Editorial
Digital Psychology as a Growing Field of Research

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The Journal *Digital Psychology* is conceptualized as a scholarly journal and a platform for knowledge transfer at the interface between digitalization, new media, and psychology as well as related disciplines (e.g. psychiatry, communication science). The key topics of the journal include current research, applied science and practice, and upcoming technological developments in the field.

Digital Media in Psychology is a rapidly growing field and there is a strong need for increased focus on research synthesis to strengthen scientific evidence for emerging theories, methods and therapeutic interventions. Therefore, *Digital Psychology* aims on the one hand to highlight qualitative and quantitative reviews as well as practitioner reviews (opinions, clinical practice), and on the other hand to foster discussion and exchange about pertinent topics and issues in this developing area of research. Furthermore, we welcome research on the influence of technology on children and adolescents, with a particular focus on clinical, social, and economic impacts. We sincerely hope that these topics will become an integral part of our journal.

However, the journal's scope is not limited to these subjects. We also invite scholars working on other topics in the broader field of Digital Psychology (e.g. e-Learning, computer-based assessments, computer-mediated communication, Virtual Reality/Augmented Reality) to submit their research.

The journal comprises two issues per year and includes articles (reviews and original research, letters, and spotlight-communications) in English and in German. Professionals with an interest in a psychological perspective on digital media will find this journal to be of great interest.

Digital Psychology will provide rigorous peer-review by experts in the field and an editorial board covering a broad range of research topics. Moreover, this journal will be archived in PubMed Central and other full-text repositories.

We strongly believe *that Digital Psychology* is a valuable addition to the existing journal landscape on digital media. We are convinced that our collaboration with authors of high quality research, esteemed expert reviewers, and an engaged readership will ensure the success of this journal. We hope that *Digital Psychology* will provide not only a platform for open discussion, but also create fruitful ground for promoting novel insights and developments in this ever-changing area of research.

We thank our Editorial Board Team, as well as the Production Editors and our publisher for the hard work and support that made this adventurous enterprise possible.

Oswald D. Kothgassner and Anna Felnhofer
Editors-in-Chief

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Expert Views on …
… the Future of Digital Media in Psychology

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We asked three experts in the field about future perspectives on digital media in psychology and how it will affect our lives in the next decade. Jeremy Bailenson (Stanford University), Christian Montag (Ulm University) and Thomas Probst (Danube University of Krems) spoke to ***Digital Psychology*** [DP] about these topics.

[DP] How will digital media change the fields of psychology and psychological therapy in the next 5 years?

Thomas Probst: Digital media will transform mental health care and clinical research in the next 5 years. Internet-and mobile-based tools have the potential to globally disseminate evidence-based mental health interventions and to make diagnostic procedures more accurate. Research will move towards a more transdisciplinary approach in order to scientifically develop and evaluate digital media including all stakeholders.

Christian Montag: Naturally this is a hard question to answer, because we have already seen in recent years fast innovation cycles in digital related sciences causing disruptions in many areas of the global economy/societies (regardless of whether we speak of outdated concepts such as the "West" or the "East"). In so far five years are a long time to take a look into the crystal ball. Nevertheless, from what I observe in my research area, I am convinced that we will see a paradigm shift. The availability of digital footprints which can provide insights into a myriad of psychological traits and states and the underlying neurobiology is unprecedented. Therefore, I also foresee that the disciplines of psychology, medicine and computer science naturally will need to heighten their collaborative efforts – perhaps merging into a discipline called Psycho-Neuro-Informatics. Aside from this, I am also convinced that digital data layers present "only" an additional layer available to be studied by behavioral scientists. For instance, classic techniques such as self-report will always be of relevance if we want to understand how people feel or see themselves.

[DP] What are the main challenges of using VR in research?

Jeremy Bailenson: Research needs to engage larger sample sizes – samples that are not simply comprised of university students – examine repeated usage of VR over time, and look at longitudinal outcome measures.

[DP] What are the main challenges of using digital media in research and therapy?

Christian Montag: As we all know, Big Data comes in great variability concerning its variety (data formats), volume and velocity, which we refer to as the VVVs. And now comes the problem: Psychologists are used to carrying out descriptive and inferential statistics, which are still of relevance. But it is also true that when dealing with Big Data these more classic forms of data analysis need to be complemented by new analysis strategies, including machine learning. Beyond this methodological issue, the danger arises that researchers will more often detect spurious correlations which will not be meaningful, because they just appear at random. Therefore, it will be of utmost importance to bring theory guided thinking to the area of Big Data analysis. Of course, this does not mean that exploratory analyses are not valuable when examining Big Data. But such analyses have to be identified as being exploratory in nature and the findings need to be replicated.

Thomas Probst: Most of the digital media tools currently available in the fields of clinical psychology and psychotherapy are not rigorously tested in controlled trials. The challenge is to establish a quality assurance system for digital media that informs one about the digital tools' actual quality. In order to prevent harm, only scientifically-evaluated evidence-based digital tools shall be *recommended*. Other challenges include training therapists in effectively applying digital media as well as regulating who prescribes and covers the costs of their deployment.

[DP] What do you expect from mobile assessments, i-CBT, Virtual Reality, Digital Phenotyping and Big Data in the next decade? How will this affect therapeutic interventions?

Christian Montag: Predicting psychological traits/states from digital footprints produced as a result of a person's interaction with a coffee machine, the fridge or the smartphone in the Internet of Things (also called digital phenotyping or mobile sensing when done from mobile devices) will provide researchers with never before seen insights into human behavior. Crucially, such insights will be also gained on a longitudinal level. This said, I am aware that privacy concerns will dramatically increase in the coming years and it will be an important task, for both society as a whole and IRBs more specifically, to develop sound data protection plans. This is also necessary to protect the rights of participants in psychological studies in an age where researchers are increasingly asked to upload their complete (raw) data sets to repositories such as the Open Science Framework (OSF). Without doubt, frameworks such as the OSF have led to important improvements in the psychological sciences, and were a necessary response to the replication crisis in psychology. My group also supports this movement and uploads data when possible. But let's be honest: This also has the potential to exert tremendous costs on the participants-side of psychological studies. This is particularly pertinent if people participate in several studies, generating distinct data sets which could be matched by machine learning procedures. Here, important new research areas arise in psychology – namely studying privacy. Finally, an urgent discussion is required on what kind of (inferred) data can and should be used for what purposes in society? Should HR-departments be allowed to hire individuals according to their digital footprints? What about insurance companies using our digital data to set a price for policies and so forth? As our understanding of what digital traces can tell us about a person is increasing, we also currently face dramatic issues such as manipulation of elections. Should microtargeting based on digital footprints be banned in the context of elections? I am convinced that these challenges can only be solved with political regulation.

Jeremy Bailenson: What I would like to see in Virtual Reality and Augmented Reality research moving forward is methodological rigor that matches the recent availability and cost of hardware and content.

Thomas Probst: In the next decade, digital assessments of smart mobile devices will generate Big Data for digital phenotyping of mental health. This will produce totally novel scientific findings and data, and make precision-driven mental health care possible. More and more therapists will integrate Virtual Reality Therapy, Internet- and mobile-based interventions (not restricted to i-CBT), and smart digital diagnostics in their practical work. There is an urgent need to keep clinicians and consumers up-to-date about the opportunities and risks of currently available digital media. Governments must recognize the need to provide oversight and regulation to protect otherwise vulnerable consumers.

Info Interviewees

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Development and Usability Testing of SOMO, a Mobile-Based Application to Monitor Social Functioning for Youth at Clinical High-Risk for Psychosis

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Abstract

Background: Youth at clinical high-risk (CHR) for developing psychosis are characterized by long-standing social deficits and isolation compared to healthy youth. Because poor social functioning is predictive of transition to psychosis, it is important to monitor its fluctuations.

Objective: To describe the development of a mobile application to monitor social functioning for CHR youth.

Methods: App development was divided into two phases. In Phase 1, three focus groups with up to eight CHR participants were conducted to discuss (i) content, (ii) graphic design, and (iii) user experience of the app. A working prototype was developed, debugged, and systematically tested by developers. In Phase 2, 13 participants (nine CHR individuals and four healthy controls) evaluated the app through a usability testing for one week. Feedback was gathered through the 23-item Mobile Application Rating Scale user-version (uMARS). Participants were questioned further regarding improvements, positive, and negative aspects of each of the uMARS' items and app features. Focus groups and uMARS' qualitative data were audio-recorded, transcribed verbatim, and analyzed through an inductive approach.

Results: The app was named SOMO and incorporated five features: 1) home screen; 2) goal setting; 3) 11 daily questions; 4) a calendar; and 5) feedback. The application monitored number of daily in-person and online interactions, meaningfulness and time spent with each person, conflict and conflict resolution, activities performed, subjective perception of socialization, and loneliness. SOMO received a good overall score in the uMARS: an excellent score in safety, close to an excellent score in functionality; good scores in information, aesthetics and subjective quality; and acceptable scores in engagement.

Conclusion: Co-design with youth through focus groups provided effective feedback for developing SOMO, which demonstrated initial usability and acceptability. Future research should robustly test the app for efficacy, safety, and should determine that it is a valid and reliable measure of social functioning for the CHR population.

Keywords: mobile health, smartphone, at-risk, psychosis, youth, application

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1 Introduction

A major research focus in the psychosis field is youth who are at clinical high-risk (CHR) for developing psychosis. These individuals present with attenuated or subthreshold psychotic symptoms and typically have poor social and role functioning (Fusar-poli et al., 2012). Although less than a third may develop a full-blown psychotic illness within two years (Fusar-Poli et al., 2012), the majority, even those who do not transition to psychosis, are characterized by long-standing social deficits and isolation compared to healthy youth (Addington et al., 2018). If left untreated, these deficits can lead to profound disability, regardless of the presence or severity of the attenuated psychotic symptoms. Furthermore, both poor initial social functioning as well as a decline in social functioning over time are predictive of later transition to psychosis (Addington et al., 2019; Addington et al., 2017; Brucato et al., 2017). Current methods of assessing and monitoring social functioning are limited to infrequent clinician rated scales such as the Global Functioning: Social (GF:S; Cornblatt et al., 2007), or the Social and Occupational Functioning Assessment Scale (SOFAS; Morosini, Magliano, Brambilla, Ugolini, & Pioli, 2000). There is a need to develop tools to assess social functioning in a dynamic and ecologically valid way (Alvarez-Jimenez et al., 2019). Tracking youths' responses in (near) real-time ensures minimal data loss and early detection of any decline in social functioning. Without this, we remain dependent on single-point retrospective measures that do not capture the dynamics of the adolescent's social interactions or when a decline may occur. Daily assessments can be easily undertaken using new technologies such as smartphones. Today, 90% of youth in Canada own a mobile phone (Pew Research Centre, 2019). Moreover, psychiatric patients, especially those under 30, show favorable attitudes to using their smartphones to monitor their symptoms (Torous et al., 2014). Given youth's enthusiasm for mobile-based applications, these platforms may provide cost-effective, anonymous, non-stigmatizing, and continuously available support to CHR youth (McDermott et al., 2010).

However, the development of mobile-based applications faces several challenges such as user interface design, information architecture, and application context (König-Ries, 2009), which may interfere with the usability of apps by specific populations. To reduce some of these difficulties, participatory design (i.e. involving the user from the beginning to the end of the development of a mobile-based application; Scandurra, Hägglund, & Koch, 2008) has been proposed as a useful approach in creating a highly usable application that matches users' idiosyncratic needs. Participatory design through focus groups aims to design mHealth applications (Hamzah, 2018) *with* users, rather than *for* users, by involving them throughout the development process (Sanders, 2002). Participatory design usually involves three phases: (i) initial exploratory work mostly done by researchers; (ii) the discovery process, which is when most interaction occurs between researchers and users; and (iii) the prototyping phase by iteratively shaping artifacts (Spinuzzi, 2005). The most common methods for data collection in participatory design are semi-structured interviews, focus groups, workshops, or organizational games (Spinuzzi, 2005). Among others, participatory design can use different techniques to: (i) create tangible artifacts such as collages, probing, and prototyping; (ii) explain things such as storyboarding using diaries, blogs, or pictures; and (iii) act and play by using games or improvisation (Sanders, Brandt, & Binder, 2010).

Focus groups have been previously used with youth and adolescents to gather information regarding mHealth tools and user needs. These have generally been useful in obtaining information about safety, engagement, accessibility, functionality, type of information captured, and features to be included in mobile apps (Hetrick et al., 2018; Kenny, Dooley, & Fitzgerald, 2014; Lim et al., 2019; Reid et al., 2009). Adolescents and young adults are capable of providing valuable feedback related to mHealth tools and their features such as avatars, social interaction, frequency, duration, timing, and mode of delivery (Cornelius et al., 2013). Specifically, youth have an interest in smartphone applications promoting behavior change that includes tracking behaviors, setting personal goals, and getting information (Dennison, Morrison, Conway, & Yardley, 2013).

There are some mobile-delivered interventions dedicated to improving social functioning such as FOCUS for schizophrenia (Ben-Zeev et al., 2014), and +Connect (Lim et al., 2019) and myCompass (Fogarty et al., 2017) for depression and anxiety. SPAN (Social Participation and Navigation) implements social goal-setting for adolescents with a traumatic brain injury (Narad et al., 2018), and MATS (Mobile Assessment and Treatment for Schizophrenia) monitors socialization attitudes through four daily text messages for individuals with schizophrenia (Granholm, Ben-Zeev, Link, Bradshaw, & Holden, 2012). However, none have included daily monitoring of functioning comprising a diverse range of self-reported social aspects. Therefore, we have developed SOMO, an application to monitor daily social activity among youth at CHR. This article describes the development and testing phases of the app. To the best of our knowledge, this is the first time a tool has been developed to exclusively monitor social functioning, an important predictor of transition to psychosis and impairment in those at CHR for psychosis.

2 Methods

2.1 Sample

Participants were identified from current studies at the At-Risk for Mental Illness Research Program at the University of Calgary. When youth attended one of their follow-up assessments, they were asked if they would like to participate in an app study. Inclusion criteria were: 1) meet criteria for one of the three established criteria for a psychosis-risk syndrome (i.e. attenuated psychotic symptom state, brief intermittent psychotic state, or genetic risk with deterioration in functioning) based on the Structured Interview for Psychosis-Risk Syndromes (McGlashan, Walsh, & Woods, 2010); 2) ages between 12–30 years old; and 3) understand and provide signed informed consent. Ethics approval from the Conjoint Health Research Ethics Board (CHREB) was obtained for the focus groups and usability testing. All participants provided informed consent to participate in this project (parental informed consent and assent were obtained for those under the age of 18) and for the use of the material created in the focus groups for publication purposes.

2.2 Procedure

Phase 1 (Development): Three 90-minute focus groups were conducted (June-August, 2018) with a maximum of 10 and a minimum of four participants per group (Heary & Hennessy, 2002). Focus groups were facilitated by OSE, a doctoral level clinical psychologist with experience in focus groups, and co-facilitated by two undergraduates who worked on the app development (JT, JF). The first group (June 2018) focused on app content. Opinions were gathered on the existing paper tools that measure social functioning such as the Global Functioning: Social (GF:S; Cornblatt et al., 2007). See Supplementary Material for a full list of tools consulted. The second group (June 2018) focused on the graphic design in two parts: (1) Participants were shown current existing apps on the market that assess similar outcomes (i.e., goals, relationships, social skills) and participants generated opinions and design ideas; (2) Following Design Studio methodology (Warfel, 2009), participants were prompted to create free-style sketches of the features they would want in the app, which were subsequently discussed by the group (see Supplementary Material eFigure 1). The third group (August 2018) focused on user experience. Participants reviewed a working prototype of the app and were prompted initial in-group testing to offer feedback on features, design, speed of the app, data storage, and iterate on the design further. Participants were reimbursed $30.

Phase 2 (Usability Testing): The app was tested systematically on iOS and Android devices by the app developers (alpha-testing). Participants then tested the app (beta-testing) for one week (December, 2018) and were provided quantitative and qualitative feedback on their experience with SOMO. Of the 13 participants, four were healthy controls with no prior experience of the app; five were CHR participants with no prior experience of the app; and four were CHR participants who previously participated in at least one focus group. Participants were reimbursed $90.

2.3 Measures

To obtain feedback about the app following the usability testing, the Mobile Application Rating Scale user-version (uMARS; Stoyanov, Hides, Kavanagh, & Wilson, 2016) was utilized. This is a 5-point Likert scale [1=*poor,* 2=*fair,* 3=*acceptable,* 4=*good,* and 5=*excellent*] with 23 items covering questions about engagement, functionality, aesthetics, information, subjective quality, and perceived impact. All of the subscales can be evaluated by their mean score. The uMARS has demonstrated good test-retest reliability (ICC=.70) and excellent internal consistency (α=.90; Stoyanov et al., 2016), showing good internal consistency in our sample (α=.82). One question regarding perceived safety was added. The uMARS was implemented in interview form, where participants provided their quantitative rating for each item, and the interviewer prompted further questioning to gather qualitative information (i.e. on improvements, positive and negative aspects) for each of the uMARS items. No attempt was made to analyze the perceived impact, as it was beyond the scope of the article.

2.4 Data analyses

The focus groups and the qualitative interviews were audio-recorded and transcribed verbatim. For Phase 1, a general inductive approach was employed for analysis (Thomas, 2006). Transcripts were summarized and used in conjunction with the design sketches to underscore the main app design and features. The three focus groups were analyzed as a whole dataset (Braun & Clarke, 2013). When specific research questions guide the focus groups (i.e. app features), results can be extracted with focused objectives (Thomas, 2006). OSE coded the main themes and features and JT checked for accuracy until data saturation was obtained (Guest, Bunce, & Johnson, 2006). For Phase 2, descriptive information about the semi-structured interview process and the quality ratings through the uMARS were reported.

3 Results

3.1 Development of the app

Ten participants were invited to each of the three focus groups. Eight participants confirmed that they would attend focus groups 1 and 2. For focus group 3, only six participants confirmed, and two did not attend due to a last-minute schooling conflict. Eight participants attended the first focus group (age: M=20.0, SD=3.5, range: 15.6 to 27.0; 62.5% female), eight attended the second (age: M=19.7, SD=3.6, range: 15.6 to 27.0; 75% female), and four the third focus group (age: M=20.2, SD=1.4, range: 18.4 to 21.4; 75% female). Participants created the name of the app SOMO (SOcial MOnitoring) and its logo. Below, we describe the general design and the development of each SOMO feature after qualitative information was gathered (i.e., home screen, goal-setting, questions, calendar, and feedback). Figure 1 depicts the initial design showed to participants.

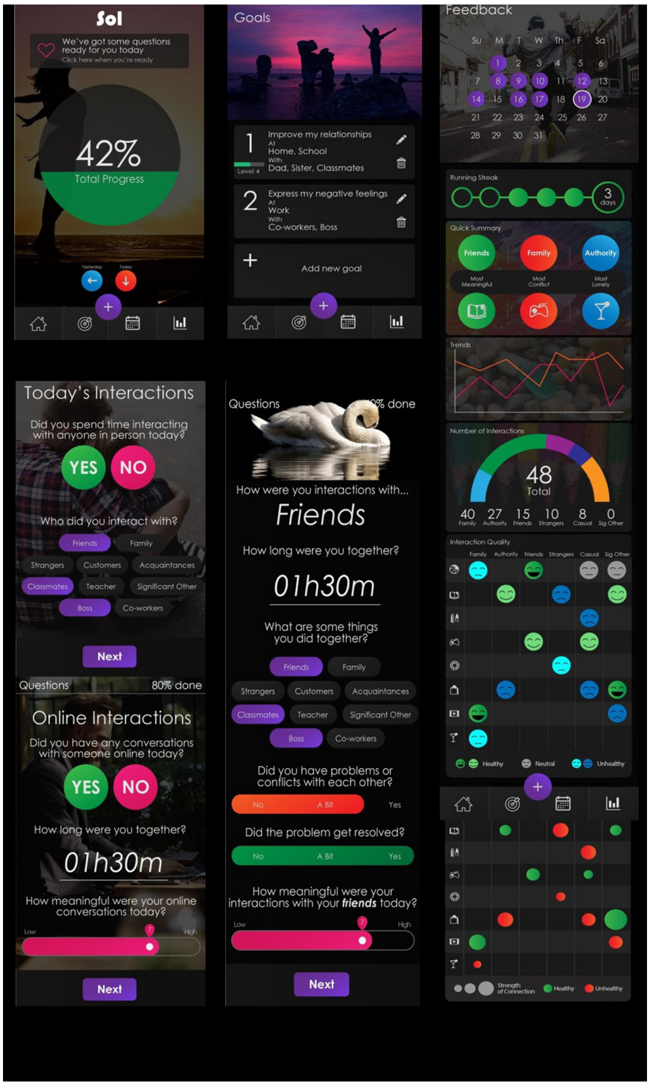

Figure 1. Initial application design.

3.2 General Design and Settings

Development was guided by the Technology Acceptance Model (TAM; Davis, 1989), which suggests that engagement with an app and its continued usage is the result of its perceived ease of use and perceived usefulness. Thus, key development aspects to take into account in monitoring apps are quick completion of questionnaires, app performance, and ease of use (Price, Sawyer, Harris, & Skalka, 2016).

Participants chose a user-friendly design including: minimal steps to access content; "info buttons" on each screen to facilitate understanding; simple screen arrangements and wording; a minimal amount of text; and graphics instead of text for the feedback. Moreover, participants made clear they wanted more neutral pictures (e.g. no gender, age, or people represented), opting for images of nature or urban backgrounds.

Participants expressed the importance of facilitating a degree of customization within the app, which ranged from changing the background themes or the color palette to having an individualized notification system. The youth discussed the need to have a reminder to log in to SOMO (e.g. setting up an alarm for a specific hour). They unanimously wanted an automatically pushed single notification on their phone screen. Although they thought the app was straightforward, there were concerns about older generations not being used to the technology, or the younger people needing more onboarding assistance when they are first introduced to the app. Thus, they expressed the need for a tutorial.

Data safety was important. Participants did not want to provide any personal information or contacts and proposed a password-protected app to safeguard their privacy. User privacy was managed by (i) a 4-digit PIN login and (ii) encrypted transmission of anonymous data stored on secure servers managed by the University IT department. Furthermore, participants expressed the concern that monitoring apps do not provide extra support in case of distress. Consequently, a phone icon directly connected to a free 24hr counseling center in Calgary was incorporated into the app.

3.3 App features

Home screen. Participants liked the initial home screen design because it was simple, intuitive, and not overwhelming. Participants wanted some basic statistics to reinforce usage and to have a general idea of their social relations: "maybe you can show a mood tracker, a percentage, or something right away on the home screen." Thus, displaying the percentage of total interactions was implemented as quick feedback on the home screen. Quick access to the daily questionnaire occurred by touching one of the two reminders integrated into the home screen (e.g., today and/or the previous day) when they had not yet been completed. Finally, a bug report button was implemented to allow real-time usability testing and users to report any technical problems.

Daily questions. Out of the initial set of 18 daily questions presented, a final set of 11 questions focusing on in-person or online social interactions were implemented, covering: type of relationship, time spent together, quality of the interaction, activities undertaken, conflict and resolution, meaningfulness of the interaction, and the subjective feelings about the amount of social engagement and perceived loneliness. All app questions are presented in the Supplementary Material. Participants assisted in wording and selecting the priority foci of the questions (e.g. less importance to online interactions) to make the questionnaire short but useful. Questions that were not implemented covered: (i) how the interaction started (i.e. we ran into each other; I contacted them, etc.); (ii) conflict resolution strategies (i.e. we talked about it); (iii) perceived supportiveness and perceived connection of the interaction; and (iv) type of online interaction (i.e. messaged, video-chat, Snapchat, etc.) or online conflict and resolution. Participants thought that some of these questions did not add useful information to their social functioning, were not easily distinguishable, made the daily questionnaire too long, or would not capture their interactions appropriately. Responding to the final questions takes approximately 30 seconds to 2.5 minutes, depending on the amount of social interaction that day.

Social goals. Participants reported that setting social goals provided an inherent purpose to the app. Some preferred to set individualized goals. However, the majority (75%) preferred a semi-structured goal-setting tool because they had difficulties in devising goals without prompts. Participants arrived at a consensus that a blend should be implemented. We presented participants a list of real social goals obtained from therapeutic groups with CHR youth (e.g., "talk to someone who is bothering me", "set boundaries", Kelsven et al., 2019), which seemed appropriate for the target users. Participants preferred broad goal categories to avoid feeling overwhelmed by too many options. Changes to the wording were proposed and the number of goals defined. Finally, participants wanted to see the progress towards the completion of their goals. One tab was dedicated to goal creation in a three-step multiple-choice process by selecting: 1) the broad goal (e.g., "motivate myself to go out"); 2) the context (e.g., at home, out in public, at work, or at school); and 3) the person (e.g., brother, girlfriend, mother, teacher, coworker, or classmate). The possibility to write an individualized goal was implemented. Goal improvement was shown via a progress bar with different levels generated by a back-end algorithm, which considers all responses to level-up. Participants entered an activity as a goal, which was then operationalized by entries of the participant. These entries were tracked through a back-end algorithm (i.e., a weighted score based on the responses to each question) that served as a goal improvement proxy (see Supplementary Material eTable 1). Participants found the goal-setting feature easy to understand and representative of the social skills they valued. Participants liked that goals could be customized and were individually tailored.

Calendar. Participants wanted a calendar for tracking their previous entries. They opted for a traditional view of the month, where a specific day can be selected and responses for that day are displayed. Most participants (87.5%) reacted against the inclusion of negative feedback in the calendar (e.g., loneliness or days not logged in marked in the calendar). "I don't want to see a red dot on the calendar every day; this would make me feel bad". After some discussion on best methods, days logged in SOMO were marked with a purple circle, and the responses for that day would pop up in a list format.

Feedback. Participants unanimously wanted to have a visual representation of their social functioning as "motivation for not being lazy, using the app, and seeing my progress". Participants preferred different types of data visualizations so they could refer to those most personally useful. Six feedback charts were implemented: (i) run streak of loggings; (ii) quick summary of correlations; (iii) meaningful interactions and loneliness trends by day; (iv) number of interactions with each person; (v) time spent interacting with each person; and (vi) full data of the correlations between activities*person*meaningfulness. Figure 2 depicts the feedback charts implemented. Participants commented on the importance of streaks in particular, e.g., Snapchat streaks, indicating that this might increase their motivation to use SOMO. Comments included: "I think like err… it would actually become like a competitive thing. How many logs I have?" "It would benefit me; like if I see I'm not logging for four days, I'd be, screw… I need to get on this right now". Moreover, they wanted the negative feedback (e.g., loneliness) to be presented with a soft-line graph rather than numbers: "It is the best way to represent loneliness without coming across as like hurtful to some people; cause if you are really lonely, it's literally a graph, it's not like –hey you've been this lonely–". Feedback regarding time and number of interactions was clear and straightforward, and participants wanted them stratified by type of person. Finally, several iterations of the design of the correlations of meaningful interactions were made until settling on the final grid design. Although not immediately clear, the concept was considered interesting because it is sometimes difficult to figure out the connection between actions and emotions. "There are people that have a hard time to know what made them being lonely, or happy, like what are the things that happen together to make me feel like that."

Figure 2. Feedback charts: [A] run streak of loggings; meaningful interactions and loneliness trends; and quick summary of correlations; [B] number of interactions with each person; time spent interacting with each person; [C] full data of the correlations between activities*person*meaningfulness; [D] example of an information button.

4 Usability Testing

Thirteen participants (nine CHR and four healthy controls; age: $M = 20.3$, $SD = 4.6$; 77% female) with iOS ($n = 8$) and Android ($n = 5$) devices tested SOMO for one week. Of the 13 participants, four were healthy controls with no prior experience of the app; five CHR participants with no prior experience of the app; and four CHR participants who previously participated in at least one focus group. Quantitative responses of the uMARS after the usability testing are provided in Table 1. The app had the highest rating in functionality, followed by information provided, aesthetics, subjective information, and engagement, respectively.

Qualitative feedback on the quality of SOMO following the usability testing is presented in Supplementary Material eTable 2. Participants' overall response to the beta version of SOMO was positive. Some technical difficulties and minor bugs were reported, such as the absence of notifications or being unable to create goals, with some Android users unable to save goals

Table 1. SOMO mean scores on the uMARS (*n* = 13)

	M (SD)
Engagement	3.77 (0.48)
Entertainment	3.08 (0.64)
Interest	4.08 (0.49)
Customization	3.15 (1.21)
Interactivity	4.00 (0.82)
Target group	4.54 (0.78)
Functionality	4.65 (0.24)
Performance	4.08 (0.76)
Ease of use	4.69 (0.48)
Navigation	4.85 (0.38)
Gestural design	5.00 (0.00)
Aesthetics	4.46 (0.66)
Layout	4.69 (0.63)
Graphics	4.31 (0.85)
Visual appeal	4.38 (0.77)
Information	4.50 (0.38)
Quality of information	4.77 (0.44)
Quantity of information	4.38 (0.65)
Visual information	4.31 (0.63)
Credibility of source	4.77 (0.60)
Subjective quality	4.00 (0.74)
Recommend the app to others	4.85 (0.55)
Use the app next 12 months	4.62 (0.65)
Pay for the app	2.38 (1.66)
Overall app rating	4.15 (0.55)
Total SOMO quality	**4.29 (0.35)**
Safety	5.00 (0.00)

Note: uMARS: Mobile Application Rating Scale – user version.

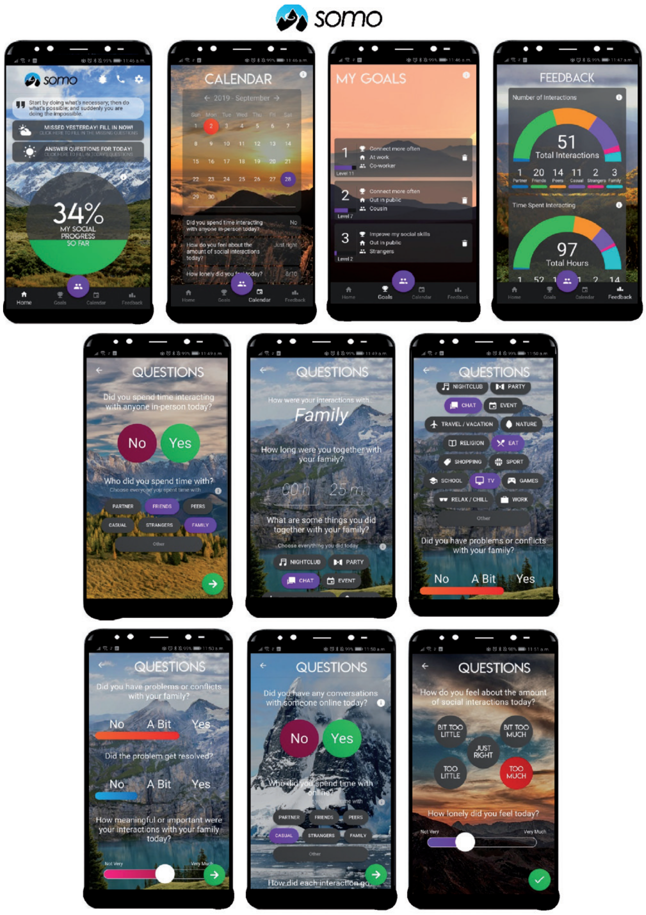

Figure 3. Final SOMO design – Mountains background.

due to a coding problem. Some suggestions for improvement were made: increasing the quality of images and graphics, adding sound, voice, games, more customization options, developing the tutorial, showing the developer credits, and adding extra resources. Common issues identified by the testing sample were addressed in the final version of SOMO, which included four different backgrounds (mountains, ocean, urban, and forest). Small information buttons with further explanation of the app features were added in each tab and for each feedback chart. Some issues could not be addressed, such as increasing the quality of images or adding sound and games. The reasons these issues were not addressed were: 1) concerns of only one user; 2) the difficulty of addressing the issue; 3) they surpassed the primary purpose of the app; or 4) installation difficulties. The development team tested the final version of SOMO in-house (alpha testing). All features worked properly for both Android and iOS devices. SOMO was subsequently made available free of charge through Apple Store and Google Play. Although anyone can download the app, a code which is provided only to study participants is needed to create an account. Figure 3 depicts the final SOMO design after gathering participants' feedback.

5 Discussion

In this paper, we describe the development of SOMO, a mobile application to improve current methods of monitoring social functioning for CHR youth. SOMO conforms to the recommended guidelines for developing apps for research (Bakker, Kazantzis, Rickwood, & Rickard, 2016). Our prototype has been: (i) co-designed including developer and end-user perspectives; (ii) debugged, iterated, and alpha- and beta-tested; (iii) refined after receiving feedback from end-users regarding design and usability; and (iv) made available in Google and Apple apps stores.

Using a co-design approach for SOMO development improves on the design of available mHealth apps. Although outcomes measured by the app, data integrity, and safety are important aspects for researchers, it is key to assess different characteristics of the app such as functionality or aesthetics (Rickard, Arjmand, Bakker, & Seabrook, 2016). These aspects are likely to increase user engagement, which is imperative for obtaining final data (Rickard et al., 2016). To do so, well-established app assessment tools (i.e., uMARS, Stoyanov et al., 2016) were employed to develop an app offering standardization and thereby enabling comparison with different mHealth apps. Satisfaction for SOMO was high, surpassing the mean ratings for 50 mHealth and wellbeing apps for all uMARS subscales (Stoyanov et al., 2015). Specifically, SOMO's highest scores were in functionality (i.e. ease of use, navigation, performance, and gestural design). The Technology Acceptance Model (Davis, 1989) describes that ease of use and perceived usefulness improve engagement with an app and its continued usage. Therefore, SOMO may have a strong potential to maintain engagement.

According to previous research, monitoring was perceived as a safe and acceptable method to gather data on social interactions (Torous et al., 2015) underscoring the need to monitor social functioning from a positive approach (Wadley, Lederman, Gleeson, & Alvarez-Jimenez, 2013). However, an important concern raised was the fact that monitoring apps do not provide extra support in case of user distress. This echoes similar safety concerns raised by clinicians in other studies (Sundram et al., 2017). Thus, efforts were made to provide links to appropriate services. Despite these considerations, monitoring apps may promote a safe and positive environment for help-seeking and enhance communication with clinicians (Hetrick et al., 2018; Sundram et al., 2017). Moreover, SOMO is password-protected and data is encrypted. Control over privacy settings has been shown to be an important concern for end-users and a key feature in the development of apps for youth (Kenny et al., 2014).

SOMO has a user-friendly design avoiding unnecessary distractions, according with principles proposed previously in the development of apps for individuals with psychosis (Rotondi et al., 2007). This may be important for those who are possibly in the at-risk stages of a psychotic illness. Furthermore, key app features are consistent with evidence-based principles for monitoring tools (Rickard et al., 2016). Customization, control of notifications, and personalization of app features were relevant, and have been addressed as important factors to take into account when co-designing monitoring apps with youth (Hetrick et al., 2018; Sundram et al., 2017). Digital tools that provide greater interactivity, choices, and control may have the potential to enhance acceptability (Knowles et al., 2014).

SOMO includes a goal-setting feature to provide a purpose to the app, which may maximize user engagement, a crucial aspect for mHealth. Following gamification principles (Kapp, 2012), goal improvement is shown via a progress bar with different levels generated by a back-end algorithm, and daily feedback in the form of graphs to users. The provision of feedback on the progress of the desired behavior has been recommended for monitoring and mHealth apps (Bakker et al., 2016). Moreover, daily feedback may increase feelings of achievement, which could be viewed as a reward, and increase engagement with the app (Kapp, 2012). Finally, one of the feedback features included in SOMO is a run streak. Previous research has shown that streaks increase motivation, and are an effective tool to support behavioral repetition, such as creating and maintaining habits (Renfree, Harrison, Marshall, Stawarz, & Cox, 2016).

To the best of our knowledge, this is the first app to monitor social relationships and social goals following a co-design approach by the inclusion of the target group – CHR youth – through focus groups and usability testing. This ensured that the final product was grounded in evidence-based science and provided an engaging, relevant, and useful tool for both Android and iPhone end-users. There are, however, several limitations. Firstly, there are limitations in the app design, where extra customization could have been included to engage more youth. Secondly, there are limitations in the co-design process, where focus groups with independent clinicians and further usability testing with end-users could have been undertaken. One of the difficulties in conducting more than one focus group per theme is that recruiting individuals who meet CHR criteria is difficult (Addington et al., 2008). Moreover, group dynamics such as groupthink may arise in focus groups (i.e. members pressure others to conform to group consensus). To mitigate the recruitment and group dynamics limitations, we performed 13 further individual semi-structured interviews, a method by which study results can reach data saturation (Bernard, 2012; Guest et al., 2006). Other limitations include: (i) a small sample size; (ii) majority of female participants, who may have had a particular design inclination not representing all users' needs and preferences; (iii) a lack of information on the app efficacy due to the development stage of the study; and (iv) a small probability of bias of the usability testing due to the overlap of four participants with the focus group.

Finally, although SOMO was designed following recommended development guidelines, it is key to robustly test the app for efficacy and safety, as well as to assess whether it is a valid and reliable measure of social functioning compared with validated measures for the CHR population such as the Global Functioning: Social (GF:S; Cornblatt et al., 2007).

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Declaration of interest

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Conflict of Interest

OSE, JT, JF, and JA list no competing interests

Supplementary Material

1 Functioning Tools

A wide range of paper tools that measure general functioning, social functioning, and quality of life were consulted to gather items that assessed social functioning in different ways. We presented a selection of items to Focus Group 1 to ascertain if these were appropriate for evaluating social functioning among youth. The following list presents the scales consulted:

- The Social Functioning Scale – SFS[1]
- Functioning Assessment Short Test – FAST[2]
- Social and Occupational Functioning Assessment – SOFAS[3]
- The Quality of Life Mental Health Index – QLI-MH[4]
- Lehman's Quality of Life Interview – QOLI[5]
- Heinrichs' Quality of Life Scale – QLS[6]
- The Camberwell Assessment of Need – CAN[7]
- Children Global Assessment Scale – CGAS[8]
- Comprehensive Quality of Life Scale, School version – ComQol-S5[9]
- Global Assessment of Functioning – GAF[10]
- The Global Assessment Scale – GAS[11]
- The Groningen Social Disabilities Schedule – GSDS[12]Health of the Nation Outcomes Scales – HoNOS[13]
- Life Chart Schedule – LCS[14]
- McGill Quality of Life Questionnaire[15]
- The MIRECC version of the Global Assessment of Functioning – MIRECC GAF[16]
- Personal and Social Performance – PSP[17]
- Quality of Life Issues – QLI[18]
- Short Screener version of the Social Adjustment Scale – SAS-SR[19]
- Social Inclusion Interview – SII[20]
- Schizophrenia Quality of Life Scale – SQLS[21]
- The Strauss and Carpenter Prognostic Scale[22]
- World Health Organization Disability Assessment Schedule 2.0 – WHODAS 2.0[23]
- Wisconsin Quality of Life Index– W-QLI[24]
- Oregon Quality of Life Questionnaire – OQLQ[25]
- Quality of Life Checklist – QLC[25]
- Satisfaction with Life Domains Scale – SDLS[26]
- Community Adjustment Form – CAF[27]

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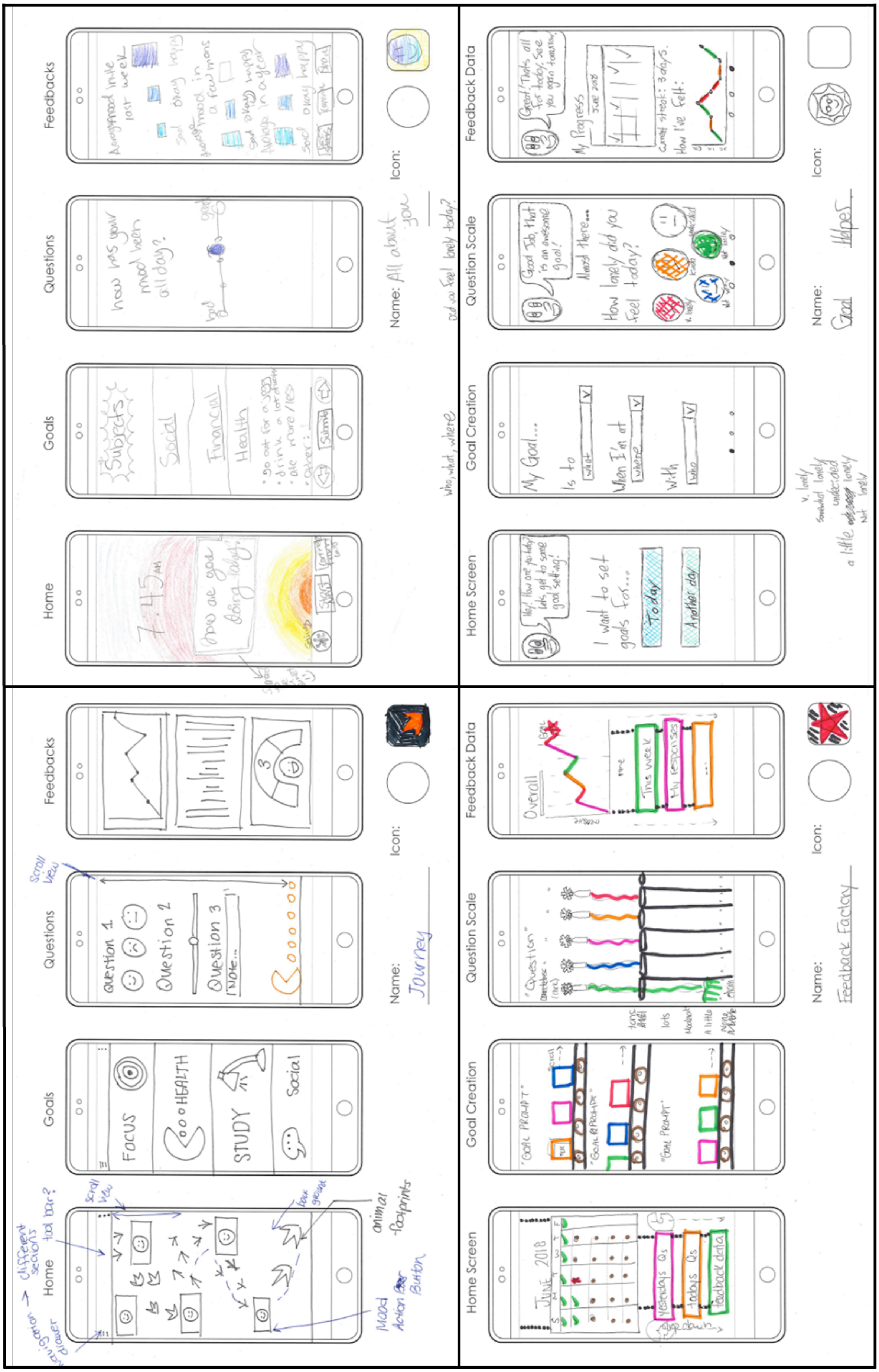
2 Final SOMO questions

1. Did you spend time interacting with anyone in-person today?
   a. Yes (if yes – go to **Q2**)
   b. No (if no – go to **Q7**)
2. Who did you spend time with? (choose everyone you spent time with) *Note:* questions Q3–Q6 get repeated for each relation chosen in Q2.
   a. Partner
   b. Friends
   c. Peers
   d. Casual
   e. Strangers
   f. Family
   g. Other [write]
3. How were your interactions with… [person] How long were you together with… [person chosen]
   a. A 24-hour drop-down menu in hours and minutes.
4. What were some things you did together with… [person] (choose everything you did)
   a. Nightclub
   b. Party
   c. Chat
   d. Event
   e. Travel/Vacation
   f. Nature
   g. Religion
   h. Eat
   i. Shopping
   j. Sport
   k. School
   l. TV
   m. Games
   n. Relax/Chill
   o. Work
5. Did you have problems or conflicts with… [person]?
   a. No
   b. A bit
   c. Yes
6. How meaningful or important were your interactions with your… [person] today?
   a. 0–10 slider.
7. Did you have any conversations with someone online today?
   a. Yes (if yes – go to **Q8**)
   b. No (if no – go to **Q10**)
8. In total, how much time did you spend in online conversations today?
   a. A 24-hour drop-down menu in hours and minutes.
9. How meaningful were your online conversations?
   a. 0–10 slider.
10. How do you feel about the amount of social interactions today?
    a. Bit too little
    b. Too little
    c. Just right
    d. Bit too much
    e. Too much
11. How lonely did you feel today?



eFigure 1. App sketches produced by participants in the secon focus group.

Note. Permission to publish this material has been obtained.

3 Goal Measurement

To design the back-end algorithm, all social goals are arbitrarily organized into four categories: 1) connection, 2) resolution, 3) expression, and 4) confidence. Each of the 11 daily questions has a weight. eTable 1 depicts the weight of each question. After responding to the questions, a score that only applies to certain goal categories is created. Two questions, with scores ranging from 0 to 10 (Q7: meaningfulness of in-person interactions; Q11: meaningfulness of online interactions), modify the final score. One question (Q1: people), multiplies the final score. The point-multiplier was based on the weight that the Global Functioning Scale: Social (GF:S; Cornblatt et al., 2007) posits to each type of interaction. Each time a participant responds to the daily questions, a score is calculated for each goal created. If relevant to the goal, goal improvement is showed via a progress bar with different levels. The decision-making for the scores was established by two researchers (OSE and JT). In case of discrepancy, a consensus was reached after discussion.

Reference

Cornblatt, B. A., Auther, A. M., Niendam, T., Smith, C. W., Zinberg, J., Bearden, C. E., & Cannon, T. D. (2007). Preliminary findings for two new measures of social and role functioning in the prodromal phase of schizophrenia. *Schizophrenia Bulletin*, *33*(3), 688–702.

eTable 1. Algorithm for goal levels

		Goal category			
		Connection	Resolution	Expression	Confidence
Q3. Time in-person	<15min	0		0	0
	15min - 30min	1		1	1
	30min - 1hr	2		2	2
	1hr - 3hrs	3		3	3
	3hrs - 6hrs	4		4	4
	6hrs -24hrs	5		5	5
Q4. Activity	Chat	2	1	2	1.5
	Relax / Chill	1	0	0.5	0.5
	Games	1	1	0.5	0.5
	TV	0.5	0	0.5	0.25
	Eat	1	1	1	1
	School	0.5	0.5	0.5	0.5
	Work	0.5	0.5	0.5	0.5
	Event	2	0.5	2	1
	Religion	1.5	1	1.5	0.5
	Travel / Vacation	2	1.5	2	2
	Shopping	0.5	0	1	1
	Nature	2	0.25	2	1
	Sports	2	1.5	2	1.5
	Party	1.5	0.5	1	2
	Nightclub	1.5	0.5	1	2
Q5. Conflict	Yes		0		
	A bit		0		
	No		1		
Q6. Conflict resolution	Yes		2	2	
	A bit		1.5	1.5	
	No		0	0	
Q8. Subjective Perception	Bit too little	0			0
	Too little	0.5			0.5
	Just right	1			1
	Bit too much	1.5			1.5
	Too much	2			2
Q9. Loneliness	[Inverse range]	[10-0]			[10-0]
Q10. Time online	<15min	0		0	0
	15min - 30min	0.5		0.5	0.5
	30min - 1hr	1		1	1
	1hr - 3hrs	1.5		1.5	1.5
	3hrs - 6hrs	2		2	2
	6hrs -24hrs	2.5		2.5	2.5

0-100% Modifiers
Q7. In-person meaningfulness
Q11. Online meaningfulness

Point Multiplier	
Q1. People	
Partner	200%
Friends	175%
Peers	150%
Casual	130%
Strangers	120%
Family	100%
Other	100%

eTable 2. Qualitative responses to the Mobile App Rating Scale – user version uMARS (positive, negative aspects, and suggestions for improvements) after the usability testing.

Usability testing	POSITIVE	NEGATIVE	IMPROVEMENTS
ENGAGEMENT			
Entertainment	• Varied and different responses. • Entertaining and fun enough for its purpose. • Informative, tracks the behavior. • Straightforward, easy, fast, practical. • Enhanced engagement through the colors.	• Seemed old or dated. • Not high technology. • Not that much fun.	• Higher quality of graphics and images: Movement, 3D, sound, relaxing (waves, blue, the sea, mountains), categorized into themes. • Add emoji's. • Home screen: More interactive with gamification and trophies.
Interest	• Interesting to track/think about relations: enhances reflection, review of the day, checkup progress, like a diary. • The feedback page: the most interesting feature as it is revealing. • Colorful and fast, maintained the interest.	• Questions seemed repetitive, boring. • The more people you interact with, the more screens you have.	• Add more "people" options (other is too general). • Change the wording of the questions from each logging. • Add pie charts instead of semicircles for the feedback page.
Customization	• Notifications are customizable. • Enough customization, has the basics (is not a social media app). • Liked the colors/backgrounds. • Goals can be customized, individually tailored.	• Notifications and goals were not working (Android). • The "other" option was not always noticed. • Not enough customization.	• Background images: add movement, themes (waves, blue, the sea, and mountains), and your own (library/camera). • Organize the feedback page in the preferred order. • Change the sentence of the notification to avoid repetition. • Choose own palette of app colors. • Add real names of people and be able to save them. • Add more notifications and more than three goals.
Interactivity	• Highly interactive. • Bug report allowed user input and communication with developers. • The feedback page provided personal information and interaction. • Notifications, goals and the running streak made it interactive.	• Goals are set up the first day, easy to forget about them.	• Add a specific reminder only for the goals. • A tutorial in video format that reads the pop-ups would be useful and more interactive.
Target group	• Covered the target group (CHR between 12–30 years old). • Simple, easy content and language, straightforward, and user friendly for the younger users. • Neutral colors and images, not gender/sex related, accommodating to everyone. • Calming. • Developed through focus groups with youth, targeting the intended audience. • Goals made from real examples of other youth's goals.	• Not visually appealing for younger users. • Targets older audience.	• Add background music to engage younger users.
FUNCTIONALITY			
Performance	• Functioned perfectly. • Short and quick to respond. • Fast, good speed and performance.	• Minor technical bugs. • Goals and notifications not working properly (Android). • Errors in the calendar: "error" message and time expressed in minutes. • Sudden log out without saving previous responses. • Lapse of time between finishing the questions and the feedback page popup. • Short pauses between screens.	• Show time spent in hours rather than in minutes. • Save the responses if you log out of the app.

eTable 2. continuation

Ease of use	• Good job in showing pre-made goals. • Extra information provided by the “information buttons”: straightforward and useful. • Easy to use, simple, obvious, self-driven, and self-explanatory. • No further explanation or prompts needed. • The researcher explained how it works with clear instructions. • Easy because it does not go deep into any section. • Each screen has a “next button” making clear what to do. • Icons helped to navigate the app without reading much.	• The goals were difficult to learn. • Unclear app purpose initially. • Without the information provided by the researcher, the user would need a bit of time to learn the app. • The “information buttons” were unnoticeable.	• Have a quick tutorial or video to learn how to use the app. • Make the “information buttons” more visible.
Navigation	• You tap in one thing and it goes where it has to go. • There is a “next button” that helps to connect to the next screen. • Good dashboard layout. • Easy, intuitive, clear, straightforward, and simple navigation. • The feedback page popped up after responding the questions.		• Scroll from left to right to move between screens.
Gestural design	• Scrolling and the sliders were good, consistent across screens. • The icons and buttons were universal. • The gestural design made sense. • Scrolling only applies for the feedback page, and was obvious.	• Technical bugs in the feedback page. • The full alphanumeric keyboard appears for the PIN. • Scrolling through the time slider takes time. • Too much scrolling in the feedback page.	• Scroll up option in the home screen to answer questions. • Have a PIN keyboard with only numbers.
AESTHETICS			
Layout	• Information, buttons, and icons were in order and organized. • The purple button in the home screen to answer the daily questions was very good. • The icons and buttons were good, consistent, professional, and perfectly sized. • The “information buttons” were small as in other apps. • Easy to read without overlapping being cluttered.	• Information buttons: small, not visible, users did not realize they were there. • Inconsistent size of the feedback icons. • Unclear number selection on the sliders (0–10). • On iPhone XSmax, the SOMO logo is cut.	• Change size/color of the information buttons (red, blue or yellow) to make them stand out. • Show the number selected in the sliders (0–10). • Change the icons colors to more relaxing and settling colors (pastel, light blues). • Increase the size of the “meaningful interactions” grid icons. • Add an option to zoom in the content.
Graphics	• High quality of graphics and images. • Images and graphic information were clear and professional. • Simplistic design. Fancier pictures would be distracting from the purpose of the app. • Nothing was blurred or pixelated.	• The half-circle feedback was confusing. • The “bug report” icon looks funny in Android devices.	
Visual appeal	• Nice font and design: Aesthetically pleasant, satisfactory. Stands out, beautiful, and attractive. • Harmonious colors, which maintained the interest, and enhanced app features and menus. • Calmed and relaxed environment, easy on the eye. • Neutral themes (nature). • Professional look by the dark grey and black.	• Unappealing images/design. • Strong color choices. • Unmatched color palette.	• Have more customization: background themes, palette of colors. • Add brighter pictures (the sky, the ocean), a clear layout would be more appealing.

eTable 2. continuation

INFORMATION			
Quality of information	• Youth friendly phrasing and content. • The "information buttons" were useful to understand all the features. • Well worded and professionally written. • The questions were general and easy to understand. • Relevant information to the. • Useful content.	• Basic content. • Unclear wording for "time spent online" (texting, Skype, Snap Chat, Facebook or reading online). • Unclear app purpose at the beginning.	• Needs a tutorial to explain its purpose. • Specify some things in/after the question rather in the info buttons.. • Have more "people" (teacher, boss, coach, and supervisor). • Save the "other" option for future loggings. • Change the representation of some icons. • Add more feelings (satisfaction, sadness, disappointment, happiness).
Quantity of information	• Concise and comprehensive information. • Fast to gather information through icons. • All the information you need is the feedback page. • Further information through the "information buttons"	• There is nothing to do in the three first screens. • Too much information/scrolling in the feedback page. • Empty home screen. • Repeated information in the feedback page.	• Add more resources ("Distress Center", "Connect Teen", or "call me because I feel very lonely"). • Use your location to search for nearby help centers. • Add the credits of the developers/research team. • Add more than three goals. • Add latest trophy and streaks to the home screen. • Add a single information button for the feedback page with a drop-down menu for each graph. • Add prompts to do things and to change the behavior.
Visual information	• Very intuitive. • Good job with visuals/colors and the visual representation of the data (meaningfulness and loneliness trends). • Original graphics (interaction grid).	• Repeated information in the feedback page. • Unclear graphs in the feedback page. • Unprecise/unrepresentative icons.	• Add monthly graphs and customize the timing view. • Export the feedback graphs to an excel sheet. • Use pie charts instead of half-circles for the feedback page.
Credibility of source	• Credible, trusted, and not suspicious source. • Professional app and logo.	• Lack of credits or company information.	• Add credits in the tutorial, the settings, or in the "report bug" button. Add the "consent form" and "terms and conditions".

Frequency and Duration of Daily Smartphone Usage in Relation to Personality Traits

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Abstract
Objectives: Daily life behavior can be studied by smart mobile devices. This study investigated associations between personality traits and smartphone usage in daily life.
Method: 526 participants (mean age 34.57 years, SD = 12.85, 21% female) used the Track Your Daily Routine smartphone app (TYDR) for 48 days, on average (SD = 63.2, range 2 to 304). The Big Five Inventory 2 (BFI-2) was deployed to measure personality traits (Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness). Using hierarchical linear models, we analyzed associations between personality traits and two indicators of smartphone usage: number of screen wakeups per day and session duration.
Results: Participants reached for a smartphone more frequently during weekdays with a shorter duration of usage compared to weekends. Younger people used their smartphones more often but with a shorter duration than older people. Female participants spent more time using smartphones per session than male participants. Extraversion and neuroticism were associated with more frequent checking of the phone per day while conscientiousness was associated with shorter mean session duration.
Conclusions: Frequency and duration of daily smartphone usage is associated with personality traits and participant demographics (age, gender). Implications for future research are discussed and include: integration of sensor measurements; extension with feedback functions; tracking changes in user behavior after providing information that increases awareness of his/her behavior; enabling customization of the questionnaires; and usage of AI-based functions for daily measurements.

Keywords: Smartphone usage, Usage duration, Usage frequency, Personality traits, Big Five Model

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1 Introduction

Communication possibilities have significantly expanded with the development of internet-based devices and applications, with the smartphone being the most popular connected device to date. The number of smartphone users surpasses three billion and is forecast to grow by several hundred million in the next few years (Holst, 2019). The finding that 95% of families in the US with children under eight years old have a smartphone indicates the level of smartphone proliferation in people's lives (Rideout, 2017).

Presently, a myriad of applications and sensors available on smartphones offer insights into human lives in a relatively direct way. As the smartphone became the most frequently used device ('Consumer device use', 2017) it opened up new possibilities for the research of human behavior. Assessing smartphone activities provides insights into a range of actual behaviors and higher precision of measured variables (Harari et al., 2016), as well as higher ecological validity (Stachl et al., 2017). In this context, analyzing patterns of smartphone usage from a computer science perspective can be a useful source of information to psychological research for the interpretation and connection of those patterns with psychological characteristics of users. The research area related to this intersection in psychological research and computer science is sometimes referred to as *psychoinformatics* (Markowetz et al., 2014; Montag et al., 2016; Yarkoni, 2012) or *digital phenotyping* (Baumeister & Montag, 2019; Insel, 2017). One of the subdisciplines of psychology that could benefit from the collection of behavioral data is personality psychology, which is primarily based on self-assessment instruments (Stachl et al., 2017). Personality traits are patterns of thought, emotion, and behavior that are relatively consistent over time and across situations (Funder, 2012, p. 177). The most common personality model is The Big Five model (John & Srivastava, 1999). It provides five broad, empirically derived traits that collectively account for the major dimensions in which individuals differ: extraversion, agreeableness, conscientiousness, neuroticism, and openness. This model inspired the development of several different personality inventories: The NEO Personality Inventory–Revised (NEO-PI-R; Costa & McCrae, 2008), The Big Five Inventory–2 (BFI-2; Soto & John, 2017) and the International Personality Item Pool (IPIP; Goldberg et al., 2006).

Different measures of personality traits have been used to predict many aspects of personal and professional life (Ozer & Benet-Martínez, 2006). However, much research in personality psychology does not include measures of actual behavior (Baumeister, Vohs, & Funder, 2007), but relies on self- and other-reports of personality. Therefore, the collection of behavioral data through the smartphone opens up new possibilities for personality research as well as higher ecological validity. With increasing technological development and extensive acceptance of smartphone usage, the possibilities for correlating digital footprints with personality traits are expanding. Regardless of user acceptance and approval, digital footprints are produced somewhat automatically by behaviors such as unlocking the smartphone, joining a Wi-Fi network, and wearing devices that track movement (Hinds & Joinson, 2019), as well as through downloads of different applications. Algorithms can analyze smartphone usage data by determining trends of usage, which could then be used to measure and interpret the actual behavior (Hinds & Joinson, 2019). Beierle et al., (2018) also recognized the possibility of tracking different types of data that might reflect the user's personality. They propose that smartphone's sensors can track the user's physical context, while the operating system can track the user's interaction with the smartphone and its apps. Additionally, Beierle et al., (2018) suggested a general context data model that consists of four categories. The latter focuses on the user's different interactions with smartphone physical conditions and activity, device status and usage, core functions usage, and app usage. This categorization enables research of different questions regarding the prediction of user's personality (Beierle et al., 2018a). In this current research, we focus on the category "device status and usage"; more specifically, screen wakeups (i.e., turning on the smartphone display) and duration of the usage session.

The association of the Big Five personality traits with smartphone usage has been demonstrated in several studies (Chittaranjan et al., 2013; de Montjoye et al., 2013; Harari et al., 2016, 2019; Stachl et al., 2017, 2019; Xu et al., 2016). One of the studies showed that only one personality trait, extraversion, could be predicted by smartphone usage (Mønsted et al., 2018). However, more recent studies showed that with modest prediction success and inclusion of a wide range of behavioral indicators, the trained models could predict personality traits of extraversion and openness (Harari et al., 2019), as well as conscientiousness, and some single facets of emotional stability (Stachl et al., 2019). The most common finding is the association of extraversion with increased smartphone usage, through receiving more calls (Chittaranjan et al., 2013), a higher number of calls, and intensive use of photography apps (Stachl et al., 2017). Conscientiousness was found to be associated to a higher usage of work email, but to a lower usage of YouTube, fewer voice calls (Chittaranjan et al., 2013), and to a low usage of gaming apps (Stachl et al., 2017). Individuals who score high on agreeableness tended to have more calls in general, while individuals with high emotional stability had a higher number of incoming SMS messages (Chittaranjan et al., 2013). Women with high scores on openness demonstrated greater usage of video/audio/music (Chittaranjan et al., 2013). Xu et al. (2016) predicted personality traits based on lists of installed apps while Schoedel et al. (2018) predicted *sensation seeking* behavior from a variety of smartphone-based features.

Building on this emerging research, we also explored the predictability of smartphone usage based on personality traits. We focus on two dependent variables: the frequency of the usage of the smartphone measured through number of screen wakeups; and mean duration of usage sessions per day. We also control for differences in usage depending on time of the week (weekdays vs. weekends). While existing research has investigated correlations between personality traits and mean duration of daily smartphone usage, to the best of our knowledge we are the first to disentangle these two features.

2 Method

2.1 Participants

We collected data from Android smartphone users that voluntarily installed the app TYDR – Track Your Daily Routine[4] from the Google Play store (Beierle et al., 2018b). For recruitment purposes, we printed flyers, advertised TYDR in lectures[5], posted on social media, and Android-related websites reported on the app. TYDR was developed solely for research purposes. The project website discloses the research question of exploring the associations between personality traits and smartphone usage.

In the 11 months of data collection, from 14th of October 2018 to 10th of September 2019, 3,634 users installed TYDR. The timeframe for which a user had TYDR installed depends on the decision of the user, so the installation time and the usage dura-

[4] https://www.tydr.de

[5] At Technische Universität Berlin, Berlin Psychological University, University of Kassel, University of Ulm, University of Regensburg, University of Zurich, and Danube University Krems.

tion differ between users. The average usage session lasted for 3:01 minutes (median = 0:53, range 2 seconds to 12 hours). Of the total number of users, 765 filled out a Big Five personality traits questionnaire available in the app. For 1,052 users, there is enough data about their phone usage[6] in order to utilize it in our analysis. Our sample – those that fulfilled the conditions of having filled out the Big Five questionnaire and having at least 1,000 app event log entries associated with them – contains 526 users, whose mean age is 34.57 years (SD = 12.85). 412 users were male (78.3%) and 114 female (21.7%). The mean age of the male participants was 36.00 (SD = 13.04); the mean age of the female participants was 29.39 (SD = 10.71).

2.2 Mobile application TYDR

TYDR – Track Your Daily Routine is an Android application, released in the Google Play store in October 2018. It tracks sensor data, e.g., steps or locations, and user interaction with the smartphone while running in the background. Opening the app, the user interface shows the user statistics about his/her usage of the phone and summaries of measurements from smartphone sensors. Figure 1 shows the main screen of TYDR.

Alongside the automatically tracked data, users can fill out three questionnaires: first, a demographic questionnaire with questions regarding age, gender, and highest completed level of education; second, the Big Five questionnaire which assesses individual differences in personality traits of the user; and third a questionnaire which assesses personality *states* and is not in the focus of this paper. The first and second questionnaire can only be completed once, while the third one can be filled out every evening.

One of the primary considerations during the development of TYDR was the focus on privacy awareness. We developed a privacy model (PM-MoDaC) for mobile data collection applications (Beierle et al., 2018a), comprising nine actions to be implemented to ensure the privacy of users of applications such as TYDR. We applied this privacy model to TYDR. It includes anonymized usage and irreversible hashing of sensitive data, for example. The study was approved by the ethics commission of the Technical University of Berlin (BEI_01_20180115).

2.3 Measures

Predictor variables were age, gender, time of the week, and five personality traits measured with BFI-2 (Soto & John, 2017). Criterion variables were frequency and duration of smartphone usage sessions per day (measured in seconds irrespective of usage type).

[6] We considered 1,000 app event log entries to be enough to give some insight into the user's phone usage behavior. More details are provided in the next section.

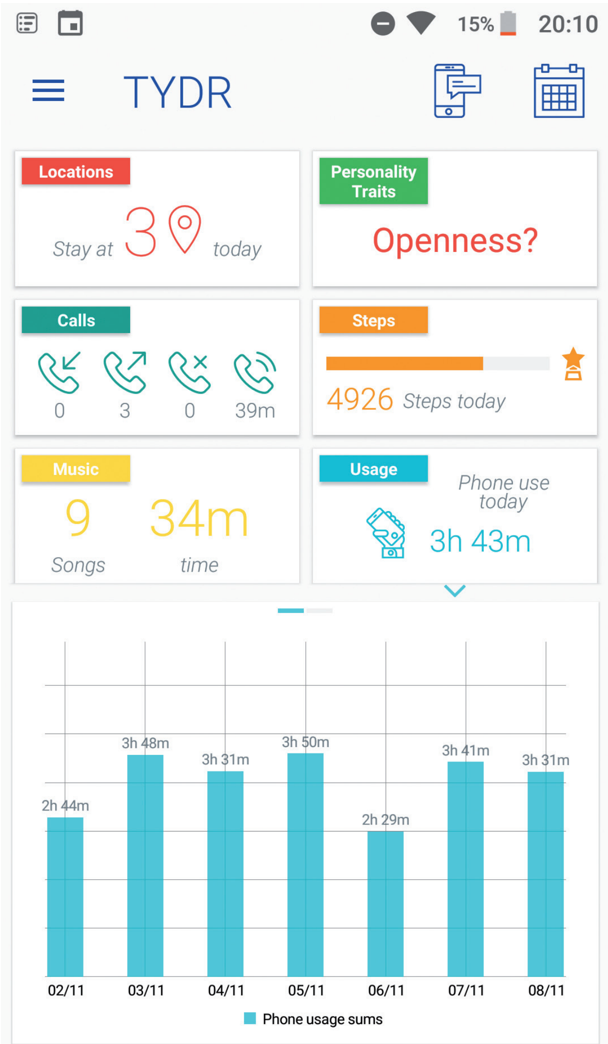

Figure 1: TYDR main screen showing smartphone sensor and usage statistics.

2.4 BFI-2

The Big Five personality traits were measured with the 60-item Big Five Inventory (BFI-2; Soto & John, 2017). This version of the questionnaire measures five personality traits: extraversion; agreeableness; conscientiousness; neuroticism; and openness. Each of the five personality traits was assessed with twelve items based on a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). Cronbach's Alpha (n = 526) for each trait is as follows: extraversion (α = .82), agreeableness (α = .70), conscientiousness (α = .82), neuroticism (α = .90), and openness (α = .81).

2.5 Smartphone usage sessions

We define a smartphone *usage session* as the time window in which a user was actively using the phone. Each session starts with turning on the display and ends with turning the screen off. We used the Android system's app event log to estimate the user's smartphone usage sessions. Each time a user opens or closes an app, the Android system records an event.[7] Given the appropriate permission by the user, TYDR can access these logs and store them in the TYDR database. We implemented a heuristic for estimating actual usage sessions, including background app removal, detection, and imputation of missing events that were not recorded correctly. Based on 40,140,665 app events, our heuristic yielded 1,826,060 usage sessions in total by the 526 users in our sample. On average, users provided data across 48 days. They had on average 72 sessions per day (median = 63, range 1 to 555), lasting for 221 seconds on average (median = 164, range 2 to 4198).

2.6 Statistical Analyses

We used *R* (R version 3.6.0, and the package lme4, sjstats, (Bates et al., 2015)) to conduct all statistical analyses (R Core Team, 2018). We used a random-intercept, random-slope multilevel regression analysis to analyze the effect of personality and time (weekday vs. weekend) on daily smartphone usage patterns (number of screen wakeups per day, mean session duration per day). The multilevel model accounts for the nested design of our study with measurement occasions aggregated on a daily level (level 1) nested within persons (level 2). We ran a baseline model without any predictors to determine the overall intraclass correlation (ICC, i.e., the relative extent to which dependent variables varied between people). We then ran a model in which weekend vs. weekday was entered at level 1 and age, gender, extraversion, openness, neuroticism, agreeableness, and conscientiousness simultaneously entered on level 2 (level 2 variables were all grand-mean centered except Gender; Enders & Tofighi, 2007)[8].

The final model is displayed below:

Level 1 (within person): Wakeups per day [Mean session duration per day]$_{ti}$ = $\pi_{0i} + \pi_{1i}$ Weekday vs. Weekend$_{ti}$ + e_{ti}

Level 2 (between people): $\pi_{0i} = \beta_{00} + \beta_{01}$ Age$_i$ + β_{02} Gender$_i$ + β_{03} Extraversion$_i$ + β_{04} Agreeableness$_i$ + β_{05} Conscientiousness$_i$ + β_{06} Neuroticism$_i$ + β_{07} Openness$_i$ + r_{0i}

Level 2: $\pi_{1i} = \beta_{10} + r_{1i}$

We used R^2_{GLMM} (Nakagawa et al., 2017; Nakagawa & Schielzeth, 2013) as a measure of explained variance, which can be interpreted like the traditional R^2 statistic in regression analyses. $R^2_{marginal}$ represents the proportion of variance explained by the fixed effects alone. As the effect size measure, we used standardized β and 95% confidence intervals.

One might argue that the act of having installed the app and getting regular feedback about one's usage patterns may in and of itself change one's behavior. To account for this, we calculated MLMs with an additional variable at level 1 reflecting the time since the first usage of TYDR. Because this variable revealed only tiny effects and beta values for the other predictors did not substantially change, we did not include this variable into the final analyses in order to keep the model comprehensible.

3 Results

The multilevel analysis revealed several statistically significant predictors of smartphone usage (see Table 1; for intercorrelations, see Table S1 in the online supplement), respectively: time of the week (weekdays vs weekends); age; gender; and three personality traits (extraversion, neuroticism and conscientiousness).[9]

In more detail, there was a noticeably lower number of screen wakeups during weekends compared to weekdays (β = -.10, 95% CI [-.11, -.08]). On the other hand, mean session duration per day (β = .06, 95% CI [.04, .07]) was higher during the weekend compared to the weekdays. That means that reaching for a smartphone was more frequent during weekdays with shorter duration of usage, while during a weekend screen wakeups were less frequent but the mean duration of sessions per day was longer.

Age was a significant negative predictor for the number of screen wakeups per day (β = -.19, 95% CI [-.25, -.13]) and a significant positive for the mean session duration per day (β = .06, 95% CI [.01, .12]). Younger individuals had a higher number of screen wakeups per day, while older individuals had higher mean session durations per day. In other words, younger people seem to check their smartphone more often, but with a shorter duration, while older individuals spend more time using their smartphone per session.

Participants' gender was also a significant predictor for the mean session duration per day (β = -.06, 95% CI [-.12, -.01]), meaning that female participants spent 31.6 seconds more time per session than males.

Extraversion was a significant predictor for the number of screen wakeups per day (β = .11, 95% CI [.04, .17]), meaning that higher extraversion was associated with more frequent smartphone checking. Additionally, neuroticism was also a significant predictor for the same variable (β = .12, 95% CI [.05, .18]), which means that higher neuroticism was associated with higher number of the phone checking per day. The personality trait conscientiousness was also found to be a significant predic-

7 Additionally, other app events are recorded for other types of actions of apps. For the usage session estimation, we only need the events for opening an app to the foreground and closing it.

8 We have also calculated the models by including the number of days participants had the TYDR app installed as a measure of participant motivation. Because this predictor was non-significant in all models, we excluded this predictor on the basis of efficiency.

9 For possible gender * personality interactions, see supplementary table S2.

Table 1. Results of the multi-level analysis.

	Fixed						Random	
	Coeff.	β	*95% CI*	*B*	*SE*	*t*	Coeff.	*SD*
Screen wakeups per day								
Intercept	β_{00}			72.0	3.14	22.89***	r_{0i}	33.9
Within-person								
Weekend (ref weekday)	β_{10}	-.10	-.11 – -.08	-9.6	0.82	-11.78***	r_{1i}	13.8
Between-person								
Age	β_{01}	-.19	-.25 – -.13	-0.7	0.11	-6.21***		
Gender (ref female)	β_{02}	.04	-.02 – .10	4.2	3.52	1.20		
Extraversion	β_{03}	.11	.04 – .17	7.2	2.33	3.08**		
Agreeableness	β_{04}	>-.01	-.07 – .06	-0.3	2.86	-0.10		
Conscientiousness	β_{05}	.01	-.06 – .07	0.6	2.28	0.26		
Neuroticism	β_{06}	.12	.05 – .18	6.6	1.96	3.34***		
Openness	β_{07}	-.02	-.08 – .05	-1.0	2.16	-0.46		
ICC = 57.5%, $R^2_{marginal}$ = 6.5%								
Mean session duration per day								
Intercept	β_{00}			225.0	12.50	18.01***	r_{0i}	120.0
Within-person								
Weekend (ref weekday)	β_{10}	.06	.04 – .07	26.1	3.11	8.38***	r_{1i}	37.9
Between-person								
Age	β_{01}	.06	.01 – .12	1.0	0.45	2.28*		
Gender (ref female)	β_{02}	-.06	-.12 – -.01	-31.6	14.31	-2.21*		
Extraversion	β_{03}	<.01	-.06 – .06	0.6	9.49	0.06		
Agreeableness	β_{04}	-.02	-.07 – .04	-6.8	11.65	-0.59		
Conscientiousness	β_{05}	-.14	-.20 – -.08	-41.1	9.28	-4.43***		
Neuroticism	β_{06}	.01	-.05 – .08	3.8	7.98	0.48		
Openness	β_{07}	.03	-.03 – .09	8.7	8.81	1.00		
ICC = 39.1%, $R^2_{marginal}$ = 2.8%								

Note. All level 2 variables were grand mean centered except for gender and weekend. CI = Confidence Interval.
* $p < .05$, ** $p < .01$, *** $p < .001$.

tor for the mean session duration per day (β = -.14, 95% CI [-.20, -.08]). That means that a high conscientiousness was associated with a shorter duration of the session per day.

Furthermore, because our criterion measures were non-normally distributed, we recalculated all analyses by using log-transformed measures of *Screen wakeups per day* and *Mean session duration per day*. None of the significances changed except for the *Mean session duration per day* analysis, where the very small effect for gender (β = -.06, see Table 1) was now no longer significant (β = -.05, p = .14; detailed results omitted for brevity).

In order to keep the beta values interpretable, we present the results for the non-log-transformed criterion measures.

Additionally, we analyzed a potential self-selection bias (i.e., participants might be different from non- participants) regarding our dependent variables (non- participants: n = 523). We calculated MLMs with only the group variable (participant vs. non-participant) as the predictor. We did not find any significant differences, neither for wakeup frequencies, nor for session duration on a day level (detailed results omitted for brevity).

4 Discussion

This study evaluated whether personality traits are associated with smartphone usage. We found that both extraversion and neuroticism were associated with a higher number of screen wakeups per day, and conscientiousness was related to shorter session durations per day.

Our results regarding extraversion are broadly in line with previous studies showing connections of extraversion with higher frequency and duration of calls or other communication behavior (Baumeister & Montag, 2019; Chittaranjan et al., 2013; Harari et al., 2019; Mønsted et al., 2018; Montag et al., 2019, 2014; Stachl et al., 2019, 2017). In the study by Chittaranjan et al. (2013), emotional stability was connected to a higher number of incoming SMS messages, while our study showed neuroticism to be related to a higher usage of the smartphone measured as the number of wakeups per day. Azucar et al. (2018) reported individuals who are highly conscientious are using social media less. Our results showed decreased usage for conscientious users as well, as those individuals tend to have shorter duration of smartphone usage sessions. Montag et al. (2015) investigated correlations between gender, age, personality, and usage of WhatsApp. Similar to our findings about general smartphone usage, they reported that female and younger users were using WhatsApp more, while conscientiousness was correlated with a shorter length of WhatsApp usage. Andone et al. (2016) reported similar findings about age, gender, and smartphone usage. They reported that the daily mean of phone usage time was higher for female and younger participants but did not investigate wakeup frequencies or correlations with personality.

We can speculate somewhat about the nature of the relationships between neuroticism and extraversion and higher phone usage. For extraversion, the reason for increased usage might be social, e.g., checking the phone for a message that came in (Costa & McCrae, 2008; Goldberg et al., 2006). For higher levels of neuroticism, the reason might be anxiousness with respect to missing important things (Stead & Bibby, 2017). Longer usage sessions on weekends could indicate that there is more time for longer searches or tasks. We do not know if the smartphone was used by the user only for private purposes, only for business purposes, or for both. More screen wakeups during weekdays could also be a result of work-related phone usage, which is lesser during weekends. Younger people might show a different phone usage pattern because they might demonstrate a different approach to technology in general. Users scoring higher on the trait of conscientiousness maybe consciously reduce their phone usage to not be distracted (Costa & McCrae, 2008). Further studies are required to confirm these interpretations. Analyses of used apps during the usage sessions could also deepen the understanding of the relationship between personality traits and smartphone usage.

When interpreting the results of the present study, several limitations have to be considered. On a technical level, usage session estimation is not as straightforward as it seems. One way to track smartphone usage is to track the display's state. It can only be tracked while TYDR is running. Due to fragmentation – having many different devices with different Android versions and different software adaptations by smartphone manufacturers – and because other apps can interfere with background processes, it is not always possible to ensure that an app is not closed while running in the background. This leads to display state events being missed. Given these constraints, we opted to use the Android system's app event log to determine usage sessions. In contrast to the display state events, Android itself already records the app events. This has the advantage that even when TYDR is not running for some time, the app events can still be tracked. The errors and potentially faulty records that we found in the app event logs were processed by a simple heuristic that we implemented which removed background apps and imputed missing app closing events.

Although our sample was relatively large, it was not representative. Moreover, we have to consider that our results might be biased by excluding users who did not provide enough app event log entries (of 3,634 users who installed the app, only 526 could be analyzed). Another limitation relates to the smartphone behaviors analyzed in the current study. It is important to state that usage behaviors only reflect a small percentage of data that it is possible to collect with passive sensing technology (Ben-Zeev et al., 2015; Cornet & Holden, 2018). For example, geospatial data (e.g., by GPS) would be additional behavioral data that can be monitored with smartphones (e. g., Kerr, Duncan, & Schipperjin, 2011; Pryss et al., 2019). While also tracking the usage behavior of iOS users would potentially increase the user base, research suggests that such a study would likely yield similar results (Götz et al., 2017). Additionally, this study is only correlational therefore does not provide information about causal relations between frequency and duration of daily smartphone usage in relation to personality traits.

Despite the limitations, the study has a number of strengths. The data was collected in daily life and this increases the ecological validity of the results. Compared to many previous studies, our sample was relatively large, improving the precision of our results. The findings indicate that, for TYDR users, personality traits were associated with smartphone usage.

There are several directions in which future work in this area could be taken. One direction could be to integrate sensor measurements that gather, for example, vital signs, which might be then correlated with the smartphone-based indicators. Second, the app could be extended with feedback functions that investigate the smartphone-based indicators by influencing them purposefully (e.g., Rabbi, Klasnja, Choudhury, Tewari, & Murphy, 2019). For example, the app could learn based on gathered GPS data, which movement behavior is beneficial for a user. Such behavior could then be recommended to a user. Third is the possibility to make the user aware of his/her behavior and track the changes after providing such information. Fourth, the users could be enabled to adapt the questionnaires to their individual needs. Fifth, recent smartphones are often equipped with CPUs (central processing units) that incorporate Artificial intelligence (AI)-based functions. The latter are used, for example, to save resources on the smartphone. If such features are beneficial, then they can be exploited for TYDR. On the other, if such features are unfavorable, then they should be addressed by the implementation of TYDR. As an example, if notifications are automatically deactivated by AI-based functions due to a low battery, then such behavior is not intended for the study and must be addressed.

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Author contributions

F.B., T.P., M.A., J.Z., R.P., P.N., W.S. are part of the TYDR team and contributed with ideas to the development of the TYDR app, F.B. had the lead in programming the TYDR app and drafted the manuscript, T.P. contributed the study idea and revised the manuscript, M.A. revised the manuscript, J.Z. revised the manuscript and contributed to the statistical analyses, R.P. revised the manuscript, P.N. revised the manuscript and contributed to the statistical analyses, W.S. revised the manuscript and contributed to the statistical analyses; S.S. performed the statistical analyses, S.B. drafted the manuscript.

Supplementary Material

Table S1. Descriptives and intercorrelations.

	M (SD)	1	2	3	4	5	6
1. Age	34.6 (12.85)						
2. Gender	–	.21***					
3. Extraversion	3.1 (0.66)	-.06	-.01				
4. Agreeableness	3.7 (0.51)	.06	-.11**	.12**			
5. Conscientiousness	3.4 (0.65)	.14**	-.03	.27***	.18***		
6. Neuroticism	2.9 (0.82)	-.14**	-.21***	-.33***	-.32***	-.31***	
7. Openness	3.6 (0.66)	-.11*	-.06	.26***	.10*	.07	.01

Note: sex: 1. female, 2. male

Table S2. Results of the multi-level analysis by including gender * personality interactions.

	Fixed					Random	
	β	95% *CI*	*B*	*SE*	*t*	Coeff.	*SD*
Screen wakeups per day							
Intercept			69.4	3.49	19.87***	r_{0i}	34.04
Within-person							
Weekend (ref weekday)	-.10	-.11 – -.08	-9.6	0.82	-11.77***	r_{1i}	13.85
Between-person							
Age	-.20	-.26 – -.14	-0.7	0.11	-6.31***		
Gender (ref female)	.06	-.01 – .12	6.6	3.78	1.75+		
Extraversion	.13	-.01 – .26	8.5	4.52	1.89+		
Agreeableness	.01	-.12 – .14	0.9	6.00	0.16		
Conscientiousness	-.01	-.13 – .12	-0.5	4.27	-0.12		
Neuroticism	.25	.11 – .40	14.3	4.20	3.40***		
Openness	-.03	-.16 – .10	-2.0	4.18	-0.78		
Gender * Extraversion	-.03	-.16 – .10	-2.0	5.26	-0.38		
Gender * Agreeableness	-.01	-.14 – .12	-1.3	6.84	-0.19		
Gender * Conscientiousness	.02	-.11 – .15	1.7	5.04	0.33		
Gender * Neuroticism	-.16	-.31 – -.01	-10.1	4.74	-2.12*		
Gender * Openness	.02	-.11 – .15	1.3	4.88	0.27		
ICC = 57.3%, $R^2_{marginal}$ = 6.8%							
Mean session duration per day							
Intercept			229.1	13.98	16.39***	r_{0i}	120.28
Within-person							
Weekend (ref weekday)	.06	.05 – .07	26.1	3.12	8.37***	r_{1i}	37.92
Between-person							
Age	.06	.01 – .12	1.0	0.45	2.10*		
Gender (ref female)	-.07	-.13 – -.01	-35.3	15.45	-2.29*		
Extraversion	.01	-.11 – .13	2.2	18.44	0.12		
Agreeableness	-.08	-.20 – .04	-32.8	24.60	-0.133		
Conscientiousness	-.17	-.29 – -.06	-53.1	17.45	-3.05**		
Neuroticism	.01	-.13 – .14	1.6	17.12	0.09		
Openness	.02	-.10 – .13	4.5	17.06	0.27		
Gender * Extraversion	-.01	-.13 – .11	-3.8	21.49	-0.18		
Gender * Agreeableness	.07	-.05 – .19	33.2	28.03	1.19		
Gender * Conscientiousness	.05	-.07 – .16	16.0	20.60	0.78		
Gender * Neuroticism	.01	-.13 – .14	2.0	19.36	0.10		
Gender * Openness	.02	-.10 – .14	6.3	19.94	0.32		
ICC = 38.9%, $R^2_{marginal}$ = 2.9%							

Note. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$.

Digital Family Life: A Systematic Review of the Impact of Parental Smartphone Use on Parent-Child Interactions

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Abstract
Smartphone use among parents is rising sharply, as they seek connectedness with partners, friends and work during the sometimes socially disconnected times of parenthood. Since parents increasingly use smartphones while interacting with their children, there is a growing body of research about the implications of parental smartphone use for parent-child interactions. However, previous reviews have not examined whether the effects of parental smartphone use on parent-child interactions vary depending on children's age. Additionally, no systematic review has summarized the potential benefits of parents' smartphone use for parent-child interactions. Therefore, the goals of this systematic review were: (1) to explore the links between parental smartphone use and the quality of parent child-interactions in four different age groups of children; and (2) to review potential benefits of parental smartphone use for these interactions. Following PRISMA guidelines, a total of k = 21 papers met all eligibility criteria and were included in this review. Results suggest associations between parental smartphone use and parent-child interactions across all age groups, but the foci and outcomes of the studies differed. Only a few studies have focused on the potential benefits of parental smartphone use for parent-child interactions. The review provides an overview of areas of future research to explore how smartphone use changes family interactions. Families have to find adequate ways of dealing with new technology in everyday life, which inevitably affects the nature of their daily interactions.

***Keywords*:** parental mobile phone use, parent-child relationship, parenting, technoference, digital media

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Digital media are ubiquitous in modern societies. In 2015 82% of adults (25–54 years) accessed the internet via a smartphone in Europe (Eurostat, 2016). In addition, 94% of adults use their smartphone on a daily basis for more than three hours a day in Austria (Mobile Marketing Association Austria, 2018). Interestingly, 34% of adolescents (aged 11–17 years) stated that they think their parents use their phone too often (Saferinternet, 2019). The permanent virtual connectedness of parents has resulted in a shift from traditional face-to-face interactions towards technology-based interactions (Stern & Messer, 2009), which inevitably affects everyday family interactions too. Similarly, the more adolescents used their smartphone, the lower they rated the overall quality of the relationship with their parents (Kildare & Middlemiss, 2017). Hence, there might be mutual effects of family members' smartphone use: Parents as well as their children seem to be absorbed by their smartphones in everyday family life, which likely affects parent-child relations.

The phenomenon of interference and interruption of everyday face-to-face interactions through technology, in particular smartphones, has been referred to in the literature as "technoference" (McDaniel & Coyne, 2016). Recently, parental smartphone use and the implications for parent-child interactions have received increasing scientific attention (Kildare & Middlemiss, 2017). Parents are engaged in screen media on personal and work-related matters throughout the day, and thus likely also use smart devices during parent-child interactions (e.g. text messaging while playing with their children; Beamish, Fisher, & Rowe, 2019). The presence of digital media devices during family quality time (e.g. meals, playtime, and bedtime) may impair the social-emotional development of children, because parental attention is shifted away from their children's needs and towards their device (McDaniel & Radesky, 2018). Given the rise and topicality of this research area, two recent narrative reviews (Kildare & Middlemiss, 2017; McDaniel, 2019) outlined the impact of parental technoference on parent-child interactions. However, the reviews lacked a systematic approach, included a broad range of studies (including studies focusing on mobile devices other than smartphones), and exclusively focused on the negative effects on parenting (e.g. more accidents as parents are distracted) as well as the negative effects on children (e.g. insecure attachment, irritated children).

The potential negative impact of technoference on parent-child relations can theoretically be explained by attachment theory (Ainsworth, 1979, Bowlby, 1969). According to attachment theory, parental sensitivity is one of the strongest predictors of high parent-child relationship quality and the children's secure attachment, which in turn, affect children's long-term social, psychological and health outcomes (e.g. Fearon, Bakermans-Kranenburg, van IJzendoorn, Lapsley, & Roisman, 2010). Parental sensitivity is conceptually defined as the parents' awareness of their child's needs, their accurate interpretation of those needs, and the contingent and appropriate response to those needs (Ainsworth, Blehar, Waters, & Wall, 1978). It is well conceivable that technoference impairs parental sensitivity. That is, when parents are distracted by their smartphones, they are likely to be less attentive and responsive to their children's needs, which can negatively affect child attachment and development (Kildare & Middlemiss, 2017).

The role of parental sensitivity for children's attachment has traditionally been examined in infancy. Especially in the first years of their lives, infants depend on their parents to survive, and with increasing mobility rely on their parents to guide them through challenges and to provide a secure base. However, albeit initially developed in infancy, attachment still has regulatory functions during middle childhood and through adolescence (Grossmann, Grossmann, Kindler, & Zimmermann, 2008). As children grow older, they need less parental support because they are more able to handle their emotions and feelings of distress independently, have a greater capacity for self-regulation, and receive increasing social support outside the family (Zimmer-Gembeck et al., 2017). Although adolescents less frequently express their attachment needs by physical proximity in times of stress, they still seek emotional support from their parents when needed (Zimmermann, Mohr, & Spangler, 2009). Hence, parental sensitivity is not only relevant in early childhood, but remains an important protective factor across the child's development through adolescence until young adults leave home.

Only a small number of studies have examined whether the effects of parental smartphone use on parent-child interactions vary depending on the age of the child. Moreover, no reviews have systematically investigated previous research about the impact of parental smartphone use across different developmental stages of children. This is particularly lamentable, as there is evidence that parents' use of information and communication technology increases with the age of children (Rudi, Dworkin, Walker, & Doty, 2015). Therefore, the first goal of this systematic review is to explore the role of children's age in the link between parental smartphone use and parent-child interactions, as this allows for a more thorough understanding of the meaning of technoference for families.

In addition, the existing literature has mainly focused on the negative effects of parental smartphone use on parent-child interactions (McDaniel, 2019), for instance distraction of mothers while feeding their babies (Golen & Ventura, 2015) or while at the playground with their children (Hiniker, Sobel, Suh, Sung, Lee, & Kientz, 2015). Given the importance of awareness of this potential negative impact, it becomes evident that more research, especially longitudinal, is required to fully explore this highly relevant topic. Nevertheless, far less research has been devoted to date to investigating the possible benefits of parental smartphone use for family interactions. Recent research has begun to focus on benefits of smartphone use for children's and parents' feelings of connectedness in the family (Coyne, Padilla-Walker, Fraser, Fellows, & Day, 2014; Devitt & Roker, 2009), but, to our knowledge, no systematic review has summarized the potential benefits of parental smartphone use for parent-child interactions. Therefore, the second goal of this review is to address this gap.

The Current Review

This systematic review summarizes studies examining a specific form of technoference, i.e. the effects of parental smartphone use on parent-child interactions, with a focus on two main research questions:

First, do the links between parental smartphone use and the quality of parent child-interactions vary across four different age groups of children (infancy, preschoolers, school-age children, and adolescents)? We hypothesize that the impact differs insofar as with younger children parental sensitivity is impaired, whilst with older children the quality of parent-child interactions and perceived parental support are affected.

Second, what are the benefits of parents' smartphone use for parent-child interactions? We expect that there are possible benefits of parental smartphone use for parent-child interactions, which have been neglected in previous research that has focused on the negative consequences of technoference for parent-child interactions.

1 Method

1.1 Search Strategy

The systematic literature search followed PRISMA guidelines (Moher, Liberati, Tetzlaff, Altman, & the PRISMA Group 2009) and was conducted by the first author in June and July 2019. The following databases and search engines were searched for relevant literature by using a combination of key search terms in English and German (see Table 1 in the electronic supplements): Pubmed, Psychnet, Web of Science, Proquest, Ebsco, and Google Scholar. During the process of literature search, references included in previous reviews and studies were screened in terms of our eligibility criteria (see below). In addition, the existing literature/library of the research team was included as additional records (k = 27). The title and abstract of 4,667 total records were screened by the first author. Among them, 4,565 records were excluded because abstract analysis revealed that they were unsuitable for the current review. As a next step, duplicates (k = 43) were removed. The remaining (k = 59) were given full consideration by a thorough full text analysis. In uncertain cases, the first author consulted the second author and discussed if the article should be included. Ultimately, a total of 21 records met all eligibility criteria and were included in this review (asterisk [*] in the reference list). The flow chart describes all stages of the selection process (see Figure 1).

1.2 Inclusion Criteria

To be included in the review, the studies had to meet the following criteria: (1) examining parental smartphone use during a parent-child interaction, defined as any form of spending time together (eating, playtime, being in the same room); (2) using methods to assess the quality of the parent-child interactions (e.g. interaction quality, parental sensitivity etc.); and (3) the age of the children had to be between 0 and 18 years. To address our first research question (i.e. whether the effects of parental smartphone use vary across children's age), we predefined four age groups to categorize the different stages of child development:

- Age group 1: infants and babies (0–3 years);
- Age group 2: toddlers and preschool children (4–6 years);
- Age group 3: school-age children (7–10 years);
- Age group 4: adolescents (11–18 years).

1.3 Exclusion Criteria

Excluded were: (1) theoretical papers or book chapters and narrative reviews (not original research); (2) intervention studies aimed at improving parental media use, as these do not reflect

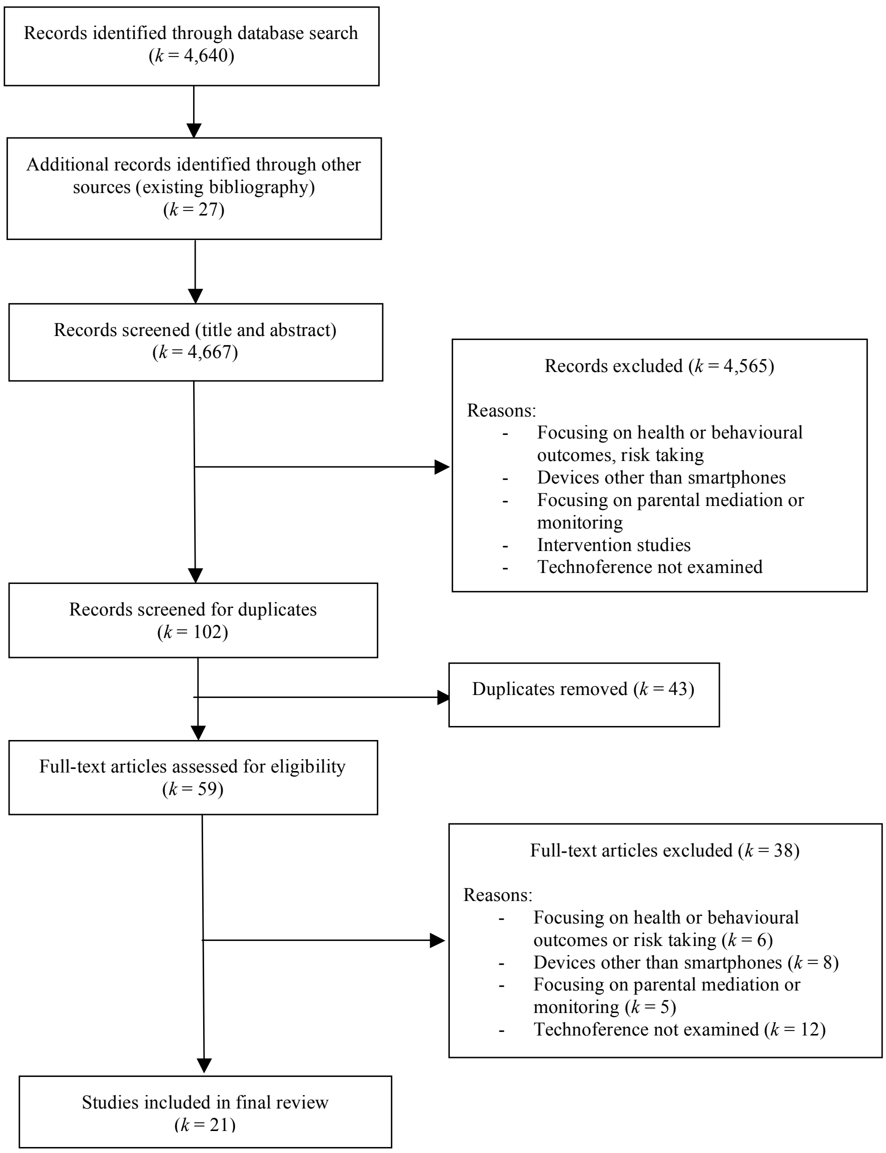

Figure 1. Flow Chart of Literature Search.

the parental smartphone use in the natural family context; (3) studies focusing on outcomes other than parent-child interactions (e.g. internet addiction, obesity, ADHD, behavioral problems, school performance); (4) studies exclusively focusing on digital media other than smartphones; and (5) studies focusing on parental mediation and monitoring, parenting, child rearing, media competency, or pedagogy.

1.4 Quality Assessment

We assessed the quality of the included studies using the Mixed Methods Appraisal Tool (MMAT; Hong et al., 2018). First, the first author categorized the study designs into qualitative (k = 2), quantitative non-randomized (k = 2), quantitative descriptive (k = 11), and mixed methods (k = 7) applying the MMAT study design categories. Subsequently, the first author assessed the quality of the studies based on two general quality criteria and five design-specific quality criteria according to the MMAT. A detailed overview of the quality assessment can be found in Table 2 (see electronic supplements).

1.5 Description of Literature

A total of 21 records met all eligibility criteria and were analyzed for this review. Notably, one paper (Kushlev & Dunn, 2019) included two separate studies, which were counted as one publication (hereinafter referred to as Kushlev & Dunn, 2019 (Study 1) or Kushlev & Dunn, 2019 (Study 2)). The 21 studies included scientific peer-reviewed publications (k = 12), post-graduate dissertations or Master's theses (k = 7), and conference papers (k = 2). Among them, 14 studies used survey, self-report or interview data, 6 included observational data, and 5 were based on a (quasi-)experimental design (some studies used mixed methods combining different designs). The sample sizes varied greatly between N = 12 participants in in-depth interviews (Johnson, 2017) and N = 3.000 participants in an online survey (Nelson, 2016). Most of the studies (k = 17) were conducted in North America (USA, Canada), two in European countries, one in Australia, and one in Asia (China) in urban or suburban regions. The studies were published between 2007 and 2019 inclusive.

Eight (k = 8) studies were unambiguously classifiable to our age groups given the mean and range of the children's age were within the predefined age ranges (Abels, Vanden Abeele, van Telgen, & van Meijl, 2018; Blackmann, 2015; Golen & Ventura, 2015; Kushlev & Dunn, 2019 (Study 1); Lanette, 2018; Myruski et al., 2018; Stupica, 2016; Ventura & Teitelbaum, 2017). Ten (k = 10) studies reported a broad age range that overlapped with two or more of our selected age groups (Ante-Contreras, 2016; Chen, Zhou, & Han 2017; Kellershohn, Walley, West, & Vriesekoop, 2018; Khourochvili, 2017; Mangan, Leavy, & Jancey, 2018; Nelson, 2016; Palen & Hughes, 2007; Radesky et al., 2018; Radesky et al., 2015; Stockdale, Coyne, & Padilla-Walker, 2018). In these cases, we always used the lower bound of the reported age range to classify the study (e.g. a study reporting the age range of 5–18 years was assigned to the second age group of 4–6 years). In sum, four (k = 4) studies were not classifiable (n/a), because age range was not specified (e.g. < 18 years) or not reported at all (Hiniker et al., 2015; Johnson, 2017; Kushlev & Dunn, 2019 (Study 2); Oduor et al., 2016).

2 Results

We first report results separated by each selected age group (research question 1), and second report results on the potential benefits of parental smartphone use as derived from the review (research question 2). Characteristics of and detailed information on the final set of studies are summarized in Table 3 (see electronic supplements).

2.1 Age Group 1: Infants and Babies (0–3 Years)

We included k = 11 studies in this section (Abels et al., 2018; Ante-Contreras, 2016; Chen et al., 2017; Golen & Ventura, 2015; Kellershohn et al., 2018; Mangan et al., 2018; Myruski et al., 2018; Palen & Hughes, 2007; Radesky et al., 2018; Radesky et al., 2015; Ventura & Teitelbaum, 2017). In this age group, a predominant line of research has focused on technoference during mealtime, a special instance of family quality time. Specifically, in an observational study (Radesky et al., 2015) one third of low-income parents who glanced at least once at their phone during eating showed fewer verbal and non-verbal interactions and displayed less engagement to try new things with their children. However, the parental phone use was not linked to parenting style or overreacting when kids sought attention. Another study found that mothers with a greater smartphone use during mealtime perceived their children as more difficult and they scored lower on a caregiving sensitivity index, as assessed by a semi-structured interview (Radesky et al., 2018). The reasons for parental smartphone use in this age group were habit, disengagement, or boredom (Radesky et al., 2018). During mealtime, 25% of adults who used their smartphone used it to take pictures (Kellershohn et al., 2018). In addition, it was observed that some parents used their phones when they were eating with their children in a restaurant, but most of them (70%) used it when their children were at the restaurant's indoor play area. In a diary study, mothers were asked to report distractions during feeding ("what else, if anything, they were doing while feeding their infants"). A quarter (26%) reported at least one technological distraction, 18% a non-technological distraction, and 56% no distraction at all during the feeding interaction. Higher amounts of technoference correlated with an unstructured maternal feeding style (e.g. feeding in front of the TV), mothers not noticing when children have eaten enough, as well as thinking children had a greater appetite (Ventura & Teitelbaum, 2017).

An observational study found a positive correlation between frequency of parental smartphone use and child age (age range of children = 0–5 years), suggesting parental phone involvement was higher when children were older (Abels et al., 2018).The authors found that parental phone involvement was negatively associated with parental responsiveness and children had to increase their effort in gaining their parents' attention. A similar finding was reported when parents were unavailable due to smartphone use; children's bids for attention increased, with a greater negative effect on children with emotion regulation difficulties (Myruski et al., 2018).

Looking at parenting styles, a study found that the amount of hours spent by parents on social media accessed with smartphones was related to an authoritarian parenting style (Ante-Contreras, 2016). Yet, this contradicts another finding in a Chinese sample showing a negative correlation between smartphone use and an authoritarian parenting style (Chen et al., 2017).

With regard to the intensity and duration of smartphone use during parent-child interactions, an observational study found that the majority of parents used their smartphones for less than 5 minutes for typing, talking or camera during a 20 min-observation period at a playground. In 4% of the total observation time, parents ignored children's bids for attention or disengaged from ongoing parent-child interactions due to phone use. The results showed a contrast between observational data and parents' self-reports, as most parents stated in the interview following the observation that they would find it inappropriate to use their phone during child supervision at the playground.

2.2 Age Group 2: Toddlers and Preschool Children (4–6 Years)

We included k = 4 studies in this section (Khourochvili, 2017; Kushlev & Dunn, 2019 (Study 1); Nelson, 2016; Stupica, 2016). Khourochvili (2017) reported that the frequency of parental smartphone use was negatively linked with parents' sensitivity towards their infants. Results further suggested that parents with a positive attitude towards smartphones were more competent to decide when it is appropriate to use the devices and when interaction with their child is more important. The findings of a study analyzing parental beliefs and behavior showed that smartphones can possibly have inadvertent, negative consequences on parent-child interactions during family mealtime, as parental happiness and feeling of connection decreased when a smartphone was present on the table (Nelson, 2016). In an experimental study (Stupica, 2016) parental availability and responsiveness were experimentally manipulated to determine the effects on children's athletic performance. Children were asked to run as fast as possible around a softball diamond twice: once while parents were available and responsive and once while parents were unavailable and unresponsive (instruction for parents: "Fully engage your attention in your mobile phone becoming completely engrossed in it while standing in the box turned toward your child. Do not respond to any of your child's attempts to initiate interaction"). Children ran about three seconds faster and were 17% less likely to trip, fall, or false start in the parental available and responsive condition. Furthermore, children ran faster as their parents' availability increased.

In an experimental approach (Kushlev & Dunn, 2019 (Study 1)), participants were asked to maximize ("high use") or minimize their phone use ("low use") during a visit to a children's museum. The manipulation was assessed through use of a parental self-report which indicated whether during the experiment they used their phone more often ("high use") or less often ("low use") than they would normally do. The "high-use" parents reported having a lower quality of attention towards their children and feeling less connected to them compared to the "low use" parents.

2.3 Age Group 3: School-Age Children (7–10 Years)

In this age group, we included k = 1 study (Blackmann, 2015). The study examined the association between parental screen time, screen distraction, and parental characteristics (beliefs and demographics). It was found that parental screen time was correlated with screen distraction and this link was mediated by income and education. Further, screen distraction was negatively linked with parental responsivity towards their children's needs (Blackmann, 2015).

2.4 Age Group 4: Adolescents (11–18 Years)

In this age group, k = 2 studies were included (Lanette, 2018; Stockdale et al., 2018). According to Stockdale et al. (2018), 12% of adolescents stated that their parents, when distracted by their smartphone, were "quite a bit" or "a great deal" ignoring them, and 11% said they had difficulties in getting their parents' attention in those situations. Results showed that parental technoference had an influence on adolescents' perceived feeling of parental warmth, which in turn was linked to increased levels of anxiety, depression, cyberbullying, and, unexpectedly, higher levels of prosocial behavior toward family members and strangers. The findings by Lanette (2018) indicated that the mere presence of smartphones had only minimal effects on parental listening qualities and meaningful parent-teen conversations were still possible. Nevertheless, parents and teens felt more distant when a smartphone was present during the conversation.

2.5 Studies not Assignable to the Age Groups

In sum, k = 4 studies were not assignable to our predefined age groups, because the age range was not specified or not reported (Hiniker et al., 2015; Johnson, 2017; Kushlev & Dunn, 2019 (Study 2); Oduor et al., 2016). Observing parents at the playground with their school-age children revealed that almost two-thirds of parents used their smartphone less than 5% of their time at the playground (Hiniker et al., 2015). Participants reported being driven by guilt to reduce their smartphone use, but felt incapable of doing so. To counter this, they developed strategies to use their smartphones when the children were safe and occupied (e.g. in bucket swings), or avoided the phone (e.g. locking the phone in the car) in general when with their children. The reported reasons for smartphone use were twice as often related to childcare (such as checking the time, coordinating with others, and taking pictures) as to parent-related activities (such as socializing, work or entertainment). In 32 cases in which parents were observed using their smartphone and children were bidding for parental attention, 56% of the parents did not at all respond to their children's bids for attention (not even looking away from the phone). In contrast, when children were bidding for their parents' attention without smartphone distraction, only 11% of parents did not respond. Notably however, the overall observation period was dominated by parent-child interactions and parents watching their children (Hiniker et al., 2015).The effects on parental attention quality were confirmed by a diary study (Kushlev & Dunn, 2019 (Study 2)), where parents reported that two thirds of parent-child interactions included a smartphone. In the study by Oduor et al. (2016), parents reported that their smartphone use affected parenting and made them feel socially disconnected from their children. Moreover, participants reported feelings of guilt and that they wanted to change their smartphone behavior (Oduor et al., 2016). In addition, adolescents reported that they made parents aware of their disconnection with the real world and that they missed face-to-face connection with their parents (Johnson, 2017).

2.6 Potential Benefits of Parental Smartphone Use

Coming to our second research question, we found that $k = 8$ studies reported any form of benefit of parental smartphone use for parent-child interactions (Chen et al., 2017; Golen & Ventura, 2015; Hiniker et al., 2015; Kellershohn et al., 2018; Kushlev & Dunn, 2019 (Study 1); Mangan et al., 2018; Oduor et al., 2016; Palen & Hughes, 2007). One direct advantage of parental smartphone use for parents reported was entertainment and moments of relaxation while infants were feeding from their bottle (Golen & Ventura, 2015). Furthermore, parents reported the benefit of getting parenting support (e.g. accessing information on parenting via the internet or social media), as well as connecting with their children (Mangan et al., 2018). Chinese mothers reported benefitting from smartphones in terms of connecting with their children on a new level, combining fun, entertainment and learning together, as well as in relation to connecting with other parents. Moreover, smartphone use was associated with lower levels of authoritarian parenting, presumably as smartphones modernize parenting and enable those parents to break away from their own traditional strict Chinese upbringing (Chen et al., 2017).

Other findings suggest that when parents used their phones to enrich the interaction (e.g. seeking information about a topic they were talking about), they reported higher levels of social connectedness (Kushlev & Dunn, 2019 (Study 1)). Similarly, parental smartphone use was perceived as helpful and beneficial when its purpose was useful to family life (e.g. looking up a location, interacting with distant family members; Oduor et al., 2016). Similarly, in interviews parents and caregivers reported positive effects including the use of smartphones as a tool to organize family life (Mangan et al., 2018) and to take pictures (Chen et al., 2017; Hiniker et al., 2015; Kellershohn et al., 2018). Benefits were particularly identified in relation to interaction with distant family members and friends, seeking social support, or feelings of safety in case of emergency (Mangan et al., 2018). Smartphones were also seen by some working parents as a beneficial way of "bringing home to work", in the event they needed to be reached in emergencies (Palen & Hughes, 2007).

3 Discussion

The aims of this systematic review were: (1) to explore the links between parental smartphone use and the quality of parent child-interactions in four different age groups of children; and (2) to review potential benefits of parental smartphone use for these interactions. Regarding our first hypothesis, findings suggest that parental smartphone use was related with the quality of parent-child interactions across all age groups. Specifically, previous research found reduced parental attention and responsiveness towards their children, impaired quality of parent-child interactions or relationships, and decreases in perceived parental warmth associated with parental smartphone use. These are important findings given the omnipresence of smartphones nowadays. That said, the overall amount of parental smartphone use during the various observed parent-child interaction time intervals varied between studies, e.g. 59% of parents used device < 5% (Hiniker et al., 2015) versus 76% of parents for over 80% of observation time (Mangan et al., 2018). This might depend on overall observation time (total time of stay at playground versus first 20 minutes) and observation frame could make a difference, as the initial minutes at the playground may typically be used to organize family life or to take a rest before playing with children again.

The foci and outcomes of the studies differed between the selected age groups. As expected, while studies of younger children predominantly examined indicators of parental sensitivity as the main outcomes, research investigating older children primarily focused on indicators of the parent-child relationship quality (such as feelings of connectedness). Concerning the reasons for smartphone use in the presence of children, parents with younger kids often reported using their phone to connect with others or out of boredom. As rearing infants and toddlers is one of the most emotionally and physically challenging tasks (Nelson, Kushlev, &

Lyubomirsky, 2014), the need of parents to "go online" at times seems understandable. Using the smartphone might serve as a tool for parents to recharge their batteries, while being "off duty". With older kids, parents stated that they use the phone more often in child-related contexts (e.g. contacting teacher) and the findings on the impact on parent-child interactions appear inconsistent.

Overall, various facets of parent-child interactions have been examined. Among them, mealtime situations were a predominant focus. Parents primarily used their phones when children were not at the table or when children were otherwise occupied. Observations of parents and children during mealtime in a restaurant without technology present revealed that these situations were usually of short duration, including only a few interactions (Kellershohn et al., 2018). Findings suggest that daily meals are a very important contributor to parental well-being and happiness, even in the presence of smartphones (Nelson, 2016). Hence, mealtime appears to be a special quality time for parents in everyday family life. Important to note with regard to family quality time is that it is a critical question who defines which moments belong to quality time. For example, adolescents perceived reduced parental warmth when parents were distracted during a time adolescents themselves defined as quality time, but the parents may not have been aware of this. The definition of quality time is always in the eye of the beholder. Therefore, setting rules for smartphone use during parent-child interactions to safeguard quality time in the family requires consideration of the different family members' perspectives.

Taken together, we can conclude from the current review that the context of the parents' smartphone use matters. Important contextual factors include frequency and duration of use, reasons for use, timing (quality time vs. arbitrary moments), and parents' attitudes towards smartphones. A frequent interpretation of the present findings is that smartphones are not the cause of parent-child interaction difficulties per se, but rather an extended arm of underlying relationship issues already present in analogue (offline) interactions (Radesky et al., 2018). In a similar vein, Abels et al. (2018) concluded that the impact of parental smartphone use could be associated with underlying parental unresponsiveness, rather than with the phone use itself. We deem it necessary to pursue this hypothesis in future research, because new technology is often discussed as an uncontrollable factor invading family life. If further investigations replicate that technoference can be regarded as a reflection of general parent-child relationship patterns, beyond digital media, it would have important practical implications in terms of preventing or reducing negative spillover of parental smartphone use on parent-child interactions.

Within our second research question, we reviewed potential benefits of parental smartphone use for parent-child interactions. In general, the benefits were mostly perceived when parents were relaxed and enjoying themselves, for example when being entertained, connecting with others, or gaining support from digital interactions. These advantages can indirectly be regarded as beneficial for parent-child interactions. Collectively, strikingly few studies have examined potential benefits of parental smartphone use. This confirms our hypothesis that this focus has been neglected in previous research when compared to the volume of studies on the negative consequences of technoference.

Against this backdrop, it is desirable that more scientific attention is devoted to comprehensively assessing possible positive effects of parental smartphone use on parent-child interactions. For instance, little is known about using smartphones to stay in contact with children when they leave their homes, to care for their relationship via online channels, or to connect on a level that children and adolescents increasingly use with peers. Such an approach would help us gain an adequate awareness in parents and professionals working with families to address this pertinent topic in an appropriate, dispassionate fashion.

3.1 Limitations

Some limitations of the reviewed studies merit consideration. First, given the high heterogeneity of measures and methods, comparability of studies was sometimes difficult to assess. In particular, the term smartphone was not used in all studies. The studies used different terms such as mobile phone or mobile device and it was sometimes unclear if they were referring to online or offline activities. We decided to use smartphone as an overall term, as currently 94% of adults use their smartphones daily. Second, some studies did not provide information about specific age ranges of children, which made it difficult (a) to categorize the studies into the a priori defined age groups, and (b) to examine differential effects between those age groups. Future studies should be more precise when reporting the age of the children, as well as analyze the impact of technoference in relation to children's age in a more systematic way. Third, the majority of studies were cross-sectional and only a few controlled for a baseline measure of the parent-child interaction or relationship quality. Furthermore, this field lacks experimental studies in particular. These issues make deducing causality impossible and we thus cannot draw definitive conclusions about whether parental smartphone use impairs parent-child interactions. Fourth, this review did not systematically account for potential moderators in the link between parental smartphone use and parent-child interactions. Looking at parental characteristics, the influence of gender, ethnicity and/or other cultural factors, income, and education level i.a. remains unclear and future studies should investigate these potential confounding factors more carefully. Additionally, almost no study considered additional forms of media use in parents (TV, computer etc.) as well as children's media use, which could possibly amplify the effects. Moreover, smartphones are not the only mode of parental distraction, as several studies also assessed other distractions (siblings, preparing dinner, etc.; Kushlev & Dunn, 2019). Future experimental studies might address whether technoference has different effects on parent-child interactions than non-technological distraction.

3.2 Conclusion and Future Directions

With these caveats in mind, the current findings add to our understanding about the impact of parental smartphone use on parent-child interactions. Given that this research field is still in its infancy, more knowledge is needed about: (1) parental user habits and absorption level; (2) underlying mechanisms and moderating factors; (3) parental and child attitudes towards smartphone use in the family setting; and (4) potential benefits for family interactions and relationships. Families have to find adequate ways of dealing with new technology in everyday life, which inevitably affects the nature of their daily interactions. It is a new form of navigation through close relationships in analogue and digital spheres. Therefore, we think that it is high time to examine more thoroughly how parents can model for their kids a well-balanced and relationship-compatible handling of smartphones in day-to-day life.

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* Studies included in the systematic review are marked with an asterisk (*k* = 21).

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Author contributions

BK conducted the systematic literature search, screened studies for eligibility, coded the studies, and wrote the manuscript.
MZ supported the literature search, supervised screening and coding of studies, and wrote the manuscript.

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Electronic supplements

Table 1. Keywords for Literature Research

Parent terms	Child terms	Smart device terms	Parent-child interaction terms
Parent*(s), parental, mother*(s), maternal, mom*(s), father*(s), paternal, dad*(s)	Child, children (child*), adolescents	Smartphone, smart phone, smart device, mobile phone, tablet, laptop, screen time, portable screen	Interaction, relationship (quality), (quality) time, sensitivity, communication, responsivity, responsiveness, conflict

Table 2. Quality Assessment of Included Studies

Author(s)	Category[a] for Study Design	Quality Criteria[b]						
		S1	S2	1	2	3	4	5
Abels et al. (2018)	4	+	+	+	+	+	+	+
Ante-Contreras (2016)	4	+	+	+	+	+	-	?
Blackmann (2015)	4	+	+	+	+	+	+	+
Chen, Zhou, & Han (2017)	1	+	+	+	?	+	-	?
Golen & Ventura (2015)	5	+	+	+	+	+	?	+
Hiniker, Sobel, Suh, Sung, Lee, & Kientz (2015)	5	+	+	+	+	?	+	?
Johnson (2017)	1	+	+	+	+	?	?	+
Kellersohn (2018)	4	+	+	+	?	+	+	?
Khourochvili (2017)	4	+	+	-	-	+	+	+
Kushlev & Dunn (2019; Study 1)	3	?	+	+	?	+	+	+
Kushlev & Dunn (2019; Study 2)	4	+	+	+	+	?	?	+
Lanette (2018)	5	+	+	+	+	?	-	?
Mangan et al. (2017)	5	+	+	+	+	+	?	+
Myruski et al. (2018)	3	+	+	+	+	+	?	+
Nelson (2016)	4	+	+	+	?	?	-	+
Oduor et al. (2016)	5	+	+	+	+	?	-	+
Palen & Hughes (2007)	5	+	+	+	?	?	+	+
Radesky et al. (2018)	4	+	+	?	+	+	+	+
Radesky et al. (2015)	4	+	+	+	?	?	+	+
Stockdale et al. (2018)	4	+	+	+	+	+	+	+
Stupica et al. (2016)	4	+	+	+	+	+	?	+
Ventura & Teitelbaum (2017)	5	+	+	+	+	+	+	+

Note: Quality of studies were assessed using the Mixed Methods Appraisal Tool (MMAT; Hong et al., 2018). [a]Study design was assigned to the MMAT design categories: 1 = Qualitative; 2 = Quantitative randomized controlled trials; 3 = Quantitative non-randomized; 4 = Quantitative descriptive; 5 = Mixed methods [b]Two general quality criteria (S1 and S2) and five design-specific quality criteria (1 to 5) were assessed: according to the MMAT; + = criterion is met; - = criterion is not met; ? = criterion is not assessable.

Table 3. Characteristics and Detailed Information of Included Studies (k = 21)

Author(s)	Kind of Publication	Country of Study	Sample (N)	Age of Children (Age Group for Review)	Study Design (MMAT[a])	Main Outcome (Measure)	Key Findings
Abels et al. (2018)	Peer-reviewed paper	Netherlands	$N = 25$ caregiver-child dyads	$M = 26.3$ months (age group 1)	Quantitative descriptive	Behavioral coding of caregivers' behavior, children's bid for attention, caregivers' responsiveness (self-developed observational rating system)	Overall responsiveness ($X^2 = 27.3$, $\beta = -1.11$, $SE\ \beta = 0.22$, Nagelkerke $R^2 = .14$, $p < .001$, $OR = 0.32$), timeliness of the response ($X^2 = 28.3$, $\beta = -1.9$, $SE\ \beta = 0.38$, Nagelkerke $R^2 = .19$, $p < .001$, $OR = 0.15$), and strength of the response ($X^2 = 10.8$, $\beta = -1.2$, $SE\ \beta = 0.43$, Nagelkerke $R^2 = .04$, $p = .007$, $OR = 0.32$) were negatively predicted by caregivers' engagement with their phone. No relation was found with the emotionality of the response ($X^2 = 0.8$, $\beta = -15.5$, $SE\ \beta = 7289.5$, Nagelkerke $R^2 = .01$, $p = .998$).
Ante-Contreras (2016)	Thesis	USA	$N = 167$ parents	0–4 years (age group 1)	Quantitative descriptive	Online survey using the Parent-child attachment and parenting style questionnaire ("Provincial Assessment of Parenting Styles"; Biletchi et al., 2013)	There was one statistically significant relationship between any of the social media usage variables and the parenting variables, that is, a positive relationship between hours of social media usage and a high score on authoritarian parenting techniques ($r(167) = .157$, $p < .049$). 75% of parents reported to use social media up to three times a day during parent child in contrast to 2% stated to never use social media during supervision of their children. However, only 10% of the parents believe their attention is inhibited while using the device.
Blackmann (2015)	Thesis	USA	$N = 93$ parents and caregivers	$M = 8.42$ years (age group 3)	Quantitative descriptive	Parenting behaviors: bonding, discipline, education, general welfare and protection, responsiveness, sensitivity, negativity) ("Parent Behavior Importance Questionnaire-Revised PBIQ-R"; Mowder, 2009).	There was a positive relationship between parental screen time and parental screen distractions among caregivers ($r = .36$, $p < .001$). Distracted parents showed less responsiveness to their children ($r = -.210$, $p = .043$) compared to screen viewing parents. The correlation between parents screen time and their screen distractions were moderated by education level (R^2 change = .205), $F(2, 87) = 13.47$, $p < .001$) and annual household income ($b = .583$, $SE\ \beta = .149$, $t(86) = 3.91$, $p = .000$).
Chen, Zhou, & Han (2017)	Peer-reviewed paper	China	$N =$ 23 mothers	Range = 1–6 years (age group 1)	Qualitative	Mothers' perception and interpretation of the role of smartphone (tablet) in daily communication and interaction with their children (interviews; interpretative phenomenology analysis IPA)	Chinese mothers have a mixed feeling toward the role of smartphone and tablet playing in their parenting practices. According to those participants, the smartphone and tablet both help and impair their communications and interactions with their children. There are both direct and indirect benefits of using smartphones for parenting.

eTable 3. continuation

Golen & Ventura (2015)	Peer-reviewed paper	USA	*N* = 24 infants (girls), N = 32 mothers, (*N* = 21 mothers were over-weight or obese)	Range = 14.4 ± 7.1 weeks (age group 1)	Mixed methods	Mothers' distraction in feeding interactions (diary report and "Infant Behavior Questionnaire-Revised Very Short Form IBQ-R"; Peterson, Waldie, Mohal, Reese, Atatoa Carr, Grant, & Morton, 2017)	For the majority of the feedings (52%), mothers did a variety of additional activities, including watching TV, laying down or sleeping, using a phone, doing housework reading, using a mobile device, traveling (e.g., the baby was in a stroller or car seat), listening to music, using the computer, and eating. During almost one-third (32.4%) of feedings, mothers reported using technological distractors. For the remaining 48% of feedings, mothers reported interacting with their infants or that they did not do anything else during the feeding.
Hiniker, Sobel, Suh, Sung, Lee, & Kientz (2015)	Conference paper	USA	*N* = 466 parents	< 10 years (age group n/a)	Mixed methods	1) Field note codes from observations covered nine areas: child-caregiver interaction, children's attempts to interrupt adults, caregiver position, supervision style, phone activities, nonphone activities, balancing phone use with child needs, behavior just before and after phone use, and children's activity during phone use; 2) Code categories drawn from interviews: beliefs about the purpose of the playground, parenting style, concerns about phone use while caring for children, and benefits of phone use	Parents reported a low usage of phones but high feeling of guilt. Some parents felt more available to their children, when they were on their phone. 28% of caregivers thought that phone use while supervising children was acceptable as long as their child was safe. 40% of parents thought phone use should be related to being at the park and 40% of parents would like to decrease their use.
Johnson (2017)	Thesis	USA	*N* = 12 parents	< 18 years (age group n/a)	Qualitative	Attitudes, practices, and opinions regarding the smartphone use in the presence of their children (semi-structured interview by author)	Parental smartphone use affected the lives of study participants. Participants who seemed to lack awareness of these costs in their own life identified the same costs. Five primary themes emerged: (1) Disengagement, (2) concern for future, (3) change in social norms, (4) boundaries, and (5) cognitive dissonance.
Kellershohn et al. (2018)	Thesis (published)	Canada	*N* = 300 families with 450 children	Range = 2–12 years (age group 1)	Quantitative descriptive	Behavioral coding of family dining behavior (direct, unobtrusive and structured observation)	The food ordering process was rapid (< 6 min), during which personal technology use was minimal, and adult/child interactions were perfunctory. Visits averaged 53 min, and only 18 min on average was spent eating. Families were observed using the fast food restaurant as a "third place" (home away from home) for many activities other than eating food. In-restaurant family behaviors included frequent use of technology (40% of children/70 % of adults), use of the indoor play area (65% of children/33min of play) and child engagement with a toy (53 % of children/10min of play).

Table 3. continuation

Khourochvili (2017)	Thesis	Canada	N = 19 mothers	Range = 4–11 months (age group 2)	Quantitative descriptive	1) Caregiver sensitivity and infant responses (modified Face-to-Face Still-Face Procedure FFSF; Tronick et al., 1978); 2) Behavioral coding based on a modified classification of the behavior categories by Mesman et al. (2009): Presence or absence of gaze, positive, neutral or negative/ distressed affect	Caregivers who used technology more frequently were less sensitive with their infant when absorbed with their mobile phones (p <.001), measured by the increase of disengagement behaviors from control (M = 2.27, SD = 5.49) to the smartphone condition (M = 32.61, SD = 11.59). In contrast, the better the caregivers' ability to divide attention, the less sensitive they were (t(14) = -2.61, p = .02, r = -0.57). Further, the higher caregivers' total MTUAS scores (their reported technology usage and attitudes toward technology), the less positive affect and gaze toward their infant was demonstrated during the caregiver divided attention phase (t(14) = -2.26, p = .04, r = -0.52).
Kushlev & Dunn (2019)	Peer-reviewed paper	USA	Study 1: N = 200 parents; Study 2: N = 114 parents	Study 1: Median = 5 years (age group 2); Study 2: < 19 years (age group n/a)	Study 1: quantitative non randomized; Study 2: quantitative descriptive	Social connectedness (adapted two items from the "Social Connectedness Scale"; Lee, Draper, & Lee, 2001)	Study 1: Frequent phone use led parents to feel more distracted, which in turn impaired feelings of social connectedness (t(197)=5.11, p < .001) and the meaning that parents derived when spending time with their children (t(195)=2.12, p = .035) compared to low phone use group. Study 2: Smartphones distracted parents from reaping a sense of social connection when spending time with their children as the study found indirect effects of phone use through attention on both general social connectedness, b =.08, p =.017, and social connectedness with children, b =.06, p =.017.
Lanette (2018)	Thesis	USA	N = 200 (100 parent-child dyadic pairs)	M = 16.04 years (SD = 2.24). (age group 4)	Mixed methods	Conversation quality ("Intrinsic Motivation Inventory"; Misra, Cheng, Genevie, & Yuan, 2014)	The mere presence or absence of smartphones did not affect parents- or teens-reported conversation quality or partner listening. The mere presence of mobile phones did overlap with a decline in parents reported conversation closeness (F(4, 87) = 2.27, p = .07).
Mangan et al. (2017)	Peer-reviewed paper	Australia	N = 50 parents in observation, N = 25 parents in interviews	Range = 0–5 years (age group 1)	Mixed methods	Behavioral coding of no parent-child interaction, adult leaves, interaction equipment interaction, independent play, talking-, play-, and touch-interaction (observational rating system "The Parent/ Caregiver and Child Interaction Scale" (adapted from Hiniker et al., 2015)	76% (N = 38) of the parents/caregivers used their mobile device, with usage time extending to 17.2 min of the 20 min-observation period. Text-/type-related mobile device use was most often used (69.6%), followed by voice-related (23.7%), and camera-related smartphone use (6.7%). The 25 interviewed parents/caregivers beliefs on mobile device use were centred on three themes: (1) Diversity of smartphone use, (2) child relationships and smartphone use, and (3) the physical environment and smartphone use.

Table 3. continuation

Myruski et al. (2018)	Peer-reviewed paper	USA	*N* = 50 mother-infant-dyads	Range = 7.20–23.60 months, (*SD* = 4.74) (age group 1)	Quantitative non randomized	Behavioral coding of negative affect, positive affect, toy engagement, engagement with mother, social bid, room exploration (modified Still Face Paradigm SFP; Tronick et al., 1978).	During maternal smartphone use infants showed more negative affect ($t(49) = 2.98$, $p = .004$; $F(2, 96) = 5.67$, $p = .005$, $\eta_p^2 = .11$) and less positive affect during still-face task. Infants showed the most need for attention and social bids ($t(49) = 6.76$, $p < .001$) during still face task. More frequent reported smartphone use was associated with less positive affect ($\beta = -.35$, $t(49) = -2.37$, $p = .022$), less recovery (i.e., engagement with mother, ($t(49) = -17.64$, $p < .001$), room exploration ($t(49) = -11.37$, $p < .001$; $F(2, 96) = 117.83$, $p < .001$, $\eta_p^2 = .71$) during reunion, even when adjusting for temperament.
Nelson (2016)	Thesis	USA	*N* = 3000 parents	Range = 5–18 years (age group 2)	Quantitative descriptive	Parental and overall happiness (self-developed questionnaire)	Daily family meals were positively associated with parents reporting being "very happy". Parents strongly desired the emotional energy that results from parent-child interactions during the family meal and these positive results may be inhibited by the mere presence of electronic devices, if this ritual does not take place daily. Thus, in the presence of electronic devices, regular family meals may not be enough to produce the meaningful interactions that produce wellbeing.
Oduor et al. (2016)	Conference paper	Australia	*N* = 20	< 18 years (age group n/a)	Mixed methods	Family dynamics when smart-phone was used during interaction (self-developed survey, diary and interview)	Family members became upset when others did non-urgent activities on their phones in the presence of others. In some cases, people developed strategies to provide a greater sense of activity awareness to warfare the problem. Smartphone usage was perceived as beneficial by providing a mechanism for needed disengagement from family members.
Palen & Hughes (2007)	Peer-reviewed paper	Denmark/ USA	*N* = 5 families	Range = 3–13 years (age group 1)	Mixed methods	Parental mobile phone use, (self-developed interview and experimental sampling method, ESM)	In presence of their children, parents did not have their phones with them. When at home, parents were less likely even to be aware of whether their phone was on/off. While around younger children, parents used their phone to connect with other adults. Parents used their phones to stay in touch with adolescents.
Radesky et al. (2018)	Peer-reviewed paper	USA	*N* = 301 caregiver-child dyads	Range = 3–4 years (age group 1)	Quantitative descriptive	Parent-child eating encounters (observational rating of videotaped home mealtimes and structured laboratory-based protocol); Semi structured interview to assess richness of perceptions, caregiving sensitivity, intensity of involvement, acceptance of the child, child difficulty, and parenting reflectivity ("Working Model of the Child Interview WMCI"; Zeanah & Benoit, 1995)	During the family mealtime, 47 (24.1%) mothers actively used a smartphone at least once, while during the structured eating protocol, 44 (22.6%) mothers used a device. Higher child difficulties (OR = 1.65), lower sensitivity (OR = 0.67) and lower richness of perceptions (OR = 0.72) were associated with smartphone use during mealtimes.

Table 3. continuation

Radesky et al. (2015)	Peer-reviewed paper	USA	*N* = 225 mother-children dyads	Range = 0–6 years (age group 1)	Quantitative descriptive	Bob and Tom's Method of Assessing Nutrition (BTMAN), Mother-Child Eating Interaction Protocol (self-developed)	Mothers with mobile device use had significantly fewer verbal interactions (11.1 vs. 14.1, $p = 0.03$) with their children than mothers who had no or negligible use during the eating protocol, particularly during presentation of halva (2.3 vs 3.7, $p = 0.03$), the most unfamiliar of the foods presented. In addition, mothers with mobile device use made significantly fewer total encouragements (8.8 vs. 12.3, $p = 0.03$) and fewer encouragements regarding unfamiliar foods (5.0 vs. 7.7, $p = 0.02$). Maternal use of mobile devices was associated with 20% (95% CI: -3%, 37%) fewer verbal and 39% (95% CI: 4%, 61%) fewer nonverbal interactions during the eating protocol.
Stockdale et al. (2018)	Peer-reviewed paper	USA	*N* = 1072 adolescents	Range = 10–20 years (age group 4)	Quantitative descriptive	Adolescents' technoference and ratings of their parents' technoference (modified version of "The Technoference Scale"; McDaniel & Coyne, 2014); Parental warmth (three items from the "Parenting Styles and Dimensions Questionnaire-Short Version PSDQ"; Robinson, Mandleco, Olsen, & Hart, 2001)	Parental technoference was related to less parental warmth ($\beta = -0.35$, $p < .001$), cyberbullying ($\beta = 0.20$, $p < .001$), anxiety ($\beta = 0.28$, $p < .001$), depression ($\beta = 0.24$, $p < .001$), civic engagement ($\beta = 0.19$, $p < .001$), prosocial behavior towards strangers ($\beta = 0.22$, $p < .001$), and family members ($\beta = 0.20$, $p < .001$), mediated through parental warmth. Adolescent technoference was directly related to cyberbullying ($\beta = 0.28$, $p < .001$), anxiety ($\beta = 0.13$, $p < .001$), depression ($\beta = 0.21$, $p < .001$), prosocial behavior towards stranger ($\beta = -0.16$, $p < .001$), family members ($\beta = -0.28$, $p < .001$), and civic engagement ($\beta = -0.12$, $p = .003$). Adolescent technoference was not related to parental warmth ($p = .10$)
Stupica (2016)	Peer-reviewed paper	USA	*N* = 50 parents	*M* = 6.8 years; *SD* = 2.72 (age group 2)	Quantitative descriptive	Behavioral coding of parental behavior: sensitivity and response (self-developed observational rating system)	Parental sensitivity and responsiveness predicted how fast a child would ran around a baseball base, as children ran 3.66 seconds faster ($SE = .75$, $p < .001$, Cohen's d = 1.409). Children's times decreased as parental sensitivity increased ($\beta = -1.51$, $SE = 0.71$, $p = .04$), and children's times increased as parental harshness increased ($\beta = 1.70$, $SE = .73$, $p = .02$).
Ventura & Teitelbaum (2017)	Peer-reviewed paper	USA	*N* = 75 mothers	< 6 months (age group 1)	Quantitative descriptive	Distraction while feeding (self developed diaries)	Among the reported 43% of feeding distractions, 26% involved technological distractors. Compared to mothers with only one child, multiparious mothers reported greater levels of any distraction during feeding ($\beta = 18.27$, $SE = 7.43$, $p = .02$). Mothers of racial/ethnic minorities reported greater levels of technological distraction ($\beta = -13.56$, $SE = 4.93$, $p = .008$), tended to show a laissez faire feeding style ($\beta = 6.83$, $SE = 2.75$, $p = .02$), and perceived their infants to have lower food responsiveness ($\beta = -13.66$, $SE = 3.62$, $p < .001$) and greater appetite ($\beta = 11.37$, $SE = 2.64$, $p < .001$).

Note: [a]Study design was assigned to the MMAT design categories by Hong et al. (2018).

Digital Phenotyping – A Case for Cognitive Functions and Dementia?

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Abstract
Background: This article provides the reader with a brief background on recent advances in the field of *Psychoinformatics*. *Psychoinformatics* represents a merger between the disciplines of computer science and psychology, thus enabling researchers to, among other activities, conduct *digital phenotyping* while exploiting the ubiquitously available digital traces resulting from interaction with the Internet of Things (IoT). IoT describes a totally interconnected world, where everything from household appliances to smartphones are linked to each other via the Internet.
Objectives: In recent years, much work has been dedicated to the question of which psychological variables, in the realm of socio-demographics and personality, can be predicted from social media platform data and/or smartphones in general. These variables are of interest to researchers, because they have been associated with many important life variables such as longevity, health behaviour and job performance.
Methods: As research concerning cognition is an area of *Psychoinformatics* which has received comparatively less attention, the focus of the present article is on ideas regarding how cognitive functions, and more specifically dementia such as Alzheimer's Disease (AD), might co-vary with data from the IoT.
Results: It is demonstrated that different socio-demographic and psychological variables, including cognitive variables, can be predicted from digital footprints.
Conclusions: The application of methods from *Psychoinformatics* provides opportunities to improve diagnostics and monitoring of AD and other causes for dementia. The limitations of such approaches are also addressed in this article alongside relevant thoughts on ethical considerations.

Keywords: digital phenotyping, dementia, Alzheimer, Psychoinformatics, personality, mobile sensing, emotion

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1 Background

According to recent data from the Alzheimer's Association (AA), (late onset) Alzheimer's disease (AD) represented the 6th leading cause of death in the USA in 2018. Moreover, it has been estimated by the AA that national cost of Alzheimer's and other dementias will probably rise from 305 billion US dollars in 2020 to a staggering 1.1 trillion dollars in 2050 (Alzheimer's Association, 2020). Such numbers can be supplemented by highly alarming AD rates in countries such as Germany, where costs are also likely to rise dramatically (e.g., Deutsche Alzheimer Gesellschaft, 2018).

AD, which was first diagnosed in 1906 by German psychiatrist Alois Alzheimer, represents the most common cause of dementia resulting in memory loss (Goedert & Spillantini, 2006). Beyond memory loss, several neuropsychiatric symptoms and behavioural impairments accompany dementia (Ismail et al., 2016). In the late stages of AD, patients are not able to perform their everyday life activities alone and are dependent on 24 hour care. This incurs a high financial burden for society and great physical and emotional distress among afflicted patients and their relatives. Significantly, effective treatments for this devastating disorder remain elusive.

The biological mechanisms underlying this neurodegenerative disorder are still poorly understood, perhaps with the amyloid-beta hypothesis being the most prominent approach to understanding AD (Wang et al., 2017). Here, it has been proposed that an imbalanced metabolism of amyloid-beta might be at the heart of AD, although this view has been challenged (Kepp, 2017). There is consensus among scientists that AD is multicausally influenced with both genetic and environmental factors playing a relevant role in the etiogenesis of AD[1] (Huang & Mucke, 2012; see also heritability estimates in Gatz et al., 1997). On the molecular genetic side in particular, genetic variations

[1] Please note that we mainly speak of late onset AD in this article. For instance, we are aware that other genetic markers, as presented in the following, are of relevance to understand some cases of early onset AD and so forth.

of the APOE gene resulting in the so called epsilon (e) e2, e3 and e4 alleles have been associated with AD (Corder et al., 1993; Montag et al., 2014). In detail, carrying one e4 allele results in a threefold risk of developing AD, whereas carrying two copies of e4 results in a tenfold risk. Work by Kunz et al. (2015) demonstrated that young e4 allele carriers are more likely to have altered grid cell activity in the entorhinal cortex while performing a navigational memory task, hinting towards an early biomarker in predicting AD. Therefore, in the near future early Alzheimer diagnostics might begin in early adulthood giving persons at genetic risk of developing the condition the opportunity to adopt health behaviours including dietary practices and physical activity. Such interventions might counteract the genetic risk for AD (e.g. Reiner et al., 2013; Müller, 2015; Scarmeas et al., 2009).

As young adults strongly engage in smartphone use in their everyday lives (about 2.5 hours each day, see Montag et al., 2015), we believe that it is necessary and important to study human-smartphone-interaction patterns to provide insights into the development of dementia including AD starting early in life. This idea will be outlined in detail following a brief description of *Psychoinformatics*.

2 A new discipline called Psychoinformatics

Recent years have seen a rise in studies in the field of *Psychoinformatics* (Yarkoni, 2012; Markowetz et al., 2014). This new interdisciplinary research area applies methods from computer science in psychology and psychiatry to obtain insights into complex human behaviour. In the realm of *Psychoinformatics*, among other methods, app-based technologies are used to study human behaviour via digital traces left from human-smartphone-interaction (Miller, 2012). Here, studies have established links between phone use behaviour and personality (Chittaranjan et al., 2013; Montag et al., 2014; Stachl et al., 2018; Montag et al., 2019a), but also between length of daily WhatsApp usage and personality/age/gender (Montag et al., 2015). Personality describes stable motivational, emotional and cognitive characteristics of a person across time and – to a lesser degree – different situations (for more on the complexities and challenges in relation to this concept see works by Bleidorn et al., 2018; Edmonds et al., 2008; Mischel & Shoda, 1995; and Montag & Panksepp, 2017. For the relevance of situation characteristics in personality science see Rauthmann et al., 2014). Beyond this work on smartphone-personality-links, social media platforms have been abundantly studied to predict person variables from digital traces such as Facebook "Likes" (Kosinski et al., 2013). In addition to the prediction of person characteristics from such "Likes", *textmining* has been applied to reveal insights into trait emotionality of a person (Schwartz et al., 2013; Settani & Marengo, 2015). Use of specific words in posts on social media platforms provides insights into whether a person, e.g., is neurotic[2] (manifested by often using words such as being depressed or anxious). Beyond Facebook other platforms are also noteworthy. A prominent example is Twitter, which also has been analyzed to reveal insights into personality (Ahmad & Siddique, 2017; Quercia et al., 2011). For a recent overview on the use of data harvested from social media platforms to predict psychological variables, please see the work of Azucar et al. (2018), but also the new work by Marengo & Montag (2020) in the present issue.

Clearly, these examples represent just the tip of the iceberg of what will come in the near future in the expanding new field of *Psychoinformatics* (Montag & Elhai, 2019). Effectively, all data derived from the interaction with a completely connected world – the Internet of Things (IoT) – can be used to conduct *digital phenotyping*, hence enabling researchers to obtain insights into a person's trait or state variables. Notably, many researchers refer to *digital phenotyping* (Insel, 2018; Onnela & Rauch, 2016; Torous et al., 2017) rather than *Psychoinformatics* (see also Montag et al., 2016), although both terms can be brought together. Whereas *Psychoinformatics* might describe a new research discipline, *digital phenotyping* currently represents one of the most often used applications in this interdisciplinary research field. One could say that a researcher aims to conduct *digital phenotyping* applying methods from *Psychoinformatics*.

Beyond the prominent examples from social media studies, researchers are also already including data from other activities of everyday life in their models to reveal insights into psychological phenomena. To name a small number of recent examples, one study predicted the gender of a driver from motor vehicle driving behaviour including velocity, gas pedal actuation, and steering wheel angle (Stachl & Bühner, 2015). A noteworthy new work by Cao et al. (2018) even predicted orderliness from the campus behaviour of students in China. Here, temporal records of showering and meal intake (recorded via a smartcard at the University of Electronic Science and Technology of China in Chengdu in n = 18,960 students) gave insights into orderliness. Higher orderliness (regular showering and meal intake) itself was a good predictor of better academic performance in this work. In our opinion, this example from China illustrates nicely the potential of data mining from ubiquitously available data stemming from the IoT.

3 How digital phenotyping might help in the early diagnosis of Alzheimer's Disease (AD) and other causes of dementia, as well as monitoring its progression.

In principle, it will also be possible to use data from the IoT in the realm of AD or general dementia diagnostics. This endeavor could be undertaken not only to uncover early markers for AD in the current smartphone-using generation, but also to monitor

[2] Neuroticism represents one of the Big Five dimensions carved out in personality psychology against the background of a lexical approach.

cognitive functions over a longer time period in elderly patients in the transit zone from mild cognitive impairment (MCI) to AD. As a consequence, the latter approach will also enable both scientists and practitioners to obtain insights into the course of AD when it has been diagnosed. Any such research endeavor will without doubt be very complex, because different causes of dementia exist, with (late onset) Alzheimer's being perhaps the most prevalent. This raises the question of whether digital footprints left on the smartphone can provide insights into the different causes of dementia of relevance in the aforementioned transit zone from MCI to a demented state of mind. MCI is characterized by both subjective and objective cognitive impairment (but not dementia) and frequently is accompanied by neuropsychiatric symptoms such as negative mood, lack of motivation and anxiety. Interestingly, those patients which display both MCI and anxiety symptoms are much more likely to develop Alzheimer's disease than those that possess MCI but lack anxiety symptoms (83.3% vs. 40.9%; Palmer et al., 2007). Hence, it will be of utmost importance to not only obtain insights into the cognitive state of a person when mining smartphone or IoT data, but also into the affective state, because both variable sets are of high interest in efforts to predict the probability of transiting from MCI to dementia. In this context, another work by Ismael et al. (2016) is noteworthy, because it not only proposes the relevance of understanding the neuropsychiatric symptoms visible in MCI, but also stresses the importance of *mild behavioural impairment (MBI) criteria* such as changes in social behaviour and speech, likely to leave their trace in smartphone variables (e.g. changes in contacting persons via the smartphone or use of more stereotyped speech in smartphone messages). Stereotyped language might also be directly investigated, when a patient is speaking to IoT devices such as Amazon's Alexa or Apple's Siri. In this context, we believe it is also of interest to infer personality from the smartphone data, because high neuroticism (via its link to higher risk for depression) and low conscientiousness are well-known risk factors in developing dementia (Low et al., 2013). Therefore, the aforementioned studies showing links between personality and digital footprints are of high relevance for dementia research. In addition to these works, the "Lancet Commission on Dementia Call for Action", which outlines modifiable risk factors for dementia over the life span, is of significant relevance. While in early life the variable of (less) education is mentioned, in midlife hearing loss, hypertension and obesity are advanced as important risk factors. In late life factors such as smoking, depression, physical inactivity, social isolation and diabetes are particularly noteworthy (Orgeta et al., 2019). Beyond this, as motoric and visual dysfunctions might leave their traces in the human-smartphone-interaction, this also represents a relevant research area. Therefore, establishing links between these variables and digital footprints at different life stages might also indirectly produce insights on risks for dementia.

From a neuroscientist's perspective, and in line with work by Kunz et al. (2015), it would be interesting to know if young persons at genetic risk for AD behave differently in everyday life. Such a research design would lead to a fusion of bio-psychological and information technology data, perhaps one of the most promising and exciting new areas in the health sciences (see Figure 1). Building on the study conducted by Kunz et al. (2015) which investigated navigational-memory abilities, an interesting idea would be to test for differences in global positioning system (GPS) related variables tracked via smartphone depending on the aforementioned APOE genotype. Such GPS variables would also provide insights into an active lifestyle, providing information on the extent to which an individual is travelling (in terms of traveled miles/km each day). Operation systems of modern smartphones also include health data functions such as calories burned per day or number of footsteps detected via the smartphone's sensors; such variables might supplement these GPS data sets. It should be noted, however, that interpreting such data will not be easy, as a (highly) active lifestyle might also be an indicator of a stressful episode in a person's life. This also demonstrates that, beyond the data that can be derived from *Psychoinformatics,* a myriad of other (classic) variables, including self-report/neuropsychological test measures, still need to be considered to gain an accurate picture of a person's health condition. Without doubt only *patterns* of variables will be able to give valid and reliable insights into psychological/psychiatric variables. In contrast a *single* variable alone will not be able to explain more than a few percent of the variance in complex psychological/psychiatric phenotypes. For example, the shared variance between a call variable from the smartphone and the personality trait of extraversion is approximately 10% (Montag et al., 2014; Montag et al., 2019a). To illustrate this further, Markowetz et al. (2014) hypothesized that smartphone use variables might provide insights into the depressed state of a person (probably also of an AD patient). In the context of AD, dementia patients often show signs of depression when being in the transit zone from MCI to full blown AD because they are consciously experiencing their own cognitive decline (for links between AD and depression see the studies by Modrego & Ferrández (2004) and Ownby et al. (2006)). What kind of *pattern* of smartphone variables could reflect a depressed state? For example, a person's lack of motivation to engage in everyday life activities could result in lower GPS activity. His/her high sadness could manifest in higher usage of negative text content in social media channels, and a lack of energy for social communication/social withdrawal could be reflected by the individual contacting their social network via their phone to a lesser degree compared to the pre-depressed state (see also Elhai et al., 2018; Saeb et al., 2015). Again, a single variable taken alone will not help to establish predictions with a high degree of accuracy.

As with AD diagnostics, the focus lies in particular on monitoring the cognitive functions of a person (but also taking into account the importance of examining affect as mentioned above). We believe that the smartphone might provide an interesting source of research for understanding individual differences in cognitive variables (for feasibility see new work by Dagum (2017) and another opinion piece by Kourtis et al. (2018)). Firstly, *textmining* of a person's diverse text messages might result in a valid estimate of how many words a person uses in everyday life. By monitoring a person's word usage longitudinally, the treating physician or neurologist can investigate how many words were used before AD was diagnosed, and how their usage of different words in everyday life shrinks with the progression of AD. Second, a source less considered to date in monitoring the cognitive functions of a person is his/her smartphone interaction (Montag, Reuter & Markowetz, 2017). In our own work it has been demonstrated in a sample of approximately one hundred students that the smartphone-screen is unlocked an average of about 50 times a day (Montag et al., 2019b). In a year this would result in 18,250 unlocks (50 unlocks x 365 days). Imagine now that instead of using a single simple swipe to unlock the phone, a user is required to complete a neuropsychological test. Implementing such a task would result in an impressive amount of longitudinal data providing insights into changes and/or stability of a person's cognitive functions (see also Montag, Reuter & Markowetz, 2017). Again, these types of activities will need to be treated very cautiously in the near future, because research has yet to develop answers to the question: which neuropsychological tasks should be implemented in such a scenario? Which tasks will be most sensitive in terms of properly diagnosing cognitive decline and indicating progress of AD?

Aside from this, psychometric quality in terms of validity and reliability needs to be ensured for such cognitive unlock-screen-measures. In short, will data derived from the smartphone be as valid and reliable as that derived from a carefully implemented neuropsychological measure in a strict lab setting? Obviously, much work needs to be conducted to establish such sound (mobile) cognitive measures. Nevertheless, we are convinced that even when persons play through these one-trial-unlock-tasks in the manifold different situations of everyday life (such as being on a crowded bus or distracted by factors in the environment), the sheer size of available data should reduce the errors in measurement and result in generally good insights into the cognitive ability of a person over the course of time.

As cognitive ability[3] arises from the brain, human-smartphone-interaction data might not only provide insights into underlying psychological states, but indirectly also into (dys-) functional brain mechanisms. Early work demonstrated the feasibility of linking both molecular genetic and MRI data to smartphone use variables. Work by Sariyska et al. (2018) demonstrated that a genetic variant of the oxytocin receptor (OXTR) gene might be linked to the size of a person's (active) social network. Note that the sample size of this study was rather small and these findings thus need to be replicated by independent work groups. For some readers it might sound like a futuristic vision to infer the molecular genetic make-up of a person from the study of digital footprints. We partially share this opinion in relation to polygenetically influenced phenotypes in psychology also shaped by the environment (Montag & Reuter, 2014), but again see the feasibility study by Sariyska et al. (2018). For neurodegenerative disorders, however, the situation may be somewhat different, because here genetic variants exert higher influence compared to the effects of a single genetic variant on a trait such as personality (again being influenced by hundred of genetic variants shaped by the environment). In particular, this should be true for monogenetically inherited disorders such as Chorea Huntington (e.g. Andrew et al., 1993). Beyond the OXTR gene smartphone paper, a study by Montag et al. (2017) observed a robust link between lower gray matter volume of the nucleus accumbens and longer/higher frequent use of the Facebook app installed on the smartphones of study participants. Although these statistically significant associations could "only" be established at the group level (and causality has not been established), in the future accuracy rates might increase with respect to individual diagnostics. Again, this will only happen when *patterns of variables* are be taken into account (see argumentation above). In sum, we believe that the time is ripe to investigate both psychological and biological variables in the context of digital phenotyping. Hence, bio/neuro-psycho-tech and info-tech are merging into the area of *Psycho(neuro)informatics* (Montag et al, 2016). Please see also Figure 1.

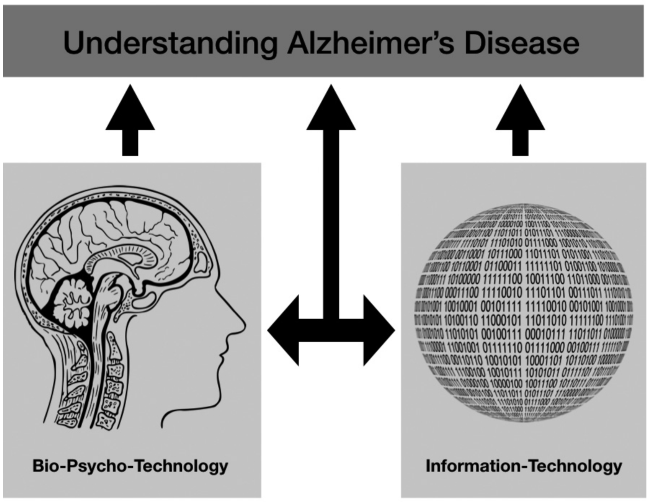

Figure 1: Whereas in the past Bio-Psycho-Technology data were investigated individually from psychologists, psychiatrists, neurologists or computer scientists in the context of Alzheimer's Disease (AD), new research approaches are applied to derive – by means of a combination of Bio-Psycho- and Information Technology data – insights into AD (images courtesy of licence free picture platform pixelbay.com).

4 Limitations

Although the future of *Psycho(neuro)informatics* seems to be bright, many challenges must be overcome before this new interdisciplinary research area can blossom. Psychologists/psy-

[3] Here we use cognitive ability as a broad term. In psychology many different cognitive functions are investigated, perhaps most prominently executive functions comprising working memory, task switching and behavioural inhibition (Hofmann et al., 2012). But see also some relationships between executive functions and intelligence (Friedman et al., 2006).

chiatrists/neurologists and computer scientists have different publication cultures (e.g. conference proceeding publications in computer science) and not all scientists from each distinct research area are necessarily aware of what is published in the other discipline. Beyond this, prediction accuracy varies strongly depending both on the specific digital trace investigated and the to-be predicted psychological/psychiatric/neurological variable. The work by Azucar et al. (2018) concluded that "the predictive power of digital footprints over personality traits is in line with the standard "correlational upper-limit" for behaviour to predict personality, with correlations ranging from 0.29 (Agreeableness) to 0.40 (Extraversion)" (p. 150). Other variables such as gender can be much more accurately predicted from Facebook "Likes" or the aforementioned motor vehicle data. In the work by Kosinksi et al. (2013) accuracy rates for gender predicted from Facebook "Likes" were .93. Although this estimate is much better than the figures presented in the summary by Azucar et al. (2018), this approach still does not result in perfectly accurate predictions. Fittingly, Stachl & Bühner's (2015) work on motor vehicle behaviour and gender yielded the insight that their "model is more successful in classification of males (positive class) in comparison with females." (p. 5590).

A further issue concerns the statistical approaches used to analyse data derived from the IoT. Many researchers in the life sciences have primarily applied classic inferential statistics to obtain insights from their collected data. But classic inferential statistics are only partly useful in terms of achieving higher accuracy rates from the statistical models. Therefore, other approaches such as machine learning need also to be applied to more effectively analyse the data. This will require the acquisition of new statistical skills for those working in *Psychoinformatics*.

Montag & Elhai (2019) note the importance of keeping expectations in check about this new digital data layer. While both authors are convinced that *digital phenotyping* via *Psychoinformatics* represents a powerful layer, it is "only" a further data layer to be collected and applied by scientists to understand complex human behaviour. Taking information from a digital layer derived via methods from *Psychoinformatics* alone to predict human behaviour might result in an overly narrow view of human nature, and ultimately risks generating incorrect predictions.

A further problem of applying *digital phenotyping* in health care and other relevant areas relates to questions concerning the generalisability of observed associations between digital traces and a psychic variable. Even if a researcher reveals a robust set of variables linked to a psychological or psychiatry trait/state, it is not clear if this translates easily to other populations. Scientists always need to gather new data to infer psychological variables from digital traces to ascertain if a certain association remains valid. This is very relevant, because in the contemporary fast-moving world the topics people discuss on social media change on a very regular basis – the topics discussed a year ago are unlikely to be the same as those being discussed today. Hence, some facets of digital phenotyping (e.g. relying on *textmining* of social media messages) might underlie more rapid changes over time concerning the validity and reliability of established associations, because of advances in technology. In this limitation section we also wish to explicitly mention problems in the study of Alzheimer's Disease and other dementias. First and foremost, the current generation of patients suffering from dementia are not "digital natives", and hence many of them do not own a smartphone – or if they do, they did not learn to use it "naturally". Hence, much of the relevant research on dementia can only be conducted when the generation of digital natives and the somewhat older digital immigrants reach the age at which dementia becomes a critical topic. Another important aspect of this research will be to fully grasp the different stages of dementia, from preclinical to late stages (Förstl & Kurz, 1999), from the study of digital footprints. Beyond this, it is relevant that there are different causes of dementia. This opinion piece has strongly focused on (late onset) Alzheimer's Disease as the most common cause for dementia. Nevertheless, *Psychoinformatics* might be particularly successful in carving out co-varying patterns with frontotemporal dementia in the near future (Ratnavalli et al., 2002), because its onset is earlier compared to (late onset) Alzheimer's, and the current generation of smartphone users may soon be facing neurodegenerative disorders with earlier onset (Neary et al., 2005; but note that an early form of Alzheimer's Disease also exists, which has not been discussed in this article).

5 Ethical considerations

Given the power that *Psychoinformatics* can have on psychodiagnostics, misuse of digital phenotyping has the potential to facilitate unethical practices (Montag, Sindermann & Baumeister, 2020). Among these are influencing political or marketing campaigns via microtargeting. Insurance issues are also significant in this regard (e.g. Kosinski et al., 2015; Matz & Netzer, 2017; Matz et al., 2017). As this article focuses on AD and other causes of dementia, we stress in particular the latter point. Without doubt the inclusion of *Psychoinformatics* in the psychodiagnostic process of dementia brings advantages in terms of better and more cost-effective monitoring of cognitive decline on a longitudinal basis. However, a framework underpinned by governmental regulation is needed to secure data relating to individual cognitive decline. Insurance companies should not be allowed to utilize these data in decisions regarding whether a person will obtain health insurance. The same should be true for the costs of such insurance. Beyond regulation of the application of *digital phenotyping* in the context of insurance, human resources departments should not be permitted to administer such digital variables in hiring decisions (or at least the tracking level needs to be made very transparent to the persons undertaking the application process). In one prominent case from the United States, the retailer Target determined via digital phenotyping that a young woman was pregnant before her father (Forbes, 2012). These examples illustrate that the area of digital phenotyping is accompanied by complex ethical problems, which cannot be tackled in a short opinion piece such as this. What is presented on the ethical issues in digital phenotyping in this article is limited and provides only a brief overview of this highly relevant and critical area. For further reading we point to recent published works dealing with privacy issues (Kargl et al., 2019) and ethical views from a practitioner's perspective (Dagum & Montag, 2019) in the age of digital phenotyping (by others critically referred to as surveillance capitalism; Foster & McChesney, 2014; Zuboff, 2015, 2019). Inferring (genetic) risk for developing dementia from digital footprints also raises problems with respect to genetic counseling: e.g., carrying the e4 risk allele on the APOE gene goes along with heightened risk for developing Alzheimer's, but we speak of risk, not a certainty. Therefore: do people want to know about their genetic risk of developing the condition? If they are unaware of their risk, will they act to reduce risk factors across the life span as is noted in the work of Orgeta et al. (2019)?

Although misuse of digital data represents a problem, the ethical use of techniques from *Psychoinformatics* may also be valid in some of the above discussed areas, as long as the inclusion of health and related data was banned. For example, in a hiring process a company may want to assess intelligence from data derived from the IoT. This procedure could be permitted, as it is common practice in many companies for applicants to undergo intelligence testing, as intelligence is a good predictor of job performance (e.g. Ree & Earles, 1992). After a few years of analyzing data from the IoT, this method may even come to represent a more effective intelligence test, as a one-time assessment of intelligence which takes place in a company environment might be biased by the individual's test anxiety. It is clear that there is a thin line between use and misuse of digital phenotyping. Establishing trust through absolute transparency will be key to usage of digital phenotyping in a given business and research area. There is no other way than to make sure that a person understands exactly what is tracked and for what period of time. Moreover, a person must always have the option to not give consent to such a procedure (without fear of negative consequences). Furthermore, the depth of tracking should also be regulated. From a privacy aspect it makes a difference if the content of a message is read in full, or if on a meta-level the variable "number of positive/negative words" is counted. These few examples demonstrate how difficult it will be to answer many of the pressing questions in the field of *Psychoinformatics*, in particular with respect to the treatment of brain disorders. Without a visible public and political debate on how such data should be implemented in diagnostic processes in the near future, new data and privacy scandals such as the recent incidents around the Facebook-Cambridge Analytica scandal are very likely to occur (Wikipedia.org, 2019).

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Nevertheless, for reasons of transparency, Dr. Montag mentions that he has received (to Ulm University and earlier University of Bonn) grants from agencies such as the German Research Foundation (DFG). Dr. Montag has performed grant reviews for several agencies; has edited journal sections and articles; has given academic lectures in clinical or scientific venues or companies; and has generated books or book chapters for publishers of mental health texts. For some of these activities he received royalties, but never from the gaming or social media industry. Dr. Montag mentions that he is part of a discussion circle (Digitalität und Verantwortung: https://about.fb.com/de/news/h/gespraechskreis-digitalitaet-und-verantwortung/) debating ethical questions linked to social media, digitalization and society/democracy at Facebook. In this context, he receives no salary for his activities. Finally, he mentions that he currently functions as independent scientist on the scientific advisory board of the Nymphenburg group. This activity is financially compensated.

Outside the scope of the present paper, Dr. Elhai notes that he receives royalties for several books published on posttraumatic stress disorder (PTSD); is a paid, full-time faculty member at University of Toledo; is a paid, visiting scientist at Tianjin Normal University; occasionally serves as a paid, expert witness on PTSD legal cases; and receives grant research funding from the U.S. National Institutes of Health and Department of Defense.

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Digital Phenotyping of Big Five Personality Traits via Facebook Data Mining: A Meta-Analysis

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Abstract
Background: About 2.5 billion people around the world currently have an active account on Facebook. By interacting with Facebook, users generate a vast dataset of information with potential links to psychological and behavioral characteristics. In particular, several researchers have already demonstrated that it is feasible to predict personality from activity logs, posted text, or "Like" behaviors on Facebook.
Objectives: In this study, we carried out a meta-analysis of the available literature on predicting personality from Facebook data.
Methods: Meta-analysis computations were performed using a multilevel approach.
Results: Results showed that, on average, the accuracy of prediction of user personality scores through the mining of Facebook data is moderate (r = .34). However, prediction accuracy was improved when models included demographic variables, and multiple types of digital footprints.
Discussions: Currently, generating personality predictions from Facebook data is feasible, but accuracy is at best moderate. Therefore, current predictions cannot be used for assessment purposes at the individual level, but may provide useful information when conducting group-level assessments. However, prediction accuracy is expected to improve as larger datasets and new types of data are mined for prediction purposes.

Keywords: social media, personality, Facebook, digital phenotyping, psychoinformatics

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1 Introduction

Use of social media platforms is widespread, particularly amongst young people (Perrin, & Anderson, 2019). Among existing platforms, Facebook remains the leading social media platform in terms of active users (2.45 billion monthly active users as of third quarter of 2019 (Rabe, 2019)). Every day online users come to Facebook and share content, such as text, pictures and videos, which can be liked, commented upon, or shared by other users. This interactive process produces a massive dataset of user-generated data, also referred to as "digital footprints" "digital records", or "digital traces", with significant connections to users' behavioral and psychosocial characteristics (e.g. Settanni & Marengo, 2015; Marengo, Azucar, Longobardi & Settanni, 2020; Marengo, Azucar, Giannotta, Basile, & Settanni, 2019), including personality (Azucar, Marengo & Settanni, 2018). These digital footprints can be downloaded and mined to gain insight about users' characteristics, interests, and online and offline behaviors (Kosinski, Matz, Gosling, Popov, & Stillwell, 2015). Research in this field of study, typically referred to as *Psychoinformatics*, uses methods derived from both psychology and computer science (Montag, Duke, Markowetz, 2016; Yarkoni, 2012) to improve the collection and analysis of psychosocial data, including datasets from mobile devices and online social networks.

Concerning in particular Facebook, based on the analysis of digital traces left by users on the platform it has been possible to develop predictive models detecting demographic variables and psychological characteristics, sometimes with remarkable accuracy (Kosinski et al., 2013; Montag, Duke, & Markowetz, 2016). In this study, when referring to such predictive models we mean to establish links between Facebook activity logs, text, pictures and individual traits, as opposed to using predictive models for explanatory purposes (e.g. theory building and testing, Yarkoni, & Westfall, 2017). Mining Facebook data has been shown to be especially beneficial for the purpose of personality prediction (Azucar, Marengo & Settanni, 2018), to the extent that computer-based personality predictions have been shown to be more accurate than those made by close acquaintances of the users (e.g. friends, and relatives, Youyou, Kosinski, Stillwell, 2015). Overall, findings from meta-analyses have shown that the overall predictive power of social media data for users' personality is moderate, with correlations between observed and predicted personality scores ranging from .30 to .40 (Azucar, Marengo & Settanni, 2018).

Typically, studies investigating the use of Facebook data for personality prediction employ a common methodological approach. First, researchers collect information about users' personality scores by administering validated self-report personality questionnaires, with the large majority of studies focusing on personality traits drawn from the Big Five/Five Factor model (McCrae & Costa, 1987; McCrae & John, 1992). Next, having obtained authorization from users and from Facebook (Facebook for Developers, 2019) to access user data, digital footprints are collected and processed to extract predictive features based on a variety of approaches, depending on the nature of the data collected (e.g. demographic data, activity information, Likes, texts, or pictures). Such predictive features include *categorical variables* giving insights into socio-demographics (e.g. age group, gender, education level), and *count variables* representing frequency of online activities (e.g. number of posts, pictures, and videos posted in a specific time frame). Beyond this, *count variables* such as the number of Likes expressed to specific online pages, as well features representing topics, words, and phrases naturally occurring in posted text (e.g. open-vocubulary features, Schwartz et al., 2013), or visual features in posted pictures (e.g. facial expressions, style of make-up, hair style, etc., Torfarson, Agustsson, Rothe Timofte, 2016) are also studied. Next, predictive analyses are performed using a machine-learning approach to study the feasibility of using the features extracted from digital footprints to predict users' personality scores as derived from self-report questionnaires. Different models, varying in relation to the number and type of features examined, are compared based on the accuracy of predictor scores compared to self-report scores, typically by examining the correlation between predicted and observed scores, and/or by looking at absolute measures such as the mean absolute error (MAE). Based on these metrics, the best performing models are retained. Online services based on predictive models developed using this approach are now available for both research and commercial purposes (e.g. Apply Magic Sauce, https://applymagicsauce.com, IBM Watson Personality Insight, https://www.ibm.com/watson/services/personality-insights/). These services can be used to generate unobtrusive personality predictions for individual users uniquely based on their digital footprints on Facebook (and other social media platforms).

As noted above, a recent meta-analytic study has established the overall strength of association between social media data and Big Five personality traits (Azucar, Marengo & Settanni, 2018). However, the meta-analysis by Azucar and colleagues (2018) included data from studies presenting only correlation coefficients describing associations between single indicators of social media activity and personality scores (e.g. Gosling, Augustine, Vazire, Holtzman, Gaddis, 2011; Kern, et al., 2014). For this reason, the results do not strictly apply to studies developing predictive models based on more than one digital variable for personality prediction. Another limitation of the study by Azucar and colleagues (2018) is that, in order to deal with the non-independence of studies sharing a common source of data (e.g. MyPersonality dataset, Kosinski, Stillwell, & Graepel, 2013), results from many studies were not included in the meta-analysis. Finally, the majority of the included studies were published before 2017, whereas many new papers which have been published since now also have to be considered.

Based on these considerations, in this article we present an update of this meta-analytic study which aims to determine the overall predictive accuracy of model-based personality predictions performed using digital footprints on Facebook. Building on previous findings by Azucar and colleagues (2018), we focus our analysis on studies performing predictions of Big Five personality traits because they represent the large majority of existing studies. Further, we only include studies analyzing Facebook data. In limiting our scope to these studies, we aim to provide a clearer view of the potential of mining Facebook data for the prediction of Big Five personality traits. Analyses are performed using a multilevel meta-analytic approach, allowing for non-independent studies (i.e. studies sharing the same data source) to be included in a single analysis, therefore retaining important information which would be excluded using traditional meta-analytic approaches.

2 Methods

2.1 Selection of literature

We started by searching for research papers examining the relationship between Big Five personality traits and digital footprints. A two-step procedure was followed, building on previous work by Azucar and colleagues (2018). First, all the records (n = 789) screened by Azucar and colleagues (2018) were obtained. Next, we applied the same literature search strategy employed by Azucar and colleagues (2018) to identify newly published papers. More specifically, we used the same keyword search strategy used by the authors to investigate the Scopus, ISI Web of Science, Pubmed, and Proquest databases. Combined, the searches performed on the databases resulted in a total of n = 935 unique papers. After removing records overlapping with those screened by Azucar and colleagues (2018), this approach resulted in 146 new papers which were eligible for selection. The original literature search was performed in July 2018. Papers selected from Azucar and colleagues (2018) (n = 24), and those identified through the new search (n = 146), were screened according to the following inclusion criteria: 1. studies must analyze digital footprints collected on Facebook; 2. studies must present results of models predicting Big Five personality traits at the individual level based on digital footprints; 3; studies must include personality scores based on self-report measures of Big Five personality traits (i.e. openness to new experiences, conscientiousness, extraversion, agreeableness, and neuroticism;

OCEAN model); 4. studies must report information about the accuracy of prediction of Big Five personality traits using correlations, or provide information that could be used to compute correlations.

Ultimately, based on the aforementioned criteria, n = 14 papers out of the n = 24 identified by Azucar and colleagues (2018) were selected. In selecting papers from this source, we excluded papers that do not focus on Facebook data (n = 7), and that do not present model-based predictions (n = 3; i.e. Gosling et al. 2011; Kern, et al., 2014; Quercia, Lambiotte, Stillwell, Kosinski & Crowcroft, 2012). The n = 14 papers selected from Azucar and colleagues (2018) included n = 8 papers which, although deemed eligible for inclusion by the authors, ultimately were not included in the analyses presented in Azucar and colleagues (2018) because they were based on non-independent samples derived from a common data source (i.e. the dataset by Golbeck et al. 2011, and the MyPersonality dataset). For the purpose of the present study, the use of a multivelel analytical approach allowed us to retain these papers in the analysis.

With regard to the papers gathered through literature search (n = 146), after removing review papers (n = 4; Azucar, Marengo & Settanni, 2018; Ihsan & Furnham, 2018; Hinds & Joinson, 2019; Settanni, Azucar, Marengo, 2018), papers that do not investigate the link between digital footprints and personality (n = 100), and papers that did not focus on Facebook data (n = 30), n = 12 eligible papers were identified from the literature search. Among those removed were n = 5 papers that did not include effect-sizes which could be transformed into a correlation coefficient (i.e. papers reporting results using mean absolute error (MAE) and root mean square error (RMSE) statistics, Al Marouf, Hasan, Mahmud, 2019; Tadesse, Lin, Xu, Yang, 2018; Tandera, Suhartono, Wongso,Prasetio, 2017; Yulianto, Girsang, Rumagit, 2018; Zhong, Guo, Gao, Shan, Xue, 2018). This approach produced a set of 21 unique papers, of which n = 14 overlap with those selected in Azucar and colleagues (2018), and n = 7 newly selected papers. A flow diagram representing the study selection process is presented in Figure 1. Because in some cases papers included more than one study (i.e. predictions are performed on different datasets within the same paper), effect-sizes were extracted from 23 distinct studies, of which 16 studies were previously analyzed by Azucar and colleagues (2018) and 7 were identified by the new literature search. The characteristics of the selected studies are presented in Table 1, along with collected effect-sizes.

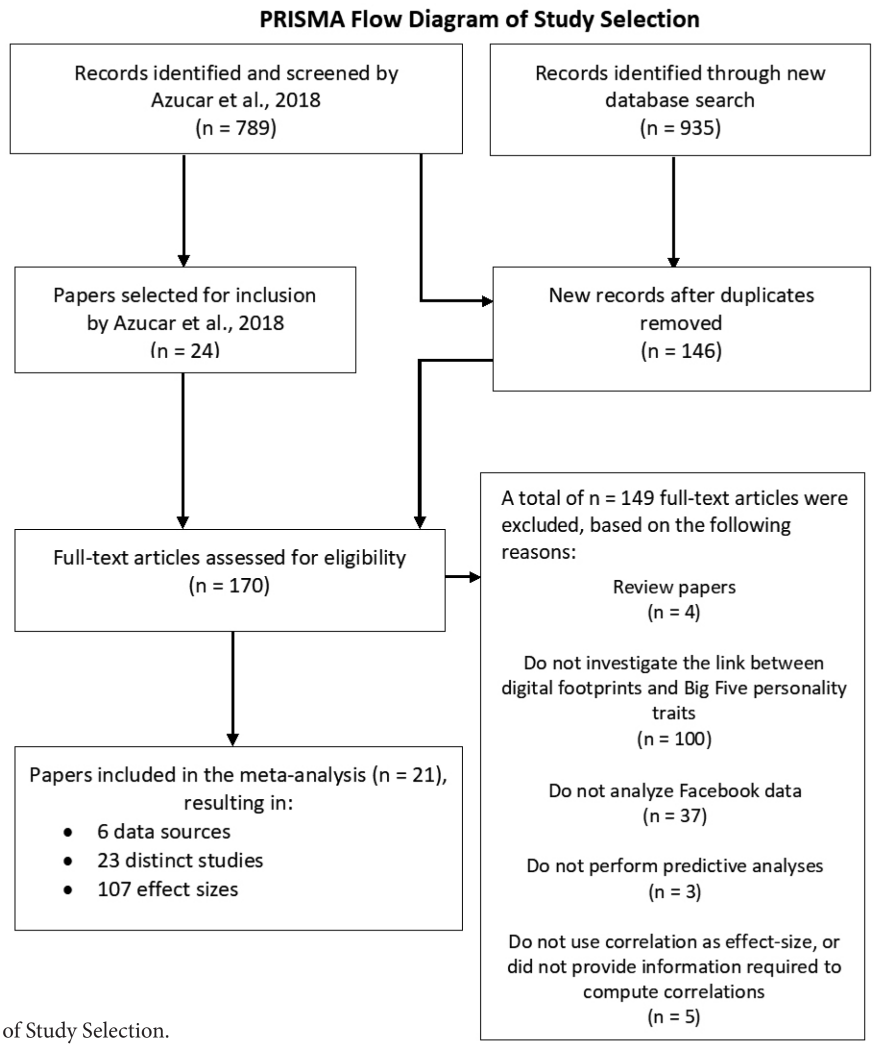

Figure 1. Flow Diagram of Study Selection.

2.2 Coding of studies

Because the studies varied considerably in relation to the type of the digital footprints collected from Facebook and mined for prediction, as well as in the approach used to validate predictions, they were coded using the strategy employed in Azucar and colleagues (2018). Specifically, concerning the type of examined digital footprints, studies were coded based on inclusion (1 = yes, 0 = no) in the analyses of specific types of digital footprints, defined based on their content: 1) user demographics (typically extracted from Facebook personal information section, including gender, age, education, etc.); 2) activity statistics (e.g. number of posts, number of friends or network density, number of received Likes, comments, and user tags); 3) Likes (e.g. Likes expressed to specific Facebook pages); 4) features derived from the analysis of language in text (e.g. features extracted using closed-and/or open-vocabulary approaches); 5) features derived from pictures (e.g. features extracted from uploaded pictures); 6) use of multiple vs. a single type of digital footprints. Additionally, we coded the selected studies based on the approach used to validate the results of predictive models. In this context, model validation refers to the step taken by researchers to determine the accuracy of trained models on new, unseen observations. Different validation approaches exist in this field (for a review, see Marengo & Settanni, 2020), including the *holdout* method and the *k*-fold validation method. Using the *holdout* method, a random split is performed on the data so that two datasets – a larger training set and a smaller test set – are obtained. Then, models are first applied to the training set, and later trained on the smaller test set to evaluate their accuracy. Similarly, the *k*-fold method also involves randomly splitting the data in a training set and a test set, but this process is repeated *k* times resulting in *k* random train/test splits. Analyses are then performed on each of the split, resulting in *k* sets of results which are combined to produce a single accuracy estimate (Hastie, Tibshirani, R., & Friedman, 2009). Here, in coding studies based on the validation approach, we distinguished between studies reporting effect-sizes as computed on the same dataset used to train the model (no validation condition = 0), and studies performing some form of cross-validation of trained models (cross-validation of results = 1, i.e. *holdout* method, or use of *k*-fold cross-validation).

2.3 Strategy of analysis

For each study, we collected the effect-sizes expressing the accuracy of prediction of Big Five personality traits based on the tested predictive models, selecting only a single effect-size per trait. For the purpose of performing the meta-analysis, Pearson's correlation coefficient was used as the effect-size of choice. In the event that a study did not report correlations but other types of effect-size, we used available information to compute correlations using the same approach (for details, see Azucar Marengo, & Settanni, 2018). In the event that a study reported results for more than one predictive model for a single trait (e.g. studies in which models with different set of predictors are compared), the effect size of the best performing model was included in the analysis. Based on this approach, there were 107 distinct effect-sizes for 23 studies (see Table 1). All studies reported effect-sizes for each of the five traits, except for one study which investigated only extraversion (Baik, Lee, Lee, Kim, Choi, 2016) and one study reporting only the average effect size across all Big Five personality traits (Torfason et al., 2016).

Next, meta-analysis computations were performed using a multilevel approach (Cheung, 2014; Van den Noortgate, López-López, Marín-Martínez, Sánchez-Meca, 2015). This approach was used because of the presence of non-independence in our data due to many studies demonstrating more than one effect-size, and sharing the same data source. Indeed, as shown in Table 1, n =17 studies were performed on data sourced from the MyPersonality dataset (Kosinski, Stillwell, & Graepel, 2013), n = 2 studies shared the same dataset used in Golbeck, Robles and Turner (2011), while n = 4 used independent datasets. To give an example, non-independent studies may show a certain degree of overlap in observations (i.e. use samples derived from the same data source, e.g. MyPersonality dataset), but use different types of digital footprints (e.g. language data vs. Likes) to perform predictions.

Using a multilevel approach, variability in effect-sizes due to different variance components is modeled using random effects. For the purpose of the present study, we employ a four-level meta-analytic model modeling four different variance components: at level 1, we model the sampling variance of the extracted effect sizes (i.e. the indeterminacy in effect-sizes due to the use of samples, as opposed to population data to estimate effect-sizes); at level 2, we model the variance existing between effect sizes extracted from the same study (within-study variance); at level 3, we model the variance at the study-level (between-study variance); and at level 4, we account for the variance related to data sources. This model is computed in order to estimate the overall meta-analytic correlation between Big Five personality scores and scores generated by predictive models based on Facebook data, while controlling for different sources of variability. In our dataset, we distinguish between 107 unique effect sizes (level 2) clustered in 23 distinct studies (level 3), and 6 data sources (level 4). In keeping with Schmidt and Hunter (2014), for the purpose of estimating the overall meta-analytic effect-size, correlations were not transformed using *Fisher's z* transformation. Such conversion is not indicated for meta-analytic random-effects models, because they yield an upward bias in the estimation of the average correlation. The distribution of variance over the four levels of the model was examined using the approach described by Assink & Wibbelink (2016), which takes advantage of the formula for estimating study sampling variance proposed by Cheung (2014, p. 215, formula 14). Overall heterogeneity of effect-sizes was examined by using the Q test. The significance of within-study variance (level 2), between-study variance (level 3), and variance due to the specific data source (level 4) was de-

Table 1. Characteristics of studies included in the meta-analysis.

Data source study	Effect-size O	 C	 E	 A	 N	Sample size	Cross-validation	Type of digital footprints
Independent datasets								
Baik et al., 2016	–	–	0.42	–	–	565	k-fold	Demographics, Usage stats, Likes
Celli et al., 2014	0.07	0.06	0.18	0.26	0.19	89	Holdout	Pictures
Kleanthous et al., 2016	0.26	0.03	0.28	-0.16	-0.01	62	No cross-validation	Usage Stats
Wald et al., 2012	0.77	0.61	0.68	0.70	0.61	537	No cross-validation	Demographics, Usage Stats, Language
Golbeck et al., 2011 Dataset								
Golbeck et al., 2011	0.65	0.60	0.55	0.48	0.53	167	k-fold	Demographics, Usage Stats , Language
Golbeck, 2016 Study 3	-0.35	-0.07	0.24	-0.35	-0.18	69	No cross-validation	Language
MyPersonality dataset								
Bachrach et al., 2012	0.33	0.41	0.57	0.10	0.51	5000	k-fold	Usage Stats
Cutler & Culis, 2018	0.41	0.35	0.38	0.30	0.32	84451	Holdout	Language
Farnadi et al., 2016 Study 1	0.19	0.24	0.27	0.16	0.24	3731	k-fold	Demographics, Usage Stats , Language
Farnadi et al., 2018	0.26	0.19	0.16	0.11	0.14	5670	k-fold	Likes, Language, Pictures
Golbeck, 2016 Study 1	0.36	0.25	0.37	0.41	0.38	127	No cross-validation	Language
Golbeck, 2016 Study 2	0.20	0.20	0.22	0.24	0.18	8569	No cross-validation	Language
Kosinski et al., 2013	0.43	0.29	0.40	0.30	0.30	54373	k-fold	Likes
Kosinski et al., 2014	0.11	0.16	0.31	0.05	0.23	9515 – 45565	k-fold	Usage Stats
Laleh & Shahram, 2017	0.38	0.29	0.34	0.22	0.27	92225	Holdout	Likes
Markovikj et al., 2013	0.71	0.71	0.70	0.60	0.59	250	No cross-validation	Demographics, Usage Stats , Language
Nave et al., 2018	0.30	0.19	0.21	0.17	0.18	21929	k-fold	Likes
Park et al., 2015	0.43	0.37	0.42	0.35	0.35	4824	Holdout	Language
Schwartz et al., 2013	0.42	0.35	0.38	0.31	0.31	18177	Holdout	Language
Thilakaratne et al., 2016	0.36	0.40	0.44	0.30	0.39	344 – 387	k-fold	Language
Torfason et al., 2016*	–	–	–	–	–	51617	k-fold	Likes, Pictures
Youyou et al., 2015	0.51	0.42	0.45	0.38	0.40	1919	k-fold	Likes
Zhang et al., 2018	0.40	0.35	0.36	0.29	0.32	55835	Holdout	Language

Note. Studies in plain text were selected from Azucar et al., 2018 (n =16). Studies in bold were selected through literature search (n = 7). O = Openness, C = Conscientiousness, E = Extraversion, A = Agreeableness, N = Neuroticism. * The study only reported an average effect-size.

termined using log-likelihood-ratio tests. Using these tests, we compared the model in which the variance at each level (2, 3, and 4) is freely estimated, with an additional model in which the variance for each level was iteratively fixed at zero, while letting the variance for the other levels be freely estimated.

It is worth noting that, by using this multilevel approach, we can provide a single correlation representing the overall predictive power of Facebook data to estimate personality as assessed using the Big Five model. However, potential differences in prediction accuracy across Big Five personality traits can be investigated by way of moderation, i.e. by including a categorical indicator grouping effect-sizes based on the relative Big Five personality trait as fixed effect in the multilevel model, and performing (Bonferroni corrected) pairwise contrasts between estimated correlations for each trait. Next, we examined the following moderating effects by using dichotomous indicators (1 = yes; 0 = no): (1) use of demographic data; (2) use of activity statistics; (3) use of Likes; (4) use of language features; and (5) use of multiple vs. single type of digital footprints. Finally, we looked at possible differences in estimated effect size based on (6) cross-validation of model results. Moderators are tested separately by including the above mentioned indicators in the model as fixed effects, while accounting for all sources of non-independence with random effects. As only n = 3 of included studies explored use of pictures as a data source, a moderator for this type of data was not included as we did not expect to reach an adequate level of statistical power. For each moderator, an assessment was made of how much incremental variance could be explained by its inclusion in the model.

Finally, we looked at possible publication bias in reported effect-sizes. More specifically, we examined: 1) asymmetry of the funnel plot visualizing the association between collected effect sizes and their associated standard errors; and 2) significance of a modified Egger's regression test (Egger, Smith, Schneider & Minder, 1997) computed by including the standard error as a predictor of effect sizes in the multilevel model. In this context, the funnel plot was generated as a scatterplot of the correlations between observed and predicted scores collected from each study plotted against their standard error, while Egger's regression test provided an estimate of the asymmetry of the scatterplot. Because the standard error of a study is a measure of (lack of) precision in estimating effects (i.e. lower standard errors indicate higher precision of the effect size estimate), publication bias might be present if less precise studies tend to show higher effect sizes than more precise studies (i.e. standard error is found to positively predict effect-size).

All analyses were performed in *R* using the *metafor* package (Viechtbauer, 2010) by adapting the code provided by Assink and Wibbelink (2016) to a four-level multilevel meta-analytic model (code is provided as Supplementary Material).

3 Results

3.1 Central tendency of effect-sizes

Information about study effect-sizes, as well characteristics of selected studies are reported in Table 1. Figure 2 shows the forest plot of collected effect-sizes. The estimated overall meta-analytic correlation emerging from selected studies for digital footprints predicting Big Five personality traits was 0.34 (SE = 0.043; 95% CI: 0.26–0.43). The result of the Q test for heterogeneity was meaningful (QE (106) = 185879.73, $p < .001$), indicating significant heterogeneity existed among the effect-sizes. However, based on the estimated proportion of sampling variance per level of the model, it emerged that only 0.08 percent of the total variance can be traced back to variance at level 1 (i.e. sampling variance). Rather, 10.78 percent of the total variance can be attributed to differences between effect sizes from the same study at level 2 (i.e. within-study variance). Further, at 89.14 percent, the largest portion of variance can be traced back to between-study differences at level 3 (i.e. between-study variance). Finally, the portion of variance that could be attributed to level 4 (i.e. variance due to different data sources) was < 0.01 percent. Accordingly, based on significance of log-likelihood tests, it emerged that both within-study variance (i.e. variability in effect-sizes extracted from the same study; ($\chi^2(3) = 6828.71$, $p < .001$) and between-study variance ($\chi^2(3) = 97.2939$, $p<.001$) represent a significant source of effect-size heterogeneity, while variance due to data source is not ($\chi^2(3) < 0.01$, $p > .99$).

Next, we take a more detailed look at differences among personality traits in estimated effect-size. Results indicate significant differences exist in the prediction accuracy of different personality traits ($F(4, 102) = 9.34$, $p < .001$). Based on the estimated effect-sizes and relative 95% confidence interval for each Big Five trait, extraversion (0.39 [0.30, 0.48]) shows the highest overall prediction accuracy, followed by openness (r = 0.38, [0.29, 0.47]), conscientiousness (r = .34 [0.24, 0.43]), neuroticism (r = 0.33 [.23, 0.42]), and agreeableness (r = 0.28 [0.19, 0.38]). However, when looking at (Bonferroni corrected) pairwise contrasts, we identify few significant contrasts: agreeableness can be less accurately predicted from the digital footprints on Facebook than extraversion (contrast = 0.11 [0.07, 0.15], $p<.05$), and openness (contrast = 0.10 [0.06, 0.14], $p<.05$).

3.2 Moderator analyses

Table 2 presents the results of moderator analyses concerning the type of digital footprints used for prediction and the approach used to validate results. Only two moderators showed a significant effect. Use of multiple types of digital footprints, as opposed to a single type, was linked to a significant increase in the predictive power of models. Use of demographic variables also showed a positive effect on predictive power. The remaining moderators did not show significant effects.

3.3 Publication bias

The investigation of publication bias via visualization of funnel plot and Egger's test provided interesting results. The funnel plot is presented in Figure 3. It is easy to see that the distribution of effect sizes is asymmetrical, with a clear pattern showing that, at least for a subgroup of estimates, the standard error of effect sizes is negatively related to the magnitude of the effect-size. Simi-

Table 2. Result of moderation analyses: effect of type of digital footprints and validation approach on prediction accuracy

Moderator	B [95% CI]	SE	t	p	Explained variance
Use of demographics	0.24 [0.05, 0.44]	0.10	2.45	0.02	.07
Use of activity statistics	0.10 [-0.09, 0.28]	0.09	1.05	0.30	.00
Use of Facebook Likes	0.06 [-0.13, 0.25]	0.10	0.63	0.53	.00
Use of language features	0.02 [-0.16, 0.19]	0.09	0.18	0.86	.00
Use of multiple types of digital footprints	0.24 [0.08, 0.41]	0.08	2.94	<.01	.17
Cross-validation of model results	0.04 [-0.16, 0.24]	0.10	0.40	0.69	.00

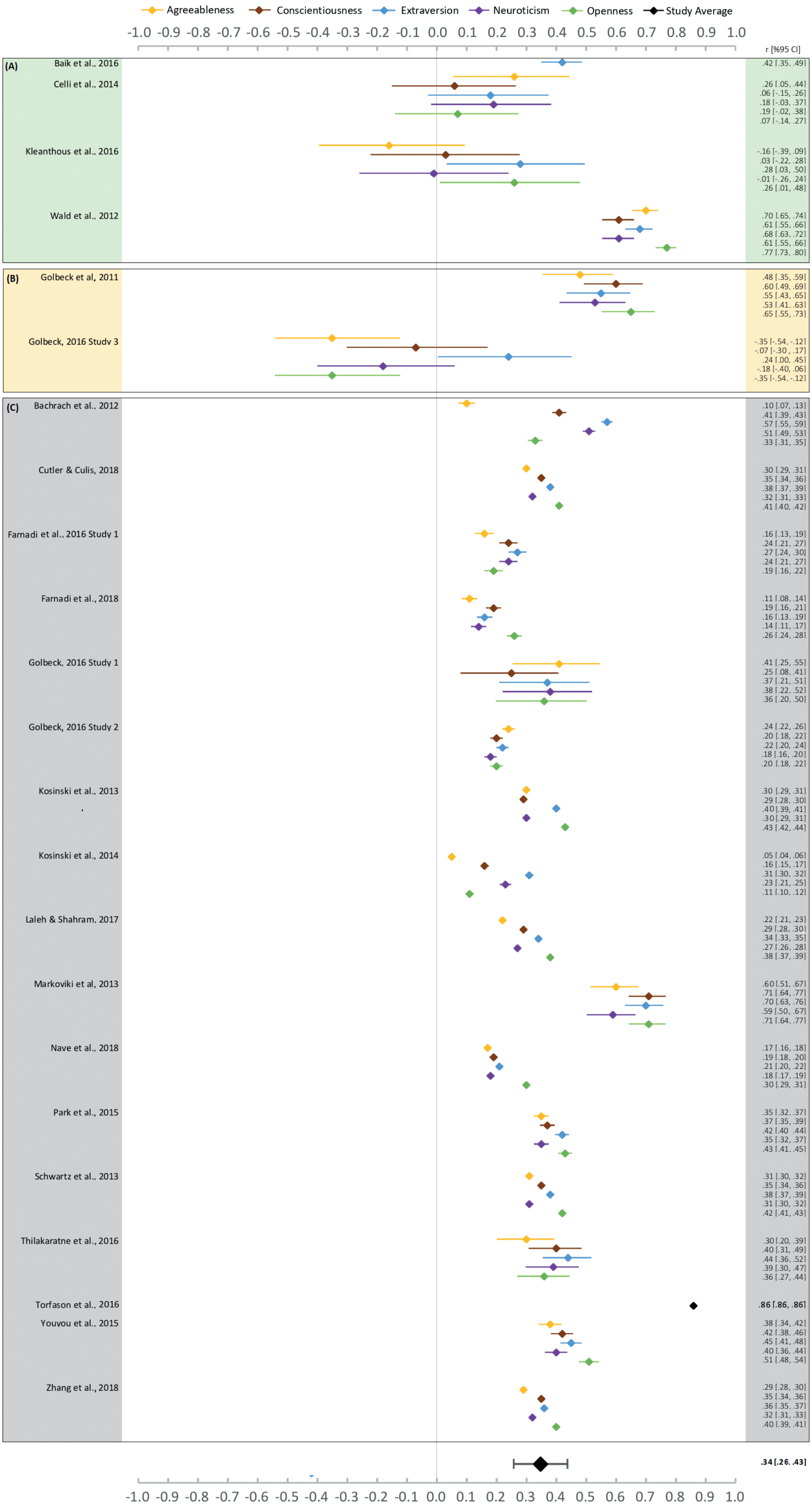

Figure 2.
Forest-plot of study effect-sizes.

Note. Studies in panel A (green box) are independent studies. Studies in panel B (yellow box) are based on data from Golbeck et al, 2011. Studies in panel C (grey box) are based on data from the myPersonality project.

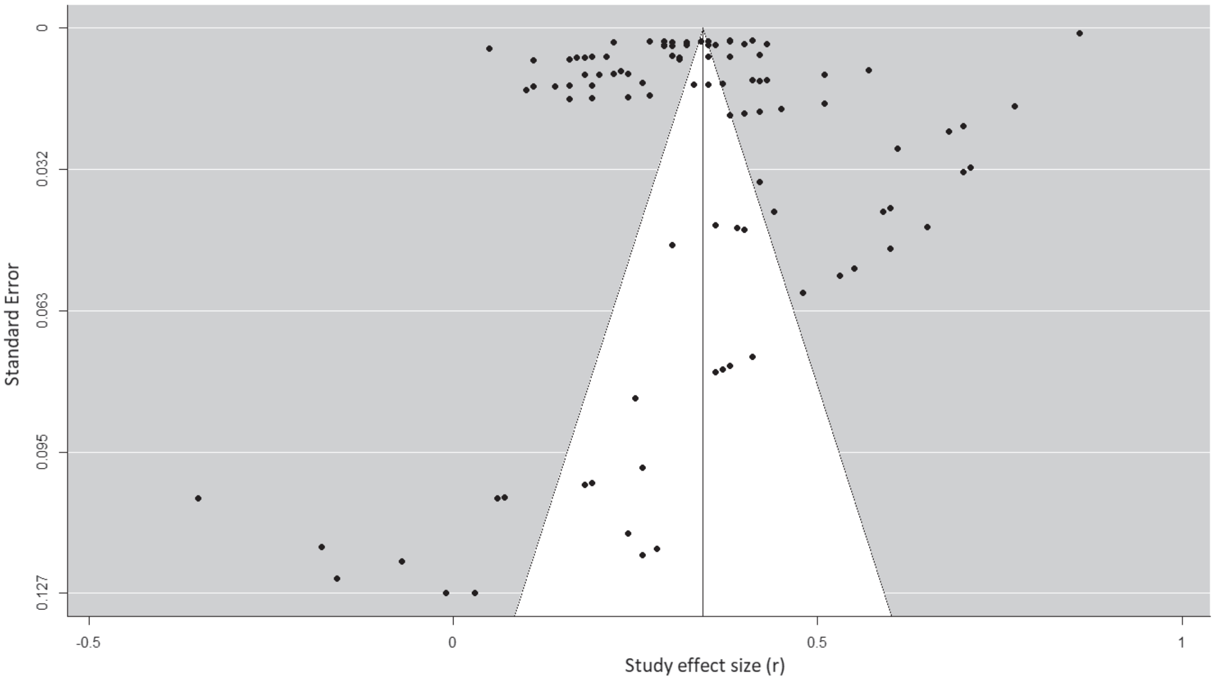

Figure 3. Funnel plot of study effect sizes by relative standard errors.

Note. Studies at the top of the funnel plot (Standard error ≤ .02) are based on sample size ≥ 1000.

larly, Egger's test was coherent in highlighting a small, negative association between magnitude of effect size estimate for digital footprints predicting personality traits and the standard error of the estimate (B = -2.60 [-4.82, -0.38], SE = 1.19, t = 2.33, p = 0.02, explained variance = .04). It is worth noting that the direction of this emerging effect is the opposite of what would be expected based on the hypothesis of publication bias (i.e. a positive association between standard error, and magnitude effect-size). Instead, the emerging effect seems to indicate that, in published studies, the accuracy of personality predictions tends to increase with precision of estimates (i.e. the inverse of standard error).

4 Discussion

In this study, we presented a meta-analysis of research exploring the feasibility of mining digital footprints of Facebook users for the prediction of Big Five personality traits. We built on a previous meta-analytic study by Azucar and colleagues (2018), including newer studies and employing a multilevel approach that allowed us to retain important information which would have been discarded using traditional meta-analytic procedures. However, in an effort to provide a clearer view on the feasibility of using Facebook data to predict personality, we limited the scope of this paper to the analysis of studies mining Facebook data using predictive modeling techniques, discarding strictly correlational studies. Results showed that on average, the accuracy of prediction of individual Big Five personality scores based on predictive models is moderate (r = .34), and most of the variability existing among included effect-sizes is linked to study-level differences (89.14%), while only a relatively small proportion is related to within-study differences among effect-sizes (10.78%). Among the traits, extraversion is associated with the highest prediction accuracy (r = .39), while agreeableness shows the lowest prediction accuracy (r = .28). However, when comparing effects across personality traits, pairwise contrasts were generally non-significant (with the exception of the contrasts comparing the agreeableness trait with extraversion, and openness), indicating a general overlap in prediction accuracy among traits. This indicates that the performance of predictive models tends to be quite stable across personality traits, while most of the differences in predictive power can be traced back to differences among individual studies, possibly due to methodological differences in the specific analytical approach used to mine collected data, as well as the amount and type of data collected. The specific data source used in the different studies does not seem to have a significant impact on accuracy of predictions: on the contrary, even among studies using the same data source (e.g. MyPersonality data), there remains a significant amount of variability in prediction performance, which is possibly related to methodological differences across studies. Accordingly, moderator analyses revealed that existing differences among studies in the use of multiple types of digital footprints (as opposed to a single type), and use of demographic information among the predictor set, significantly contribute in explaining differences in the accuracy of personality predictions. Concerning demographics, findings confirm the importance of demographic information, including age and gender, as factors in explaining individual differences in Big Five traits (e.g. Lehmann, Denissen, Allemand, & Penke, 2013; Soto, John, Gosling, & Potter, 2011).

Further, the investigation of publication bias revealed a theoretically interpretable effect showing a negative link between the standard error of estimates (i.e. the inverse of precision), and overall accuracy of personality prediction. Because precision error is directly related to study sample size (Kirkwood & Sterne, 2010), this result highlights the importance of recruiting large samples of users for the purpose of improving accuracy of prediction (Kosinski, Wang, Lakkaraju, & Leskovec, 2016). It is important to note that, looking at the funnel plot of studies effect-sizes plotted against their standard error, it is apparent that this effect is most prominent in studies using small- to moderately-sized samples ($n < 1000$). In turn, among studies performed on larger samples ($n \geq 1000$), there remains a relevant heterogeneity in effect-sizes between studies, possibly related to methodological differences between them.

Overall, this study has demonstrated that Big Five personality variables can be inferred with moderate accuracy using currently available social media data. Because the overall meta-analytic effect size presented here is moderate, it appears that the analysis of digital footprints still falls short in predicting such characteristics with accuracy allowing for assessment at the individual level. For example, for each trait, the average correlation between predicted and self-report personality scores is much lower than the correlation one would expect between consecutive self-report personality assessments of the same individual (i.e. test-retest reliability, see Kosinski et al., 2013). Similarly, the strength of the correlation between predicted and self-report personality scores is far below that expected for personality instruments that are intended to assess the same latent construct (e.g. convergent validity, $r \approx .75$ for short Big Five assessments, Pervin & John, 1999). However, it is reasonable to expect that prediction accuracy might become more precise in the future, as larger datasets become available, and new types of data are collected and mined for prediction purposes (e.g. features extracted from visual data or location data). Overall, the existing findings seem to indicate that demographic and behavioral variables may be more easily predicted than unobservable – and hence latent – personality traits (Kosinski, Stillwell, & Graepel, 2013). Still, personality remains an important topic to study, because it is associated with important life variables such as longevity (via health behaviors), (Bogg & Roberts, 2004; Bogg & Roberts, 2012; Jackson, Connolly, Garrison, Leveille, Connolly, 2015), job performance (Barrick & Mount, 1991), or vulnerability to psychiatric disorders such as depression (Lahey, 2009). Further, personality has been linked to variables such as burnout (Alarcon, Eschleman, Bowling, 2009), and personality information could be of use in adjusting work processes based on individual characteristics, such as taking into account if a person is easily stressed. Therefore, predicting who might be vulnerable to stress might be particularly useful to target work place interventions aimed at restructuring the digital work flow (e.g., such as introducing limits to e-mail checking, Kushlev & Dunn, 2015). The study of Facebook posts appears also to be suitable method for providing an initial screening of individuals for depression (Eichstaedt et al. 2017), thereby helping to potentially reduce individual suffering by enabling the provision of pre-emptive support. Further, the *digital phenotyping* scene aims not only to predict psychological traits and states from the study of human-machine interaction, but ultimately also the neurobiology underlying these traits/states (Montag et al., 2017; Sariyska, Rathner, Baumeister, Montag, 2018).

However, given the feasibility of using Facebook data to infer individual characteristics unobtrusively, there is an emerging need for a more careful consideration of ethical challenges, and related sociopolitical consequences, of the use of extracted data (Montag, Sindermann & Baumeister, 2020). As highlighted by Matz and colleagues (2017), psychological targeting procedures leveraging predictive models might be used to target and manipulate the behavior of large groups of people, without the individuals being aware of it (see also problems around the filter-bubble: Sindermann et al., 2020). Predicted traits could be used to make financial or job-related decisions without users knowing it, or without explicitly stating to users that their characteristics have been determined through their social media usage patterns (Kern et al., 2019). Indeed, Facebook data could be used for purposes that go beyond what users intended when they consented to the collection of their digital footprints, revealing information that they may wish to keep private (Wang & Kosinski, 2018). As recently noted in a *Nature* editorial (2018, March 27) concerning the Cambridge Analytica scandal, the simple availability of social media data is not a sufficient reason to conduct research bound to have putative negative consequences for individual or a group of users. For a practitioner's view on ethics in digital phenotyping, see the work by Dagum & Montag (2019).

4.1 Limitations and Future Directions

The findings of the present study should be understood in light of a number of limitations. First, existing differences in data extraction and analytical procedures across the studies as a source of variability in effect-size of personality prediction were not investigated. Second, the impact of cultural differences on the accuracy of personality predictions was not examined, as most of the included studies focused on samples of English-speaking users, and only a small number involved samples derived from samples of non-English speakers. Hence, there remains a need for more culturally diverse samples in order to determine the cultural invariance of emerging findings. An additional limitation relates to the decision to include only studies assessing prediction accuracy using Pearson's correlation, and excluding those reporting only MAE and RMSE statistics, which may have introduced bias in the selection of the studies for inclusion in the meta-analytical computations. This decision was related to the potential incomparability across studies of the metric of both MAE and RMSE statistics, which in turn is dependent on the metric of the specific questionnaire used in the study to assess personality (e.g. the number of items, and the procedure used to generate scores).

Because model-based predictions aim to provide an assessment of personality, it is important to establish their convergent validity with self-report scores. However, MAE and RMSE statistics (as opposed to correlation) do not provide information about the strength of the linear relationship between observed and predicted scores, which in turn represents an important factor in determining the convergent validity between self-report personality scores and model-based predictions. For this reason, we decided to focus on correlation as the effect-size for the meta-analysis. As noted above, in doing this, some studies were excluded from the analysis. Although the number of excluded studies was limited, the results should be understood in light of this potential bias. A final limitation concerns the examination of the use of features extracted from pictures and videos for personality prediction. Sharing of visual content has increased dramatically over the last few years, and highly visual social media platforms such as Instagram and Snapchat are now outgrowing Facebook in popularity especially among younger people (Marengo, Longobardi, Fabris, & Settanni, 2018, Marengo, Sindermann, Elhai & Montag, in press). Because only a minority of selected studies included in the meta-analysis also used picture-information as a predictor, we could not fully investigate the impact of the inclusion of features derived from visual data in influencing accuracy of personality predictions. Given the increasing importance of this data source, future studies should consider taking such information into account when detecting personality differences.

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Potential conflicts of interests

The authors report no conflicts of interest with this paper.

Nevertheless, for reasons of transparency, Dr. Montag mentions that he has received (to Ulm University and earlier University of Bonn) grants from agencies such as the German Research Foundation (DFG). Dr. Montag has performed grant reviews for several agencies; has edited journal sections and articles; has given academic lectures in clinical or scientific venues or companies; and has generated books or book chapters for publishers of mental health texts. For some of these activities he received royalties, but never from the gaming or social media industry. Dr. Montag mentions that he is part of a discussion circle (Digitalität und Verantwortung: https://about.fb.com/de/news/h/gespraechskreis-digitalitaet-und-verantwortung/) debating ethical questions linked to social media, digitalization and society/democracy at Facebook. In this context, he receives no salary for his activities. Finally, he mentions that he currently functions as independent scientist on the scientific advisory board of the Nymphenburg group. This activity is financially compensated.

Author contributions

DM and CM designed the present study. DM analyzed the data and wrote the method/result sections. CM drafted the introduction and discussion sections, which were later edited and revised by DM. Both authors worked over the manuscript and critically revised it.

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Supplementary Material

eTable 1: Data Description

Variable	Explanation
study	study identifier
correlation	effect-size data
id	effect-size identifier
dataset	data source identifier
samplevar	sampling variance estimate
stander	standard error of the correlation
n_sample	sample size for correlation
multiple	Study used multiple types of digital footprints to perform prediction (1) vs. a single type of digital footprints (0)
validation	Study used a cross-validation method (holdout or k-fold) (1) vs. no cross-validation (0)
demos	Study used demographic data to perform prediction (1) vs. no use of demographic data (0)
stats	Study used activity statistics to perform prediction (1) vs. no use of activity statistics (0)
language	Study used language features to perform prediction (1) vs. no use of language features (0)
likes	Study used Facebook Likes to perform prediction (1) vs. no use of Facebook Likes (0)
trait	Personality trait on which prediction was performed: 1 = Agreeableness; 2 = Conscientiousness; 3 = Extraversion; 4 = Neuroticism; 5 = Openness

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