Chapter 13
The Impact of Psychoinformatics on Internet Addiction Including New Evidence

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Abstract *Psychoinformatics* refers to the new collaboration between the disciplines computer science and psychology to study psychological phenotypes by means of data mining. This chapter gives an overview of how *Psychoinformatics* can aid research and therapy in the context of Internet addiction. In particular, applications on smartphones are highlighted, which track the online behavior of humans on their digital devices.

13.1 Introduction

Psychoinformatics, the fusion of psychology with computer science, will be of great importance in the treatment, diagnostics, and research of Internet addiction. In a recent paper, Markowetz et al. (2014) outline the potential of *Psychoinformatics*, as a new interdisciplinary research endeavor, for the study of mental health. This approach applies methods from computer science to psychological research, in order to obtain deeper insights into the mental states of individuals or other psychological variables such as personality (for an example for empirical research in this field see Montag et al. 2014, 2015b; a new overview is presented in Montag et al. 2016a, but see also an overview using the term *digital phenotyping* by Onnela and Rauch 2016). To date, the most frequently used methods in psychology for the assessment,

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understanding and prediction of human behavior, have been (i) the classic laboratory experiment, (ii) the administration of self-report questionnaires, and (iii) particularly in psychotherapeutic and work psychology settings, the interview. Although these techniques have several advantages, they also have some drawbacks.

First, we briefly summarize the advantages and limitations of traditional methods in psychological research. Subsequently, we outline techniques from computer science that can address these issues. Finally, we outline the impact of *Psychoinformatics* on the research and therapy of Internet addiction.

13.2 Traditional Methods in Psychology

The interview poses one of the leading tools to obtain insights into the attitudes and character of a person (e.g., Potter and Hepburn 2005; Schmidt and Hunter 1998). It is not only used widely in psychotherapy, but in many other areas such as work and organizational psychology. The information gathered is used to hire a person for a job or to help a person in overcoming biased cognitions such as being always responsible for a negative outcome while treating depression (Wright and Beck 1983; Beck 2002).

Significant research effort has been directed into the development of structured interviews, to enable a fair hiring process (Campion et al. 1988) or to form guidelines for a psychiatric diagnosis, such as depression (Riskind et al. 1987). Structured interviews follow a clear "structure," with the same items/questions being administered in the same order. In contrast unstructured interviews follow no clear line of questioning. The push toward standardized interviews has led to improved outcomes with respect to their validity, e.g., in work psychology (Wiesner and Cronshaw 1988) and clinical psychology (Miller et al. 2001). The enduring prevalence of interviews in many areas of psychology can be attributed to the fact that direct communication with a person is, in many ways, an indispensable tool (especially in therapy), in taking into account the unique perspective of a person. This subjective perspective can be supplemented with information derived from other (more objective) sources. Imagine a salesperson who pretends to be outstanding at selling cars. In reality, it turns out that, despite the self-report, he/she has never sold a car. The discrepancy between the information derived from the interview and the exact figures from a company's paperwork on sold cars, gives insights into biased cognitions. In the context of the main topic of the present chapter it is noteworthy that Tao et al. (2010) investigated the prevalence of different diagnostic criteria for Internet addiction; which represents a significant step toward a structured interview (as questions can be built based on these findings). Notable is their proposal of a "2 + 1 rule." As a first step, the symptoms "preoccupation with the Internet" and "withdrawal" must be observed. Adding to this, at least one out of several optional symptoms, e.g., development of tolerance, must also be present, in order to justify a diagnosis of Internet addiction. Finally, Tao et al. argue that clinical impairments such as problems in private or job areas and course criteria (excessive Internet use of three month with a minimum private Internet usage of 6 h each day) need to be fulfilled/observed (p. 563).

Besides the mentioned advantages of interviews, this method also has several shortcomings. First, the method is time consuming and expensive, requiring the psychologist as well as the interviewee to invest a significant amount of time in data collection. Second, it is unclear whether the interviewee provides an accurate description of his/her mental world. Social desirability may play a particularly important role, especially where individuals are asked about stigmatizing psychopathological conditions (Edwards 1957; Sugarman and Hotaling 1997). Social desirability describes the tendency to present one's own character and attitudes according to what is thought to be acceptable in terms of social norms. Usually the person describes him- or herself as "better" than he/she actually is. However, the opposite, so-called "self-handicapping," is also observed. Here, individuals "handicap" themselves to protect their self-esteem, e.g., if a goal could not be achieved. It is important to note that cross-cultural differences in tendencies toward social desirability also exist (Johnson and van de Vijver 2003).

The second dominant method in the social sciences is the use of self-report questionnaires. Here, a person fills in items on a given topic of interest—e.g., in this instance, Internet addiction. Although questionnaires are relatively easy to handle, they also need to be analyzed (i.e., through use of statistical tests) and they too are subject to the problem of social desirability. This is especially true if the information provided on the questionnaire is not anonymized, but needs to be used further, e.g., in a therapeutic or employment context. Besides this, classic forms of self-report-inventories, such as paper-pencil questionnaires, constitute extra work for the researcher, as the information must be transferred to a digital form (to enable statistical analysis) and the hard copy questionnaires must then be stored for a longer time. This is especially true where paper-pencil questionnaires have been part of a research endeavor, employment scenario, etc. Of course, this can be circumvented through use of electronic versions of questionnaires, whereby some of the aforementioned problems can be diminished. Yet, the major drawback of self-report methods and interviews remain; the reliance upon the ability of the participant to recognize, recollect, and present the subject matter accurately.

Last but not least, social scientists rely on experiments, in which strict experimental laboratory settings provide the possibility of controlling potential confounding factors, e.g., if a researcher aims to assess the influence of Internet addiction on cognitive function. Although experiments provide a high scientific standard, they are vulnerable to several problems. Due to the artificial environment of the laboratory, it is not clear whether results derived from laboratory experiments can be generalized to the "real world." In other words, laboratory experiments often lack ecological validity, especially when only a small aspect of a broad phenotype is assessed in the lab. For example, shorter fixation times to threatening stimuli (a marker for anxiety) do not imply that a participant has difficulties in giving a talk in front of a broad audience (social phobia). Besides this, and in-keeping with the other methods, participants' motivational factors play an important role. If a participant in a study is not motivated to follow the instructions of the experiment, the quality of the data will be poor. Moreover, conducting experiments is very expensive, because a room for the experiment needs to be rented and highly trained specialists are needed to carry out the experiment properly.

Methods from computer science can help to overcome some of the above-mentioned problems encountered by interviews, self-report-measures and experiments. They can be of particular value to research efforts in Internet addiction.

13.3 Psychoinformatics and Internet Addiction

Methods from computer science have been used in psychological research for several decades. The use of computers and the Internet, such as online surveys and computer-based psychological experiments, illustrate this point nicely. Such, rather obvious, methods will not be discussed in the present chapter. Instead, we focus on new developments in the assessment of human behavior, via mobile devices but also by monitoring the human–machine interaction in everyday life, e.g., the use of the computer in a workplace situation.

Most humans in industrialized societies possess and use a smartphone on a daily basis. These powerful little machines provide access to the Internet, entertainment, including computer games, and of course the classic functions of mobile phones, such as telephone and short text message features. Furthermore, the new generation of smartphones includes intelligent sensors, which are able to track the location of a person (via the global positioning system, GPS) and their bodily movements. Of note, the smartphone is usually carried on the body of a person, thereby accompanying humans in nearly all daily activities. Many smartphone users even carry their smartphone when going for a run to track the speed and distance of the workout. This being said, smartphones and the data recorded from the human–machine interaction, provide genuine insights into the life and even mental states of a person. Most importantly, data derived from this source can be collected on a longitudinal basis, whereas the traditional methods discussed above usually do not go beyond one or two measures. Anyway, traditional methods do not provide a fine grained monitoring of a person's behavior over a long time.

In the context of assessing and treating Internet addiction, an exact recording of the length of online sessions over a longer time window provides a significantly more accurate picture of a person's Internet usage than numbers derived via self-report. Direct monitoring of the smartphone also provides insight into the most important addictive behaviors in the context of computer or smartphone use. The need to distinguish between different forms of online addiction has been demonstrated recently by Montag et al. (2015a).[1] Figure 13.1 depicts our recently self-developed app for monitoring smartphone behavior.

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[1]Of note, smartphone addiction (and the broader category mobile phone addiction) and Internet addiction are not the exact same constructs, as questionnaires measuring both forms of addiction correlate only moderately with each other (see Jenaro et al. 2007; Kwon et al. 2013a, b; Montag et al. 2016b). But: As a rising number of smartphone users surf the Internet via these devices, it is very likely that correlations will be higher in the future (see also Chap. 21).

Fig. 13.1 *Left side* of the figure shows the recording of actual time spent on the smartphone each day and the *right side* shows the most often used application of a user. The figure depicts *screenshots* from the app "Menthal"

By tracking Internet activity directly on a smartphone or computer, classic symptoms from addiction research can be examined (Andrews et al. 2015; Lin et al. 2015; Montag et al. 2015c). If one thinks of development of tolerance in the context of Internet consumption, this symptom should be reflected in increasing hours spent online over a given time window (for methodological issues see Chap. 20, please). Of course, here a patient's wellbeing will also need to be considered, and will play an important role in diagnosing Internet addiction. The therapist's impression of a patient completes the assessment of this potential new behavioral addiction. Besides asking a person about his/her wellbeing, it will be also possible to assess wellbeing via *textmining* in the future. Here, the content of E-Mails, messages of online social network channels (e.g. Kern et al. 2014; Schwartz et al. 2013), etc., can be analyzed in terms of the number of positive and negative words used by the patient. This will give indirect insights into the individual's mental state. This topic will prove less intrusive than anticipated, as the text can be analyzed on the phone and only the derived quantitative assessment is transmitted to a server (not the content of an individual's messages).

In the following section, we outline a short example demonstrating how a distinct pattern of different variables from smartphone use, could help to monitor and diagnose affective disorders such as depression. Depression is of interest in the context of Internet addiction as a subgroup of Internet addicts concurrently experience a form of this affective disorder (Kim et al. 2006; Sariyska et al. 2015). Imagine that a person usually phones ten different contacts a day; this person is very active in terms of recorded GPS locations, and shows signs of positive emotionality reflected in the large number of positive words used in communication channels (including lots of smiley emoticons). Suddenly a different data pattern occurs: The same person calls no one for several weeks, seems to stay at home (no GPS activity) and the use of negative words (and a lower number of messages) prevails. The shift in the data pattern recorded on the smartphone could represent a sign of social withdrawal accompanied by negative emotionality, possibly indicating a depressive state. In line with this, new studies demonstrated that variables such as loneliness, shyness (Bian and Leung 2015) and also depression can be linked to smartphone usage patterns (Saeb et al. 2015).

Psychoinformatics can also aid in the therapy of Internet addicts. Traditional settings such as Cognitive Behavioral Therapy (CBT) usually encounter longer time windows between therapy sessions. Here, the therapist often sees his/her patient not more than once a week. In addition, in some psychotherapeutic approaches (see also the Chaps. 15, 16 and 17), patients are required to write a daily diary monitoring their Internet usage and/or their mental states. The inclusion of the above-mentioned techniques from *Psychoinformatics* aids and simplifies the therapeutic process, because events in the everyday life of a patient can be better included in therapy, without the problem of distorted memory. For example, if the therapist verbally asks the patient "How often have you used the Internet over the last week in hours?", this question can only be answered with a vague number. It might even be trickier if the patient is required to recall the use of last Monday. In contrast to this, direct measurement of time spent using the device will provide accurate numbers and facilitate more direct therapeutic interventions. If an Internet addict uses a certain function of the Internet, such as Facebook, for more than one hour, a virtual "red flag" could be raised alerting the user to quit the session. It is even possible that after excessively long online sessions a notification will be send directly to the therapist. In the context of psychodiagnostics, it is noteworthy that recorded behavior on the smartphone is stronger linked to self-reported addictive tendencies on the smartphone compared to the associations with self-assessed hours and other relevant variables on the phone (Montag et al. 2015c).

Last but not least, *Psychoinformatics* can help to assess the development of cognitive function in Internet addicts. Among others, Park et al. (2011) provided evidence that Internet addiction is associated with lower cognitive functions in the domain of attentional processes. As this data stems from a cross-sectional study, longitudinal evidence is needed to obtain insights into the cause–effect principles. Again, the smartphone may be of help. Instead of "swiping" the log-in-screen to gain access to the functions of a smartphone, cognitive games can be incorporated at log-in (e.g., instead of swiping, the patient participates in a short cognitive test). Thousands of data points on cognitive functions could thus be collected by the therapist or the researcher, giving valuable insights into the development of cognition in light of Internet and smartphone use. Naturally, it is not practical to include a 5 min experiment at log-in, but this may be viable for shorter trials (such as a ten second game when logging in). Longer experiments would possibly serve to demotivate participants' smartphone usage (albeit arguably show some therapeutic effects), but also could demotivate participants' participation in the experiment. Although no data yet exist on the validity and reliability of cognitive data collected via a smartphone log-in-screen, clearly the collection of thousands of data points should drastically diminish the standard error of the mean in the registered data and therefore provides a more precise picture of the user's smartphone usage cognitive functions.

13.4 Psychoinformatics, Multiple Testing, and Data Privacy

The use of *Psychoinformatics* also presents several problems. First of all, we would like to consider the important issue of data protection/privacy. The recording of data from smartphones or from other digital devices bears the great danger of data misuse. Therefore, it is of importance to explain in detail which data will be recorded, and what kind of data will *not* be recorded. In the above-mentioned "Menthal Balance" app (Fig. 13.1), users are informed prior to installation, that no calls or message content will be recorded. Furthermore, in this research scenario, each smartphone is used as a small computer to conduct the statistical analyses. Only numbers, i.e., no direct content, from the smartphone is sent to the server of the researchers. Nevertheless, for many areas, such as therapy, direct content from mails could be a valuable data source. Again, we wish to note the difference between categorizing words into positive or negative categories and sending numerical data on the use of these positive/negative words to a server, compared with sending the complete content. Of note, the long recognized system of confidentiality between medical/psychological practitioners and patients provides a valuable guideline on how to use the data derived from *Psychoinformatics*.

A second problem of *Psychoinformatics* applies primarily to research related areas. Correlating thousands of variables from Big Data[2] will inevitably lead to some false positive results. Therefore, strong correction procedures, such as those applied in genetics and brain imaging research areas need to be adapted in this kind of research approach. Results derived from exploratory data analyses will also need to be replicated (and tested in strict laboratory experiment).

[2]In our context, Big Data refers to the enormous amount of information being collected on devices such as a smartphone.

13.5 Conclusions

Psychoinformatics, the introduction of methods from computer science to the area of psychology, can aid the diagnostics process, therapy, and also research in the field of Internet addiction. To date, there is a dearth of empirical data in support of the above-mentioned hypotheses. The future will show how these methods can be included in the various areas dealing with Internet addiction.

References

Andrews S, Ellis DA, Shaw H, Piwek L (2015) Beyond self-report: Tools to compare estimated and real-world smartphone use. PloS one 10(10):e0139004

Beck AT (2002) Cognitive models of depression. Clin Adv Cogn Psychother Theor Appl 14:29–61

Bian M, Leung L (2015) Linking loneliness, shyness, smartphone addiction symptoms, and patterns of smartphone use to social capital. Soc Sci Comput Rev 33(1):61–79

Campion MA, Pursell ED, Brown BK (1988) Structured interviewing: raising the psychometric properties of the employment interview. Pers Psychol 41:25–42

Edwards AL (1957) The social desirability variable in personality assessment and research. Dryden Press, USA

Jenaro C, Flores N, Gómez-Vela M et al (2007) Problematic internet and cell-phone use: Psychological, behavioral, and health correlates. Addict Res Theor 15:309–320

Johnson TP, van de Vijver FJ (2003) Social desirability in cross-cultural research. Cross Cult Surv Methods 195–204

Kim K, Ryu E, Chon MY et al (2006) Internet addiction in Korean adolescents and its relation to depression and suicidal ideation: a questionnaire survey. Int J Nurs Stud 43:185–192

Kern ML, Eichstaedt JC, Schwartz HA, Dziurzynski L, Ungar LH, Stillwell DJ, Seligman, ME et al (2014) The online social self an open vocabulary approach to personality. Assessment 21 (2):158–169

Kwon M, Kim DJ, Cho H, Yang S (2013a) The smartphone addiction scale: development and validation of a short version for adolescents. PloS one 8(12):e83558

Kwon M, Lee JY, Won WY, Park JW, Min JA, Hahn C, Kim DJ (2013b) Development and validation of a smartphone addiction scale (SAS). PloS one 8(2):e56936

Lin YH, Lin YC, Lee YH, Lin PH, Lin SH, Chang LR et al (2015) Time distortion associated with smartphone addiction: Identifying smartphone addiction via a mobile application (App). J psychiatric Res 65:139–145

Markowetz A, Błaszkiewicz K, Montag C et al (2014) Psycho-informatics: big data shaping modern psychometrics. Med Hypotheses 82:405–411

Miller PR, Dasher R, Collins R et al (2001) Inpatient diagnostic assessments: 1. Accuracy of structured vs. unstructured interviews. Psychiatry Res 105:255–264

Montag C, Bey K, Sha P, Li M, Chen YF, Liu WY, Reuter M (2015a) Is it meaningful to distinguish between generalized and specific Internet addiction? Evidence from a cross-cultural study from Germany. Asia Pac Psychiatry 7(1):20–26. Taiwan and China, Sweden

Montag C, Błaszkiewicz K, Sariyska R, Lachmann B, Andone I, Trendafilov B, Markowetz A et al (2015b) Smartphone usage in the 21st century: who is active on WhatsApp?. BMC Res Notes, 8(1):331

Montag C, Blaskiewicz K, Lachmann B, Sariyska R, Andone I, Trendafilov B, Markowetz A (2015c) Recorded behavior as a valuable resource for psychodiagnostics in mobile phone addiction: evidence from psychoinformatics. Beh Sci 5:434–442

Montag C, Błaszkiewicz K, Lachmann B et al. (2014) Correlating personality and actual phone usage: evidence from psychoinformatics. J Ind Differ, 35:158–165
Montag C, Duke É, Markowetz A (2016a) Towards psychoinformatics: computer science meets psychology. Comput Math Methods Med 2016, Article ID 2983685
Montag C, Sindermann C, Becker B, Panksepp J (2016b) An affective neuroscience framework for the molecular study of Internet addiction. Front Psychol 7:1906
Onnela JP, Rauch SL (2016) Harnessing smartphone-based digital phenotyping to enhance behavioral and mental health. Neuropsychopharmacology. doi:10.1038/npp.2016.7
Park MH, Park EJ, Choi J et al (2011) Preliminary study of internet addiction and cognitive function in adolescents based on IQ tests. Psychiatry Res 190:275–281
Potter J, Hepburn A (2005) Qualitative interviews in psychology: problems and possibilities. Qual Res Psychol 2:281–307
Riskind JH, Beck AT, Berchick RJ et al (1987) Reliability of DSM-III diagnoses for major depression and generalized anxiety disorder using the structured clinical interview for DSM-III. Arch Gen Psychiatry 44:817
Saeb S, Zhang M, Karr CJ, Schueller SM, Corden ME, Kording KP, Mohr DC (2015) Mobile phone sensor correlates of depressive symptom severity in daily-life behavior: an exploratory study. J Med Int Res 17(7):e175
Sariyska R, Reuter M, Lachmann B, Montag C (2015) Attention deficit/hyperactivity disorder is a better predictor for problematic Internet use than depression: evidence from Germany. J Addict Res Therapy 6(209):1–6
Schmidt FL, Hunter JE (1998) The validity and utility of selection methods in personnel psychology: practical and theoretical implications of 85 years of research findings. Psychol Bull 124:262
Schwartz HA, Eichstaedt JC, Kern ML, Dziurzynski L, Ramones SM, Agrawal M, Ungar LH et al (2013) Personality, gender, and age in the language of social media: the open-vocabulary approach. PloS one 8(9):e73791
Sugarman DB, Hotaling GT (1997) Intimate violence and social desirability a meta-analytic review. J Int Violence 12:275–290
Tao R, Huang X, Wang J et al (2010) Proposed diagnostic criteria for internet addiction. Addiction 105:556–564
Wiesner WH, Cronshaw SF (1988) A meta-analytic investigation of the impact of interview format and degree of structure on the validity of the employment interview. J Occup Psychol 61:275–290
Wright JH, Beck AT (1983) Cognitive therapy of depression: theory and practice. Psychiatric Serv 34:1119–1127