0.54 (0.20, 0.88)**		**0.51 (0.04, 0.97)**	**0.49 (0.02, 0.95)**

[a] Models are adjusted for age (continuous), sex, pubertal status, HDAS, snack consumption, parental ISCED, observation period, (age at follow-up – age at baseline), country and baseline z-scores of the respective outcome. Bold significance is provided via confidence limits

[b] Models are based on the accelerometer sample and are adjusted for same confounders as in the main analysis. N varied due to missing values for each outcome

[c] Models based on sample with accelerometer data are further adjusted for MVPA, SED and valid accelerometer wear time

[d] WC- waist circumference, BP-blood pressure, TRG- triglycerides, HDL-c– high density lipoprotein cholesterol, HOMA- homeostasis model assessment for insulin resistance, MetS- metabolic syndrome, DM- digital media

[e] Models for the z-scores of BP, HDL-c, TRG and HOMA-IR are additionally adjusted for z-score of WC at the last measurement point. The number of participants varied for metabolic outcomes due to missing values

DM trajectories and risk of developing MetS—differences by sex

Children with DM trajectory above average showed higher risk of developing MetS, abdominal obesity and elevated BP. Both boys and girls with increasing average DM (intercept) showed an increased risk of developing MetS (58% in boys and 35% in girls), IR and abdominal obesity, indicating that a high, although stable DM use can deteriorate children's metabolic outcomes in the long-term, independently of sex, supporting previous evidence [11, 44]. An increased risk for elevated BP and dyslipidemia as average DM increased was found only in boys, but not in girls. Boys also showed a steeper DM trajectory compared

Table 3 Risk of metabolic syndrome and its components by DM slope and DM intercept in children and adolescents

Metabolic outcomes [a]	DM use	Analysis Population				Boys		Girls	
		N	Unadjusted OR (95% CI)	N	Adjusted OR (95% CI) [b]	N	Adjusted OR (95% CI) [c]	N	Adjusted OR (95% CI) [c]
Abdominal obesity	**Slope** [d]	8114	1.00 (0.89–1.13)	7966	1.05 (0.92–1.19)	3966	0.97 (0.81–1.16)	4000	1.12 (0.94–1.34)
	Intercept		**1.49 (1.32–1.67)**		**1.53 (1.35–1.75)**		**1.30 (1.09–1.56)**		**1.85 (1.53–2.24)**
High BP [e]	**Slope**	8425	1.01 (0.89–1.14)	7693	1.04 (0.91–1.20)	3809	1.13 (0.94–1.36)	3884	0.96 (0.78–1.17)
	Intercept		**1.18 (1.04–1.33)**		1.08 (0.94–1.25**)**		1.15 (0.96–1.38)		1.01 (0.81–1.26)
Dyslipidemia	**Slope**	6248	1.07 (0.93–1.23)	5001	1.00 (0.85–1.18)	2469	1.04 (0.82–1.32)	2532	0.93 (0.73–1.17)
	Intercept		**1.30 (1.14–1.48)**		**1.28 (1.08–1.51)**		**1. 42 (1.13–1.78)**		1.08 (0.84–1.39)
Insulin resistance	**Slope**	6797	0.96 (0.85–1.09)	5435	1.00 (0.87–1.16)	2728	**1.22 (1.00–1.50)**	2707	0.83 (0.68–1.02)
	Intercept		**1.35 (1.20–1.52)**		**1.16 (1.00–1.35)**		1.15 (0.93–1.41)		1.12 (0.90–1.41)
MetS	**Slope**	6843	**1.21 (1.01–1.46)**	5288	**1.30 (1.04–1.62)**	2636	**1.62 (1.17–2.24)**	2652	1.08 (0.80–1.47)
	Intercept		**1.55 (1.30–1.84)**		**1.50 (1.21–1.85)**		**1.58 (1.20–2.11)**		1.35 (0.97–1.87)

[a] The reference category for the metabolic outcomes is below the monitoring level

[b] Models are adjusted for age (continuous), sex, pubertal status, country, parental ISCED, HDAS, snack frequency intake, observation period, and abdominal obesity (when BP, IR and dyslipidemia were modeled). Bold significance is provided via confidence limits

[c] Models are adjusted for all covariates, besides sex (and physical activity variables)

[d] Slope was used as a categorical variable (above vs. below population mean random slope)

[e] BP-blood pressure, MetS- metabolic syndrome, DM- digital media

to girls. Previous evidence showed that boys are more likely to develop an increasing media use trajectory than girls [38]. A previous study reported that boys compared to girls, had higher screen-time, systolic BP and triglycerides, while lower HDL-c levels [10]. Furthermore, male sex has been described as a risk factor for childhood to early-midlife BP trajectories [48]. The different mechanisms of self-regulation and its role on health may provide further explanation. Digital media use (TV and mobile device) [49] is associated with poor self-regulation in children (e.g. inhibitory control, frustration tolerance), which in turn tends to be lower for boys than for girls [50]. Lower self-regulation in children increases the risk for elevated BP and cholesterol [51], as well as higher levels of stress [52]. A previous study based on our cohort [53] showed that lower psychological well-being was associated with cardio-metabolic disturbances. These data underline the importance that more efforts should be undertaken by physicians and parents to reduce DM use in boys, especially limiting (online) video-game use, which yet remains the most common screen-based activity among boys [54].

DM trajectories and risk of developing MetS—differences by country

DM duration above the average (slope) increased the risk of developing metabolic disorders in countries with the steepest DM trajectory- Cyprus and Sweden. Nevertheless, increasing average DM consistently increased the risk for MetS in all countries. Clear differences were observed between northern (Estonia, Sweden) and southern countries (Spain) on DM trajectories, which could be due to the different cultures in handling DM exposure in children. In Northern countries, a media-rich bedroom culture is more common in comparison with southern countries, i.e. children and adolescents have their own bedrooms installed with a TV set, game console, and PC [55] which raises concerns about parent's ability to control and regulate their children's media use. Moreover, differences in parental digital literacy between countries may also relate to the parenting role in childhood DM exposure [54]. However, no clear patterns were observed on the risk of developing MetS, indicating that globalization of DM exposure influences children's health independently of cultural/geographical differences.

Clinical relevance and recommendations

Evidence suggests that prevention, early identification and control of cardio-metabolic risk factors throughout childhood, to adolescence and into adulthood will substantially reduce clinical risk for cardio-metabolic diseases beginning in young adult life [56]. Our study shows that prolonged childhood DM exposure is an independent risk factor for metabolic syndrome and its components at later stages of life and may thus contribute to the development of MetS over time. In light of the current COVID-19 pandemic, these findings are of utmost importance. The implemented policies (e.g. school closures, lockdown) have led to higher screen-time in

Table 4 Age-dependent digital media use trajectories by country of residence and risk of developing metabolic syndrome [a]

Metabolic outcome [b]	DM use	Italy	Estonia	Cyprus	Belgium	Sweden	Germany	Hungary	Spain
	Mean intercept (h/day)	2.0258	2.3790	2.1022	1.7932	2.0210	1.6706	1.7521	1.5931
	Mean slope (h/day/year)	0.1144	0.1785	0.1583	0.1483	0.1746	0.1493	0.1298	0.1012
		Adjusted odds ratios (OR) and 95% confidence intervals (95% CI)							
Abdominal obesity	**Slope [c]**	0.90 (0.68–1.20)	1.21 (0.86-1.70)	1.03 (0.75–1.41)	0.74 (0.46–1.20)	**1.69 (1.05–3.23)**	0.93 (0.63–1.36)	1.31 (0.90–1.92)	0.99 (0.67–1.46)
	Intercept	1.28 (0.96–1.69)	**1.62 (1.17–2.23)**	**1.53 (1.11–2.09)**	**2.07 (1.21–3.54)**	**1.84 (1.05–3.23)**	**1.78 (1.24–2.57)**	1.13 (0.75–1.73)	**2.11 (1.32–2.38)**
Elevated BP [d]	**Slope**	1.28 (0.94–1.74)	0.98 (0.68–1.41)	1.12 (0.73–1.70)	**1.87 (1.16–3.02)**	0.68 (0.40–1.18)	0.79 (0.47–1.32)	1.17 (0.84–1.64)	0.71 (0.49–1.03)
	Intercept	0.96 (0.72–1.28)	1.28 (0.90–1.81)	1.24 (0.83–1.85)	1.66 (0.99–2.80)	1.04 (0.52–2.07)	0.86 (0.50–1.47)	1.05 (0.73–1.50)	0.88 (0.55–1.41)
Dyslipidemia	**Slope**	0.96 (0.67–1.17)	1.00 (0.63–1.58)	**1.66 (1.05–2.63)**	0.61 (0.18–2.04)	1.19 (0.73–1.94)	0.86 (0.50–1.50)	0.86 (0.56–1.30)	0.77 (0.45–1.30)
	Intercept	1.10 (0.80–1.52)	1.46 (0.94–2.28)	1.09 (0.69–1.73)	2.37 (0.52–10.8)	1.72 (0.92–3.19)	1.37 (0.80–2.33)	1.30 (0.83–2.03)	1.37 (0.75–2.52)
Insulin resistance	**Slope**	0.86 (0.61–1.22)	1.36 (0.92–2.01)	1.45 (0.96–2.16)	0.73 (0.40–1.36)	0.94 (0.63–1.40)	1.05 (0.63–1.75)	0.81 (0.53–1.22)	0.98 (0.64–1.50)
	Intercept	0.84 (0.60–1.17)	1.42 (0.97–2.08)	1.20 (0.80–1.80)	1.51 (0.72–3.15)	**1.87 (1.12–3.12)**	1.58 (0.95–2.62)	1.12 (0.70–1.77)	0.73 (0.43–1.24)
MetS	**Slope**	0.99 (0.66–1.49)	1.69 (0.87–3.23)	**2.66 (1.38–5.14)**	2.08 (0.37–11.58)	1.29 (0.54–3.08)	0.82 (0.25–2.66)	1.34 (0.74–2.41)	0.91 (0.48–1.73)
	Intercept	0.95 (0.66–1.38)	1.78 (0.97–3.24)	1.66 (0.94–2.83)	1.14 (0.14–8.86)	**2.78 (1.04–7.41)**	**4.35 (1.68–11.29)**	**2.38 (1.33–4.25)**	1.57 (0.76–3.25)

[a] Models are adjusted for age (continuous) sex, pubertal status, parental ISCED, HDAS, unhealthy snack intake, observation period and abdominal obesity (when not part of the outcome). The number of participants varied across countries due to missing values for different metabolic outcomes. Bold significance is provided via confidence limits

[b] The reference category for the metabolic outcomes is below the monitoring level

[c] Slope was used as a categorical variable (above vs. below population mean random slope)

[d] *BP* blood pressure, *DM* digital media, *MetS* metabolic syndrome

children [57, 58]. Clinicians and health authorities should educate families in developing effective family media use plans [59] in order to reduce excessive screen-time and prevent future health emergencies. Clinicians, who are perceived as credible messengers for health information, should incorporate the history of child's media use in their routine health maintenance visits as they do for nutrition or tobacco exposure, and provide personalized, age-specific advice to limit DM exposure, as also recommended by the American Academy of Pediatricians [60]. Among the strategies that parents may incorporate include: to take DM devices (e.g. TV and PC/game console) out of the child's bedroom [47]; to supervise their children's DM use and take advantage of the new tools (i.e. parental controlling apps) that monitor the content children are exposed to in their mobile devices; and model a healthy DM use themselves [61].

Limitations and strengths

Our study has some methodological limitations. DM exposure was proxy-reported by parents of young children and self-reported by adolescents, thus we cannot exclude a social-desirability bias. Additionally, DM use patterns have changed since W1 (2007). TV has been replaced by use of smartphones and social media platforms, and we could not consider the influence of these newer media types on MetS. At W3, a lower sample was contacted for participation in Belgium and Spain compared to other countries, as they received no full funding [62]. At baseline, the percentage of children providing venous blood was low especially in Cyprus (7.7%). This explains the high number of excluded Cypriot children (25%) from the final analysis population. The reason behind is that most parents were unable to accompany their children to the examination center. Moreover, the modular approach facilitated the possibility to opt out of single examinations. This explains the high proportion of subjects with missing data on diet variables in the excluded sample. External validity may be limited, but a potential selection bias cannot be ruled out, as the main aim of the IDEFICS/I.Family cohort was to identify the role of lifestyle factors on shaping health-related behaviors in children and adolescents by asking the whole population to attend, and not subjects suffering from a specific health condition, as is the case in clinical studies [15, 16]. Further, children's weight status but not their media exposure was associated with attrition rate at follow-up [63]. Accelerometer-data were collected only for a sub-sample of children; hence we cannot draw conclusions about MVPA- and SED-time for the entire population. However, the results were not affected by selection bias, as the low participation was due to budgetary limitations that restricted the number of devices provided. Since type of sedentary behaviors was not recorded by accelerometers (e.g. screen-based SED) we could not objectively assess screen-time. Internet exposure was measured only at T3 and we did not distinguish between its access via a smartphone/tablet or computer. Current literature suggests that smartphones were the most popular devices children used to go online [64]. Future studies should investigate the ubiquitous exposure to internet via smartphones on children's metabolic health. Further, due to the low number of repeated measures, we could not consider a change in DM slope around puberty, e.g. modelling an exponential or quadratic slope. Additionally, AVM latent profile / transition analysis was not considered [65], due to the high age range and the unbalanced data (two or three observations per participant) that could be handled with the linear mixed models.

To our best knowledge, this is the first study evaluating the longitudinal association of DM exposure with MetS in children and adolescents. The availability of fasting blood samples represents an advantage in evaluating objectively-measured metabolic risks. In comparison to most other studies, besides TV, we included computer and internet exposure, thus capturing a larger picture of DM patterns. The availability of objectively-measured MVPA reduced the level of misreporting due to socially-desirable answers on physical activity [66]. The information on various covariates (e.g. consumption frequency of snacks, parental ISCED), enabled us to control for confounders. The large sample size of 10,359 children from 8 European countries providing harmonized data, allowed us to evaluate country-differences on DM trajectories and its association with MetS.

Conclusions

Increased digital media exposure over time is associated with higher risk for metabolic syndrome in children and adolescents, with boys being at higher risk. These findings are of relevance for clinicians and families and ask for action by health authorities. Future health policies should focus on the reduction of screen-time throughout childhood and starting at an early age to prevent cardio-metabolic diseases.

Abbreviations

DM: Digital media use; BP: Blood pressure; HDAS: Healthy diet adherence score; HDL-c: High density lipoprotein cholesterol; HOMA: Homeostasis model assessment for insulin resistance; IDEFICS: Identification and prevention of Dietary- and lifestyle-induced health EFfects In Children and infantS; I. Family: Determinants of eating behavior in European children, adolescents and their parents; ISCED: International standard classification of education;

IR: Insulin resistance; MetS: Metabolic syndrome; TRG: Triglycerides; WC: Waist circumference.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12966-021-01186-9.

Additional file 1: eTable 1. Characteristics of participants excluded from the analysis compared to those included in the analysis population. **eTable 2**. Metabolic risk profiles and characteristics of analysis population at each study wave[a]. **eTable 3**. Association of digital media use trajectories with metabolic syndrome and its components in children, stratified by parental educational status[a]

Acknowledgements
This research was done in the framework of the IDEFICS (http://www.idefics.eu) and I.Family (http://www.ifamilystudy.eu) studies. We are grateful for the participation of European children and their parents in the three examinations as well as the support received from school boards, headmasters, and communities.

Authors' contributions
The authors' contributions were as follows: ES wrote the paper; ES and CB performed the data analysis; ES, AH, CB, WA designed research; TV, AS, LR, HP, VP, LM, LL, DM, GE, YK, SDH, and WA participated in the coordination of data collection and the project administration; ES, CB and AH had primary responsibility for the final content; All authors were responsible for critical revisions and final approval of the manuscript.

Funding
This research was funded by the European Community within the Sixth RTD Framework Programme Contract No. 016181 (FOOD) and Seventh RTD Framework Programme Contract No. 266044. The funders had no role in the design of the study and collection, analysis, and interpretation of data and in writing the manuscript. Open Access funding enabled and organized by Projekt DEAL.

Availability of data and materials
Due to the sensitive nature of data collected, ethical restrictions prohibit the authors from making the minimal data set publicly available. Each cohort centre received approval of the corresponding local Ethical Commission and participants did not provide consent for data sharing. Data are available on request and all requests need approval by the study's Steering Committee. Interested researchers can contact the study co-ordinator (ahrens@leibniz-bips.de) to request data access. All requests for accessing data of the IDEFICS/I.Family cohort are discussed on a case-by-case basis by the Steering Committee.

Declarations

Ethics approval and consent to participate
Informed consent was obtained from adolescents (≥ 12 years), and the assent was given from younger children, in addition to parental informed consent. Ethical approval was obtained from local ethic committees of each study center in accordance with the ethical standards of the Declaration of Helsinki (1964) and its later amendments as follows- Belgium: Ethics Committee of the Gent University Hospital, 15/10/2007, ref.: No. EC UZG 2007/243 and 19/02/2013, No. B670201316342; Cyprus: Cyprus National Bioethics Committee, 12/07/2007, ref.: No. EEBK/EM/2007/16 and 21/Feb/2013, No.EEBK/ETI/2012/33; Estonia: Tallinn Medical Research Ethics Committee (TMREC), 14/06/2007, ref.: No. 1093 and 17/January 2013, No. 128; Germany: Ethic Commission of the University of Bremen, 16/01/2007 and 11/12/2012; Hungary: Medical Research Council, 21/Jun/2007, ref.: 22–156/2007-1018EKU and 18/12/2012, 4536/2013/EKU; Italy: Ethics Committee of the Local Health Authority (ASL) in Avellino, 19/06/2007, ref.: No. 2/CE and 18/Sep/2012, No. 12/12; Spain: Ethics Committee for Clinical Research of Aragon (CEICA), 20/06/2007, ref.: No. PI07/13 and 13/Feb/2013, No. PI13/0012; Sweden: Regional Ethics Research Board in Gothenburg, 30/07/2007, ref.: No. 264–07 and 10/Jan/2013, No. 927–12).

Consent for publication
Not applicable.

Competing interests
The authors declare that they have no competing interests.

Author details
[1]Leibniz Institute for Prevention Research and Epidemiology-BIPS, Achterstraße 30, 28359 Bremen, Germany. [2]Department of Chronic Diseases, National Institute for Health Development, Tallinn, Estonia. [3]Institute of Food Sciences, National Research Council, Avellino, Italy. [4]Department of Management, Society and Communication, Copenhagen Business School, Copenhagen, Denmark. [5]Department of Preventive and Predictive Medicine, Fondazione IRCCS, Istituto Nazionale Dei Tumori, Milan, Italy. [6]GENUD (Growth, Exercise, Nutrition and Development) Research Group, Instituto Agroalimentario de Aragón (IA2), Instituto de Investigación Sanitaria Aragón (IIS Aragón), Centro de Investigación Biomédica en Red Fisiopatología de La Obesidad Y Nutrición (CIBERObn), University of Zaragoza, Zaragoza, Spain. [7]Department of Pediatrics, Medical School, University of Pécs, Pécs, Hungary. [8]School of Public Health and Community Medicine, University of Gothenburg, Gothenburg, Sweden. [9]Research and Education Institute of Child Health, Strovolos, Cyprus. [10]Department of Public Health and Primary Care, Ghent University, Ghent, Belgium. [11]Department of Public Health, School of Health Sciences, University of Skövde, Skövde, Sweden. [12]Institute of Statistics, Faculty of Mathematics and Computer Science, University of Bremen, Bremen, Germany.

Received: 7 April 2021 Accepted: 11 August 2021
Published online: 18 October 2021

References
1. World Health Organization. Global status report on noncommunicable diseases 2014. Geneva: World Health Organization; 2014.
2. Alberti KG, Zimmet P, Shaw J. Metabolic syndrome–a new world-wide definition. a consensus statement from the International Diabetes Federation. Diabet Med. 2006;23(5):469–80.
3. Wittcopp C, Conroy R. Metabolic syndrome in children and adolescents. Pediatr Rev. 2016;37(5):193–202.
4. Koskinen J, Magnussen CG, Sinaiko A, Woo J, Urbina E, Jacobs DR, Jr., et al. Childhood age and associations between childhood metabolic syndrome and adult risk for metabolic syndrome, type 2 diabetes mellitus and carotid intima media thickness: the international childhood cardiovascular cohort consortium. J Am Heart Assoc. 2017;6(8):e005632.
5. Lee AM, Gurka MJ, DeBoer MD. Trends in metabolic syndrome severity and lifestyle factors among adolescents. Pediatrics. 2016;137(3):e20153177.
6. World Health Organization. WHO guidelines on physical activity and sedentary behaviour. Geneva: World Health Organization; 2020.
7. Rideout VJ, Robb MB. The common sense census: Media use by tweens and teens. San Francisco, CA: Common Sense Media; 2019.
8. Sayin FK, Buyukinan M. Sleep duration and media time have a major impact on insulin resistance and metabolic risk factors in obese children and adolescents. Child Obes. 2016;12(4):272–8.
9. Elmaogullari S, Demirel F, Hatipoglu N. Risk factors that affect metabolic health status in obese children. J Pediatr Endocrinol Metab. 2017;30(1):49–55.
10. Barstad LH, Juliusson PB, Johnson LK, Hertel JK, Lekhal S, Hjelmesaeth J. Gender-related differences in cardiometabolic risk factors and lifestyle behaviors in treatment-seeking adolescents with severe obesity. BMC Pediatr. 2018;18(1):61.
11. Mark AE, Janssen I. Relationship between screen time and metabolic syndrome in adolescents. J Public Health (Oxf). 2008;30(2):153–60.
12. Tahir MJ, Willett W, Forman MR. The association of television viewing in childhood with overweight and obesity throughout the life course. Am J Epidemiol. 2019;188(2):282–93.
13. Reid Chassiakos Y, Radesky J, Christakis D, Moreno MA, Cross C. Children and adolescents and digital media. Pediatrics. 2016;138(5):e20162593.
14. Ahrens W, Moreno LA, Mårild S, Molnár D, Siani A, De Henauw S, et al. Metabolic syndrome in young children: definitions and results of the IDEFICS study. Int J Obes. 2014;38(2):S4–14.

15. Ahrens W, Bammann K, Siani A, Buchecker K, De Henauw S, Iacoviello L, et al. The IDEFICS cohort: design, characteristics and participation in the baseline survey. Int J Obes (Lond). 2011;35(Suppl 1):S3-15.
16. Ahrens W, Siani A, Adan R, De Henauw S, Eiben G, Gwozdz W, et al. Cohort Profile: The transition from childhood to adolescence in European children-how I. Family extends the IDEFICS cohort. Int J Epidemiol. 2017;46(5):1394–5j.
17. Suling M, Hebestreit A, Peplies J, Bammann K, Nappo A, Eiben G, et al. Design and results of the pretest of the IDEFICS study. Int J Obes. 2011;35(1):S30–44.
18. Alpert BS. Validation of the Welch Allyn Spot Vital Signs blood pressure device according to the ANSI/AAMI SP10: 2002. Accuracy and cost-efficiency successfully combined. Blood Pressure Monitoring. 2007;12(5):345–7.
19. Barba G, Buck C, Bammann K, Hadjigeorgiou C, Hebestreit A, Marild S, et al. Blood pressure reference values for European non-overweight school children: the IDEFICS study. Int J Obes (Lond). 2014;38(Suppl 2):S48-56.
20. Stomfai S, Ahrens W, Bammann K, Kovács É, Mårild S, Michels N, et al. Intra- and inter-observer reliability in anthropometric measurements in children. Int J Obes. 2011;35(1):S45–51.
21. Peplies J, Jiménez-Pavón D, Savva SC, Buck C, Günther K, Fraterman A, et al. Percentiles of fasting serum insulin, glucose, HbA1c and HOMA-IR in pre-pubertal normal weight European children from the IDEFICS cohort. Int J Obes. 2014;38(2):S39–47.
22. Nagy P, Kovacs E, Moreno LA, Veidebaum T, Tornaritis M, Kourides Y, et al. Percentile reference values for anthropometric body composition indices in European children from the IDEFICS study. Int J Obes (Lond). 2014;38(Suppl 2):S15-25.
23. De Henauw S, Michels N, Vyncke K, Hebestreit A, Russo P, Intemann T, et al. Blood lipids among young children in Europe: results from the European IDEFICS study. Int J Obes (Lond). 2014;38(Suppl 2):S67-75.
24. Bel-Serrat S, Mouratidou T, Pala V, Huybrechts I, Bornhorst C, Fernandez-Alvira JM, et al. Relative validity of the children's eating habits questionnaire-food frequency section among young European children: the IDEFICS Study. Public Health Nutr. 2014;17(2):266–76.
25. Lanfer A, Hebestreit A, Ahrens W, Krogh V, Sieri S, Lissner L, et al. Reproducibility of food consumption frequencies derived from the children's eating habits questionnaire used in the IDEFICS study. Int J Obes (Lond). 2011;35(Suppl 1):S61–8.
26 Arvidsson L, Eiben G, Hunsberger M, De Bourdeaudhuij I, Molnar D, Jilani H, et al. Bidirectional associations between psychosocial well-being and adherence to healthy dietary guidelines in European children: prospective findings from the IDEFICS study. BMC Public Health. 2017;17(1):926.
27. Evenson KR, Catellier DJ, Gill K, Ondrak KS, McMurray RG. Calibration of two objective measures of physical activity for children. J Sports Sci. 2008;26(14):1557–65.
28. Cliff DP, Jones RA, Burrows TL, Morgan PJ, Collins CE, Baur LA, et al. Volumes and bouts of sedentary behavior and physical activity: associations with cardiometabolic health in obese children. Obesity. 2014;22(5):E112–8.
29 Carson V, Janssen I. Volume, patterns, and types of sedentary behavior and cardio-metabolic health in children and adolescents: a cross-sectional study. BMC Public Health. 2011;11:274.
30. Saunders TJ, Tremblay MS, Mathieu M-È, Henderson M, O'Loughlin J, Tremblay A, et al. Associations of sedentary behavior, sedentary bouts and breaks in sedentary time with cardiometabolic risk in children with a family history of obesity. PloS one. 2013;8(11):e79143-e.
31. van Jaarsveld CHM, Fidler JA, Simon AE, Wardle J. Persistent impact of pubertal timing on trends in smoking, food choice, activity, and stress in adolescence. Psychosom Med. 2007;69(8):798–806.
32. Carskadon MA, Acebo C. A self-administered rating scale for pubertal development. J Adolesc Health. 1993;14(3):190–5.
33. Tanner JM. Growth and maturation during adolescence. Nutr Rev. 1981;39(2):43–55.
34. UNESCO. International Standard Classification of Education. 2011. Montreal: UNESCO; 2012.
35. Börnhorst C, Siani A, Russo P, Kourides Y, Sion I, Molnár D, et al. Early life factors and inter-country heterogeneity in BMI growth trajectories of European children: The IDEFICS Study. PLOS ONE. 2016;11(2):e0149268.
36. Sayers A, Heron J, Smith A, Macdonald-Wallis C, Gilthorpe MS, Steele F, et al. Joint modelling compared with two stage methods for analysing longitudinal data and prospective outcomes: a simulation study of childhood growth and BP. Stat Methods Med Res. 2017;26(1):437–52.
37 Buck C, Eiben G, Lauria F, Konstabel K, Page A, Ahrens W, et al. Urban moveability and physical activity in children: longitudinal results from the IDEFICS and I.Family cohort. Int J Behav Nutr Phys Act. 2019;16(1):128.
38. Trinh MH, Sundaram R, Robinson SL, Lin TC, Bell EM, Ghassabian A, et al. Association of trajectory and covariates of children's screen media time. JAMA Pediatr. 2019;174(1):71–8.
39 Iguacel I, Michels N, Ahrens W, Bammann K, Eiben G, Fernández-Alvira JM, et al. Prospective associations between socioeconomically disadvantaged groups and metabolic syndrome risk in European children. Results from the IDEFICS study. Int J Cardiol. 2018;272:333–40.
40. Kang H-T, Lee H-R, Shim J-Y, Shin Y-H, Park B-J, Lee Y-J. Association between screen time and metabolic syndrome in children and adolescents in Korea: The 2005 Korean National Health and Nutrition Examination Survey. Diabetes Res Clin Pract. 2010;89(1):72–8.
41. Hardy LL, Denney-Wilson E, Thrift AP, Okely AD, Baur LA. Screen time and metabolic risk factors among adolescents. JAMA Pediatr. 2010;164(7):643–9.
42. Peplies J, Börnhorst C, Günther K, Fraterman A, Russo P, Veidebaum T, et al. Longitudinal associations of lifestyle factors and weight status with insulin resistance (HOMA-IR) in preadolescent children: the large prospective cohort study IDEFICS. Int J Behav Nutr Phys Activ. 2016;13(1):97.
43. Börnhorst C, Russo P, Veidebaum T, Tornaritis M, Molnár D, Lissner L, et al. The role of lifestyle and non-modifiable risk factors in the development of metabolic disturbances from childhood to adolescence. Int J Obes. 2020;44(11):2236–45.
44. Danielsen YS, Júlíusson PB, Nordhus IH, Kleiven M, Meltzer HM, Olsson SJ, et al. The relationship between life-style and cardio-metabolic risk indicators in children: the importance of screen time. Acta Paediatr. 2011;100(2):253–9.
45. Klesges RC, Shelton ML, Klesges LM. Effects of television on metabolic rate: potential implications for childhood obesity. Pediatrics. 1993;91(2):281–6.
46. Society CP. Impact of media use on children and youth. Paediatr Child Health. 2003;8(5):301–17.
47. McKetta S, Rich M. The fault, dear viewer, lies not in the screens, but in ourselves: relationships between screen media and childhood overweight/obesity. Pediatr Clin North Am. 2011;58(6):1493–508 (**xii**).
48. Theodore RF, Broadbent J, Nagin D, Ambler A, Hogan S, Ramrakha S, et al. Childhood to early-midlife systolic blood pressure trajectories: early-life predictors, effect modifiers, and adult cardiovascular outcomes. Hypertension. 2015;66(6):1108–15.
49. Lawrence AC, Narayan MS, Choe DE. Association of young children's use of mobile devices with their self-regulation. JAMA Pediatr. 2020;174(8):793–5.
50. Anderson SE, Whitaker RC. Association of self-regulation with obesity in boys vs girls in a US National Sample. JAMA Pediatr. 2018;172(9):842–50.
51. Miller HV, Barnes JC, Beaver KM. Self-control and health outcomes in a nationally representative sample. Am J Health Behav. 2011;35(1):15–27.
52. Aparicio E, Canals J, Arija V, De Henauw S, Michels N. The role of emotion regulation in childhood obesity: implications for prevention and treatment. Nutr Res Rev. 2016;29(1):17–29.
53. Thumann BF, Börnhorst C, Ahrens W, Arvidsson L, Gwozdz W, Iguacel I, et al. Cross-sectional and longitudinal associations between psychosocial well-being and cardiometabolic markers in European children and adolescents. Psychosom Med. 2020;82(8):764–73.
54. Smahel D, Machackova H, Mascheroni G, Dedkova L, Staksrud E, Ólafsson K, Livingstone S, Hasebrink U. EU Kids Online: Survey results from 19 countries. 2020.
55. Bovill M, Livingstone S. Bedroom culture and the privatization of media use.
56. Expert Panel on Integrated Guidelines for Cardiovascular Health, Risk Reduction in Children and Adolescents, National Heart Lung and Blood Institute. Expert panel on integrated guidelines for cardiovascular health and risk reduction in children and adolescents: summary report. Pediatrics. 2011;128(Suppl 5):S213–56.

57. Nagata JM, Abdel Magid HS, Pettee GK. Screen time for children and adolescents during the coronavirus disease 2019 pandemic. Obesity. 2020;28(9):1582–3.
58. Kovacs VA, Starc G, Brandes M, Kaj M, Blagus R, Leskošek B, et al. Physical activity, screen time and the COVID-19 school closures in Europe - an observational study in 10 countries. Eur J Sport Sci. 2021:1–10. Epub ahead of print. PMID:33641633.
59. Hill DAN, Chassiakos YR, et al. Media and young minds. Pediatrics. 2016;138(5):e20162591.
60. Pediatrics TAAo. Media use in school-aged children and adolescents. Pediatrics. 2016;138(5):e20162592.
61. He M, Piché L, Beynon C, Harris S. Screen-related sedentary behaviors: children's and parents' attitudes, motivations, and practices. J Nutr Educ Behav. 2010;42(1):17–25.
62. Bammann K, Reisch LA, Pohlabeln H, Williams G, Wolters M. Core questionnaires. In: Bammann K, Lissner L, Pigeot I, Ahrens W, editors. Instruments for health surveys in children and adolescents. Cham: Springer International Publishing; 2019. p. 189–207.
63. Langeheine M, Pohlabeln H, Lauria F, Veidebaum T, Tornaritis M, Molnar D, et al. Attrition in the European Child Cohort IDEFICS/I.Family: exploring associations between attrition and body mass index. Front. Pediatr. 2018;6:212.
64. Livingstone S, Winther DK, Saeed M. Global kids online: comparative report. UNICEF Office of Research – Innocenti.
65. Sina E, Buck C, Jilani H, Tornaritis M, Veidebaum T, Russo P, et al. Association of infant feeding patterns with taste preferences in European Children and adolescents: a retrospective latent profile analysis. Nutrients. 2019;11(5):1040.
66. Adams SA, Matthews CE, Ebbeling CB, Moore CG, Cunningham JE, Fulton J, et al. The effect of social desirability and social approval on self-reports of physical activity. Am J Epidemiol. 2005;161(4):389–98.

Publisher's Note

Erratum

Erratum to: Int J Behav Nutr Phys Act 2021 Oct 18;18(1):134. doi: 10.1186/s12966-021-01186-9.

Media use trajectories and risk of metabolic syndrome in European children and adolescents: the IDEFICS/I.Family cohort

Sina, Elida, Buck, Christoph, Veidebaum, Thomas, Siani, Alfonso, Reisch, Lucia, Pohlabeln, Hermann, Pala, Valeria, Moreno, Luis A., Molnar, Dénes, Lissner, Lauren, Kourides, Yannis, De Henauw, Stefaan, Eiben, Gabriele, Ahrens, Wolfgang, Hebestreit, Antje, & IDEFICS, I.Family consortia (2021). Media use trajectories and risk of metabolic syndrome in European children and adolescents: the IDEFICS/I.Family cohort. *The international journal of behavioral nutrition and physical activity*, *18*(1), 134. https://doi.org/10.1186/s12966-021-01186-9

Erratum to: Int J Behav Nutr Phys Act 2021 Oct 18;18(1):134. doi: 10.1186/s12966-021-01186-9.

Media use trajectories and risk of metabolic syndrome in European children and adolescents: the IDEFICS/I.Family cohort

Sina, E., Buck, C., Veidebaum, T. *et al.* Media use trajectories and risk of metabolic syndrome in European children and adolescents: the IDEFICS/I.Family cohort.

Following publication of the original article(1), the authors provided changes in the text and modified the numbers in tables 2, 3 and 4 as well as in figures 1 and 2.

A programming error was detected in the calculation of the media use trajectories over age. The correction led to slightly higher media use intercept (hours/day) and slope (hours/day/year) for the overall analysis population, as well as for the sex-specific and country-specific media use trajectories. All analyses were re-run using the corrected media trajectories, leading to similar results compared to the previous (published) results, with the regression coefficients and 95% confidence results (95%CI) now slightly attenuated. However, the directionality of the associations has not changed for any of the reported associations. Meaning that the interpretation of the corrected results does not change from the interpretation of the previously published results and the conclusions of the paper remain the same.

Figure 1 and **Figure 2** (both corrected) illustrate a slightly higher and steeper media use trajectory compared to the published results. Nevertheless, the pattern of media use over age remains the same, as media use increased over age for both girls and boys, as well as across countries.

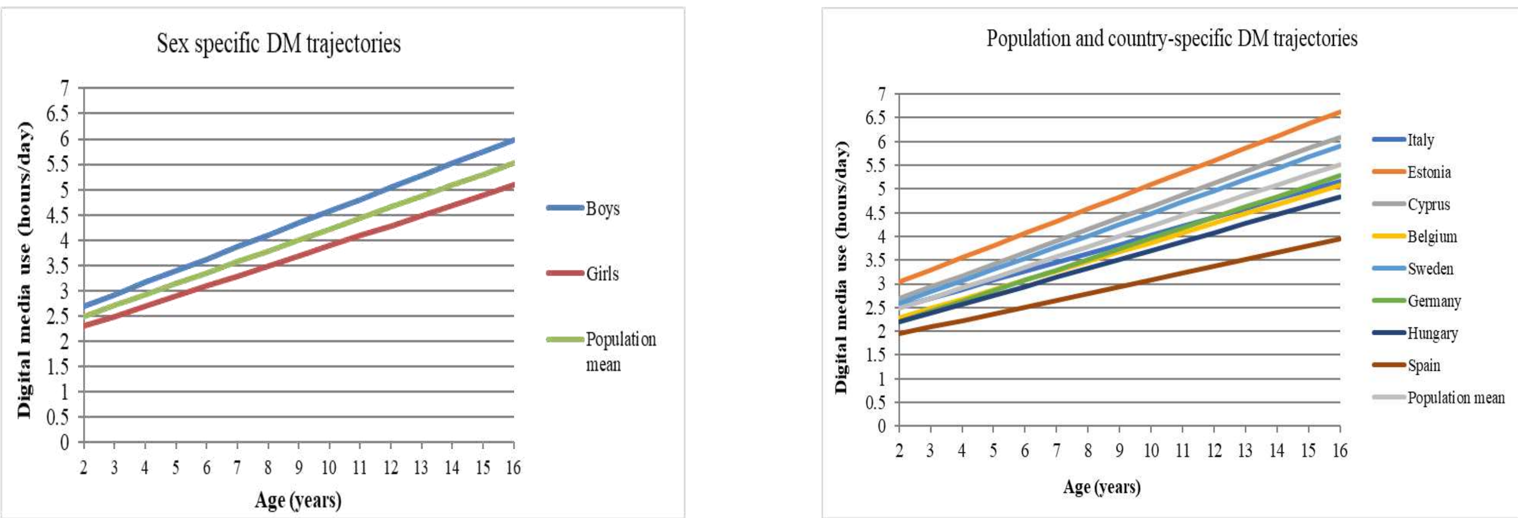

Figure 1. Sex- and country-specific digital media use trajectories in European children and adolescents (Corrected)

In **Table 2**, it is shown how the corrected Beta coefficients and 95%CI are attenuated only for the z-scores of metabolic syndrome (z_MetS), homeostasis model assessment for insulin resistance (z_HOMA) and waist circumference (z_WC), both in the overall analysis population and the accelerometer sample. Nevertheless, the directionality of associations remains the same and the interpretation of results does not change.

Table 2. Association of average DM across childhood (intercept) and increase of DM over time (slope) with metabolic syndrome score and its components in children and adolescents

Metabolic outcomes	DM use	Analysis Population (Published results) [a]		Analysis Population (Corrected results) [a]		Accelerometer Sample (Published results) [b]			Accelerometer Sample (Corrected results) [b]		
		N	Adjusted β (95%CI)	N	Adjusted β (95%CI)	N	Adjusted β (95%CI)	Adjusted β (95% CI) [c]	N	Adjusted β (95%CI)	Adjusted β (95% CI) [c]
z_WC [d]	Intercept	10,153	**0.15 (0.11, 0.19)**	10,070	**0.14 (0.10, 0.19)**	4258	**0.19 (0.13, 0.26)**	**0.19 (0.12, 0.25)**	4211	**0.17 (0.10, 0.24)**	**0.17 (0.10, 0.24)**
	Slope		0.19 (-0.04, 0.43)		-0.03 (-0.22, 0.15)		0.26 (-0.10, 0.63)	0.26 (-0.10, 0.63)		0.03 (-0.25, 0.32)	0.04 (-0.24, 0.32)
z_BP [e]	Intercept	9409	0.04 (0.00, 0.07)	9329	0.03 (-0.007, 0.06)	4073	0.02 (-0.03, 0.08)	0.02 (-0.03, 0.07)	4025	0.005 (-0.05, 0.06)	0.004 (-0.05, 0.06)
	Slope		0.09 (-0.10, 0.30)		-0.03 (-0.19, 0.12)		0.18 (-0.13, 0.49)	0.16 (-0.14, 0.47)		0.09 (-0.14, 0.33)	0.08 (-0.15, 0.32)
z_TRG	Intercept	6193	**0.08 (0.03, 0.12)**	6182	**0.08 (0.03, 0.13)**	2683	0.06 (-0.01, 0.13)	0.06 (-0.01, 0.13)	2678	0.05 (-0.02, 0.12)	0.05 (-0.02, 0.12)
	Slope		0.02 (-0.24, 0.30)		0.005 (-0.20, 0.21)		0.01 (-0.40, 0.42)	0.00 (-0.41, 0.41)		0.05 (-0.26, 0.36)	0.04 (-0.27, 0.35)
z_HDL-c	Intercept	6506	**-0.08 (-0.12, -0.04)**	6495	**-0.08 (-0.13, -0.04)**	2857	**-0.07 (-0.14, -0.002)**	-0.07 (-0.14, -0.00)	2852	-0.06 (-0.13, 0.007)	-0.06 (-0.13, 0.008)
	Slope		**-0.28 (-0.54, -0.02)**		**-0.28 (-0.48, -0.08)**		-0.32 (-0.72, 0.07)	-0.33 (-0.73, 0.06)		**-0.35 (-0.66, -0.05)**	**-0.36 (-0.67, -0.06)**
z_HOMA	Intercept	3435	**0.12 (0.05, 0.19)**	3421	**0.11 (0.03, 0.18)**	1688	**0.15 (0.05, 0.26)**	**0.15 (0.04, 0.25)**	1678	**0.13 (0.02, 0.24)**	**0.12 (0.01, 0.23)**
	Slope		**0.64 (0.21, 1.08)**		0.27 (-0.06, 0.61)		0.58 (-0.01, 1.18)	0.59 (0.00, 1.19)		0.18 (-0.27, 0.64)	0.19 (-0.26, 0.65)
z_MetS	Intercept	2973	**0.07 (0.02, 0.13)**	2959	**0.06 (0.008, 0.12)**	1476	0.07 (-0.01, 0.15)	0.06 (-0.02, 0.14)	1468	0.04 (-0.04, 0.13)	0.04 (-0.04, 0.12)
	Slope		**0.54 (0.20, 0.88)**		**0.26 (0.001, 0.52)**		**0.51 (0.04, 0.97)**	**0.49 (0.02, 0.95)**		0.29 (-0.06, 0.64)	0.28 (-0.07, 0.63)

[a] Models are adjusted for age (continuous), sex, pubertal status, HDAS, snack consumption, parental ISCED, observation period, (age at follow-up – age at baseline), country and baseline z-scores of the respective outcome. Bold significance is provided via confidence limits; [b] Models are based on the accelerometer sample and are adjusted for same confounders as in the main analysis. N varied due to missing values for each outcome; [c] Models based on sample with accelerometer data are further adjusted for MVPA, SED and valid accelerometer wear time; [d] WC- waist circumference, BP-blood pressure, TRG- triglycerides, HDL-c– high density lipoprotein cholesterol, HOMA-homeostasis model assessment for insulin resistance, MetS- metabolic syndrome, DM- digital media; [e] Models for the z-scores of BP, HDL-c, TRG and HOMA-IR are additionally adjusted for z-score of WC at the last measurement point. The number of participants varied for metabolic outcomes due to missing values

Table 3 shows how the corrected media use trajectories are associated with the metabolic outcomes in the overall analysis population, as well as in boys and girls. Here the results are more robust and beta coefficients remain similar. Hence, the interpretation of the corrected results does not change from the interpretation of the previously published results.

Table 3. Risk of metabolic syndrome and its components by DM slope and DM intercept in children and adolescents

Metabolic outcomes [a]	**DM use**	**Analysis Group** (Published Results) [b]		**Analysis Group** (Corrected results)		**Boys** (Published results) [c]		**Boys** (Corrected results)		**Girls** (Published results) [c]		**Girls** (Corrected results)	
		N	**Adjusted OR (95%CI)**	**N**	**Adjusted OR (95%CI)**	**N**	**Adjusted OR (95% CI)**	**N**	**Adjusted OR (95% CI)**	**N**	**Adjusted OR (95% CI)**	**N**	**Adjusted OR (95% CI)**
Abdominal obesity	**Slope** [d]	7966	1.05 (0.92–1.19)	7903	1.00 (0.88, 1.13)	3966	0.97 (0.81, 1.16)	3928	0.97 (0.80, 1.16)	4000	1.12 (0.94–1.34)	3975	1.03 (0.85, 1.23)
	Intercept		**1.53 (1.35, 1.75)**		**1.48 (1.29, 1.70)**		**1.30 (1.09, 1.56)**		**1.28 (1.06, 1.55)**		**1.85 (1.53, 2.24)**		**1.75 (1.43, 2.13)**
High BP [e]	**Slope**	7693	1.04 (0.91, 1.20)	7643	1.02 (0.89, 1.17)	3809	1.13 (0.94, 1.36)	3781	1.04 (0.86, 1.26)	3884	0.96 (0.78, 1.17)	3862	1.00 (0.82, 1.22)
	Intercept		1.08 (0.94, 1.25)		1.07 (0.92, 1.24)		1.15 (0.96, 1.38)		1.08 (0.89, 1.32)		1.01 (0.81, 1.26)		1.07 (0.84, 1.35)
Dyslipidemia	**Slope**	5001	1.00 (0.85, 1.18)	4987	1.01 (0.85 1.19)	2469	1.04 (0.82, 1.32)	2465	1.01 (0.79, 1.28)	2532	0.93 (0.73, 1.17)	2522	0.99 (0.78, 1.25)
	Intercept		**1.28 (1.08, 1.51)**		**1.23 (1.03, 1.47)**		**1. 42 (1.13, 1.78)**		**1.37 (1.07, 1.74)**		1.08 (0.84, 1.39)		1.04 (0.79, 1.35)
Insulin resistance	**Slope**	5435	1.00 (0.87, 1.16)	5437	0.96 (0.83, 1.11)	2728	1.22 (1.00, 1.50)	2736	1.08 (0.87, 1.33)	2707	0.83 (0.68, 1.02)	2701	0.86 (0.70, 1.06)
	Intercept		1.16 (1.00, 1.35)		1.15 (0.98, 1.35)		1.15 (0.93, 1.41)		1.12 (0.90. 1.39)		1.12 (0.90, 1.41)		1.13 (0.89, 1.44)
MetS	**Slope**	5288	**1.30 (1.04, 1.62)**	5278	1.22 (0.97, 1.52)	2636	**1.62 (1.17, 2.24)**	2638	**1.41 (1.01, 1.95)**	2652	1.08 (0.80, 1.47)	2640	1.10 (0.81, 1.51)
	Intercept		**1.50 (1.21, 1.85)**		**1.45 (1.15, 1.83)**		**1.58 (1.20, 2.11)**		**1.55 (1.13, 2.13)**		1.35 (0.97, 1.87)		1.34 (0.95, 1.89)

[a]The reference category for the metabolic outcomes is below the monitoring level; [b] Models are adjusted for age (continuous), sex, pubertal status, country, parental ISCED, HDAS, snack frequency intake, observation period, and abdominal obesity (when BP, IR and dyslipidemia were modeled). Bold significance is provided via confidence limits; [c] Models are adjusted for all covariates, besides sex (and physical activity variables); [d] Slope was used as a categorical variable (above vs. below population mean random slope); [e] BP-blood pressure, MetS- metabolic syndrome, DM- digital media

In **Table 4**, the corrected results on the country-specific associations indicate a higher mean intercept and higher slope in the corrected results for all countries. The associations are slightly attenuated, but the directionality of the associations remains the same and thus, the interpretation of the corrected results is similar to the published results.

Table 4. Age-dependent digital media use trajectories by country of residence and risk of developing metabolic syndrome (corrected)[a]

Metabolic outcome [b]	DM use	Italy Published	Italy Corrected	Estonia Published	Estonia Corrected	Cyprus Published	Cyprus Corrected	Belgium Published	Belgium Corrected	Sweden Published	Sweden Corrected	Germany Published	Germany Corrected	Hungary Published	Hungary Corrected	Spain Published	Spain Corrected
	Mean intercept (h/day)	2.0258	2.1257	2.3790	2.5245	2.1022	2.2015	1.7932	1.8788	2.0210	2.1210	1.6706	1.7584	1.7521	1.8157	1.5931	1.6550
	Mean slope (h/day/year	0.1144	0.1897	0.1785	0.2565	0.1583	0.2434	0.1483	1.996	0.1746	0.2368	0.1493	0.2200	0.1298	0.1887	0.1012	0.1436
		Adjusted odds ratios (OR) and 95% confidence intervals (95% CI)															
Abdominal obesity	**Slope [c]**	0.90 (0.68-1.20)	0.90 (0.68-1.19)	1.21 (0.86-1.70)	1.00 (0.70-1.44)	1.03 (0.75-1.41)	1.01 (0.73-1.40)	0.74 (0.46-1.20)	0.67 (0.42-1.14)	**1.69 (1.05-3.23)**	1.40 (0.87-2.23)	0.93 (0.63-1.36)	1.10 (0.75-1.62)	1.31 (0.90-1.92)	1.10 (0.74-1.63)	0.99 (0.67-1.46)	1.04 (0.70-1.55)
	Intercept	1.28 (0.96-1.69)	1.26 (0.94-1.68)	**1.62 (1.17–2.23)**	**1.58 (1.12-2.24)**	**1.53 (1.11-2.09)**	**1.48 (1.06-2.06)**	**2.07 (1.21-3.54)**	**1.92 (1.08-3.40)**	**1.84 (1.05-3.23)**	**2.04 (1.12-3.69)**	**1.78 (1.24-2.57)**	**1.70 (1.16-2.48)**	1.13 (0.75-1.73)	1.01 (0.64-1.58)	**2.11 (1.32-2.38)**	**2.16 (1.31-3.54)**
Elevated BP [d]	**Slope**	1.28 (0.94–1.74)	1.07 (0.79-1.45)	0.98 (0.68–1.41)	1.04 (0.70-1.54)	1.12 (0.73-1.70)	1.06 (0.69-1.63)	**1.87 (1.16-3.02)**	**1.70 (1.05-2.77)**	0.68 (0.40-1.18)	1.17 (0.68-2.00)	0.79 (0.47-1.32)	0.70 (0.41-1.18)	1.17 (0.84-1.64)	1.11 (0.79-1.55)	0.71 (0.49-1.03)	0.70 (0.48-1.02)
	Intercept	0.96 (0.72–1.28)	0.99 (0.73-1.34)	1.28 (0.90–1.81)	1.34 (0.91-1.97)	1.24 (0.83-1.85)	1.03 (0.66-1.60)	1.66 (0.99-2.80)	**1.79 (1.03-3.10)**	1.04 (0.52-2.07)	0.66 (0.31-1.40)	0.86 (0.50-1.47)	1.00 (0.58-1.73)	1.05 (0.73-1.50)	1.02 (0.70-1.50)	0.88 (0.55-1.41)	0.87 (0.52-1.44)
Dyslipidemia	**Slope**	0.96 (0.67–1.17)	1.14 (0.80-1.62)	1.00 (0.63–1.58)	0.84 (0.52-1.35)	**1.66 (1.05-2.63)**	1.49 (0.93-2.37)	0.61 (0.18-2.04)	0.47 (0.12-1.81)	1.19 (0.73-1.94)	1.08 (0.66-1.76)	0.86 (0.50-1.50)	0.94 (0.54-1.64)	0.86 (0.56-1.30)	0.84 (0.55-1.30)	0.77 (0.45-1.30)	0.98 (0.58-1.64)
	Intercept	1.10 (0.80–1.52)	1.08 (0.76-1.54)	1.46 (0.94–2.28)	1.20 (0.75-1.93)	1.09 (0.69-1.73)	0.99 (0.61-1.61)	2.37 (0.52-10.8)	2.92 (0.56-15.0)	1.72 (0.92-3.19)	1.85 (0.94-3.61)	1.37 (0.80-2.33)	1.24 (0.71-2.16)	1.30 (0.83-2.03)	1.33 (0.82-2.13)	1.37 (0.75-2.52)	1.43 (0.75-2.75)
Insulin resistance	**Slope**	0.86 (0.61–1.22)	0.90 (0.64-1.27)	1.36 (0.92–2.01)	1.10 (0.74-1.65)	1.45 (0.96-2.16)	1.29 (0.85-1.95)	0.73 (0.40-1.36)	0.62 (0.32-1.19)	0.94 (0.63-1.40)	0.74 (0.50-1.11)	1.05 (0.63-1.75)	1.36 (0.81-2.27)	0.81 (0.53-1.22)	0.97 (0.64-1.49)	0.98 (0.64-1.50)	1.00 (0.65-1.53)
	Intercept	0.84 (0.60–1.17)	0.81 (0.57-1.15)	1.42 (0.97–2.08)	1.27 (0.84-1.92)	1.20 (0.80-1.80)	1.29 (0.84-1.98)	1.51 (0.72-3.15)	1.48 (0.68-3.22)	**1.87 (1.12-3.12)**	1.67 (0.97-2.87)	1.58 (0.95-2.62)	1.58 (0.93-2.68)	1.12 (0.70-1.77)	1.14 (0.70-1.87)	0.73 (0.43-1.24)	0.75 (0.43-1.32)
MetS	**Slope**	0.99 (0.66–1.49)	0.91 (0.61-1.37)	1.69 (0.87–3.23)	0.91 (0.47-1.74)	**2.66 (1.38-5.14)**	1.68 (0.87-3.13)	2.08 (0.37-11.58)	1.10 (0.18-6.49)	1.29 (0.54-3.08)	1.63 (0.68-3.90)	0.82 (0.25-2.66)	2.31 (0.71-7.57)	1.34 (0.74-2.41)	1.74 (0.94-3.20)	0.91 (0.48-1.73)	1.03 (0.54-1.97)
	Intercept	0.95 (0.66–1.38)	0.91 (0.61-1.36)	1.78 (0.97–3.24)	1.38 (0.70-2.69)	1.66 (0.94-2.83)	**1.90 (1.03-3.52)**	1.14 (0.14-8.86)	1.49 (0.19-11.7)	**2.78 (1.04-7.41)**	2.31 (0.77-6.91)	**4.35 (1.68-11.3)**	**4.84 (1.79-13.1)**	**2.38 (1.33-4.25)**	**2.25 (1.19-4.23)**	1.57 (0.76-3.25)	1.62 (0.74-3.51)

[a] Models are adjusted for age (continuous) sex, pubertal status, parental ISCED, HDAS, unhealthy snack intake, observation period and abdominal obesity (when not part of the outcome). The number of participants varied across countries due to missing values for different metabolic outcomes. Bold significance is provided via confidence limits; [b] The reference category for the metabolic outcomes is below the monitoring level; [c] Slope was used as a categorical variable (above vs. below population mean random slope); [d] *BP* blood pressure, *DM* digital media, *MetS* metabolic syndrome.

References

1. Sina E, Buck C, Veidebaum T, Siani A, Reisch L, Pohlabeln H, et al. Media use trajectories and risk of metabolic syndrome in European children and adolescents: the IDEFICS/I.Family cohort. Int J Behav Nutr Phys Act. 2021;18(1):134.