Editorial special issue addictive behaviors, networks, complexity and addictive behaviors

Wiers, R.W.; Grasman, R.P.P.P.

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Editorial

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The past two decades have witnessed a surge in interest for ideas and methods from complexity science—the study of systems of many elements that may interact with each other at multiple levels of description (Benham-Hutchins & Clancy, 2010; Niazi, 2013; Caldarelli, 2020). This comes with the recognition in many fields—from climate science to sociology to addiction—that many systems can and should be characterized as complex systems, and that, to make progress in our understanding of such systems, we must find general principles that govern the behavior of complex systems (Zhichang, 2007). Complexity science thinking has also budded in addiction research (Agar, 1999; West & Brown, 2013; Volkow & Baler, 2014). This special issue of Addictive Behaviors brings together a collection of papers that look at addiction as a complex self-sustaining interplay of mechanisms that operate at different levels of description. The levels of description range from (sub) cellular adaptations in the brain to effects of neighborhoods and health care policies. Identifying mechanisms at different levels is important for understanding and intervening with addictive behaviors. In fact, one of the heated current debates in the addiction field concerns the question to what extent addiction should be described as a chronic brain disease (Hall et al., 2015; Volkow et al., 2015). This view has been criticized on various grounds, including having a too narrow focus on adaptation at the neurobiological level. Social and environmental variables, it is argued, are at least as important in predicting in which individuals those neuroadaptations most likely take place (Hart, 2017; Heather et al., 2018, see for a recent overview, Heather et al. 2022). Importantly, changes take place as somebody develops an addiction, not only in neurocircuitries, but also in psychological and social mechanisms. Hence, rather than focusing on a single level of description, we need ways to relate mechanisms at different levels of description (Fried & Robinaugh, 2020; see also, van der Wal et al., 2021).

1. Network analysis

One promising way to do this is to use the rapidly developing range of tools from complexity science—methods designed specifically for the study of systems that consist of many components that may interact with each other.

A first popular tool from this toolbox is network analysis, which has been applied to networks identified in addiction-related phenomena at different levels of description, including brain networks, social networks and symptom networks. Symptom networks of mental disorders have received much attention during the past decade, as an alternative for the latent variable disease model of mental disorders (Borsboom, 2017; Borsboom & Cramer, 2013; Cramer et al., 2010). In these network models, symptoms are not independent manifestations of an underlying common cause (or latent variable or disease), but are connected and can causally affect each other. This dynamical perspective dovetails with clinicians' functional analysis of the dysfunctional behaviors in addiction. In many mental disorders, including addictions, symptoms in such networks can be characterized as either of more biological origin (e.g., tolerance) or of more social origin (e.g., neglecting social roles), and network analysis approaches can highlight connections between mechanisms at different levels of description. Further, symptom-networks don't stop at the border of the disorder, but often encompass symptoms from other mental disorders, which provides an interesting perspective on comorbidity—rule rather than exception in addiction (see for examples of network analyses on addictive behaviors and comorbid disorders, Anker et al., 2017; Lin et al., 2019).

This special issue contains several papers demonstrating the potential of network theory. For example, Huth and colleagues (2022), compared symptom networks in a large sample of alcohol consumers and in a clinical sample of Alcohol Use Disorder (AUD) patients, and found rather different networks in these groups. For example, the symptom *loss of control* was central in the clinical sample, while in the non-clinical sample the symptom *time spent drinking* was most strongly connected to other symptoms defined in terms of DSM-5 criteria for AUD. In addition, they showed that demographic variables moderate network structure, which calls for further research regarding underlying mechanisms. Blondino and colleagues (2022) studied the symptom networks concerning substance use, internalizing and externalizing symptoms in a large population sample and compared the networks of men and women. The three domains (internalizing, externalizing and

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substance use) formed separate clusters, with interesting links between them, specifically between internalizing problems and use of prescription drugs not prescribed (PDNP), and with cigarette and dual cigarette and e-cigarette use. Externalizing behavioral problems (defined as behavioral problems that manifest as negative outward behavior acting on the external environment), were associated with use of marijuana, alcohol and PDNP. While there were some edge-specific relationships that differed by gender, the overall structure and the global strength of the networks were similar, and gender differences appear to be primarily related to well-established gender-differences in internalizing and externalizing symptomatology (internalizing more frequent in women, externalizing in men), also observed in the present sample.

A second area in which network analysis has been applied, concerns social networks. Many studies have shown that individuals tend to affiliate themselves with individuals with similar attributes, such as marijuana use. A longstanding question is whether this phenomenon is due to selection or social influence. Barnett and colleagues (2022) tested this question in a longitudinal dataset, using a Stochastic Actor-Oriented Model, which can simultaneously assess the influence of psychological and background variables and social relations over time, while also assessing the influence of the network structure on marijuana use. They found support for both mechanisms.

Appealing as network analysis has been to researchers, it is fraught with pitfalls if not conducted with great care in both methodology and research design. Conlin et al. (2022; this issue) compared cross-sectional and longitudinal (2 wave) networks using the American NESARC (National Epidemiologic Survey on Alcohol and Related Conditions) dataset (Grant & Dawson, 2006), and found that while their network analysis using cross-sectional methodologies replicated well, their longitudinal network analysis showed very different results. The authors therefore argue the importance of not overinterpreting cross-sectional networks, and that their analysis highlights the added value of longitudinal methods for network analysis and the need for properly sampled time series data collection for this purpose.

2. Process modeling at multiple descriptive levels

Network analysis, as an exploratory methodology, is not the only approach to understanding addiction from a complex systems perspective. The special issue also contains a review of mathematical modeling approaches of addiction mechanisms by Van den Ende and colleagues (2022).[1] The authors present a selection of formal mathematical models that address the acquisition of addictive behaviors and their sustainment. They furthermore discuss models that explicitly model the influences exerted by the (social) environment, and the individual's contributions to that same environment. An advantage of formal modeling noted is that it requiring precision from researchers regarding the concepts used and their relationships. These formal models express the dynamics of physical variables (e.g., dopamine) or (abstract) theoretical variables (e.g., craving or self-control), in terms of differential and difference equations derived from conditioning theory or compartmental modeling. Van den Ende et al. contend that mathematical models thus far have either focused on intra-individual changes in (neuro-) psychological processes in addiction, *or* on inter-individual changes (social influences), but not modeled these together. The first class of models describe changes in the individual, such as changes in desire to use a drug, or in decision-making processes. Environmental influences are at best relegated to a single covariate in the model. The second class of models describe social processes in the development of addictive behaviors that borrow ideas from epidemiology, such as social contagion (like virus contagion). In these models, individual differences are typically not taken into account. The authors, therefore, call for better integration of models of intra- and interindividual processes.

A promising example of such a cross-level integrative mechanistic model is the Stochastic Actor Oriented Model analysis presented by Barnett, DiGuiseppi, Tesdahl & Meisel (2022; this issue), referred to earlier. Another example of cross-level integrative modeling is provided by Buckley and colleagues (2022): the authors present a model that integrates a planned behavior process (intentional drinking) and an automatic habit component, based on dual process models. The predictions of their model for trends in alcohol consumption frequency and quantity match up reasonably well with empirical data. The model also showed a growing percentage of habit-driven drinking with increased use and was used to estimate public health effects of the famous Dry January (voluntary abstinence) campaign and would suggest that a dry season (3 months) might have more impact in changing the drinking habit than a dry month.

3. Dual process theory

Dual process dynamics is a recurring theme in models of addictive behaviors. Where network analyses attempt to infer the big picture of causal coupling between multiple components or processes in a system, dual process models zoom in on detailed mechanisms that can explain observed dynamics for a small subset (often two) of all the processes involved. For example, Amil, Ballester, Maier & Verschure (2022) propose a dual process model for effects of cannabis use on performance on a hand-eye coordination task at the neural level: Chronic cannabis use causes CB1 receptor downregulation in Purkinje cells in cerebellum, which in turn affects a slow learning process based on dual process dynamics of explicit and implicit motor learning. The model is formalized as a system of difference equations that was derived from a synthesis of many observations of neurophysiological and behavioral processes, and their interplay.

The stochastic actor-oriented model analysis of Barnett et al. (2022), mentioned above, can also be viewed as a dual process model—albeit at a much higher level than the model of Amil et al. just described: On the one hand we have a (set of) social process(es) that influence individual behavior in making substance use decisions, and on the other, we have the influence of individual behavior in selecting an environment that matches their substance use decisions. The two processes play at the interface of an individual selecting their environment while at the same time being influenced by the same environment in making substance use decisions. In their analysis, the authors demonstrate that their powerful sociometric models—often referred to as 'SIENNA' (after a popular software package)— are especially suited for analyzing the interplay between factors at the behavioral and social level. Note that Van den Ende et al. (2022; this issue), referred to above, discuss further examples of detailed (computational) dual process theories advanced in the addiction literature.

4. Individual differences and moderate substance use

Comparison of study outcomes in addiction research is complicated by the fact that the diagnosis of addiction is not always clear cut, and different researchers use different definitions. Furthermore, individuals differ greatly in terms of the behaviors that they can engage in that would lead to addiction in some, but apparently constitute no such risk to others (Swendsen & Le Moal, 2011; Flagel, Akil, & Robinson, 2009). An example of this is the phenomenon of intermittent, or social, smoking: moderate to heavy tobacco consumption exclusively in a specific (for example social) setting (Shiffman et al., 2015). Tobacco smoking is the most costly addictive behavior in terms of disease, disabilities and preventable deaths, and heavy smokers typically have a difficult time quitting. Yet, there is a group of infrequent, "social" smokers, who

[1] [1] Note that, as one of the special issue editors was involved as author (RWW), the other served as editor (RG). Note further that almost simultaneously a complementary review came out that focused on insights of system dynamic methods other than mathematical modeling in addiction research (Naumann et al., 2021).

exclusively or primarily smoke with others. This behavior does not obviously fit in the formal models of dual process theories above: the same mechanisms are assumed to work in all individuals. Nonlinearities that are typically found in complex systems may, however, explain such very different behaviors from the same mechanism.

Two papers in this special issue use techniques from data science to classify and study the social smoking behavior patterns. Franzwa and colleagues (2022, this issue) used machine-learning methods to test different definitions of social smokers, and to pinpoint features that separate social smokers from nonsocial smokers. The authors conclude that the simple definition has the most utility: social smokers are people who only smoke with others. The existence of a distinct intermittent smoking pattern raises the question if such patterns also exist in other substance use behaviors prone to addiction. Epskamp and colleagues (2022, this issue), examined the existence of intermediate states (between zero use and heavy use), for the three most commonly used addictive substances: cigarette smoking, alcohol and cannabis use. They conclude that some individuals indeed can sustain a stable intermediate state of moderate alcohol or cannabis use—even after a history of dependency for these substances, which is directly relevant for the current discussions on desirable outcomes of treatment (see, Paquette et al., 2022). However, for cigarette smoking, the intermediate state was more rare, indicating that "social smoking" may be more risky than moderate use of alcohol or cannabis. A nice feature of this paper is that an extensive interactive tool has been made available, so that interested readers can try out how patterns change with different definitions of moderate and heavy use.

We hope this collection of papers will stimulate the use of the toolbox methods from complexity research to better understand the emergence of addictive behaviors, and to study mechanisms at different levels of explanation. Ultimately, this could lead to better interventions, by pointing to potential target-points for interventions. It is also clear that the papers here illustrate the potential of the complexity science approach, but in many cases existing datasets were used, with their limitations. Future research may benefit from optimized designs to study the complexities of addictive behaviors (c.f., Roefs et al., 2022).

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Reinout W. Wiers[a,b,*], Raoul P.P.P. Grasman[c]

[a] *Addiction Development and Psychopathology (ADAPT)-lab, Department of Psychology, University of Amsterdam, Netherlands*

[b] *Centre for Urban Mental Health, University of Amsterdam, Netherlands*

[c] *Psychological Methods, Department of Psychology, University of Amsterdam, Netherlands*

[*] Corresponding author at: Dept of Psychology, Universiteit van Amsterdam, PB 15916, 1001 NK Amsterdam, Netherlands.

E-mail addresses: r.wiers@uva.nl (R.W. Wiers), R.P.P.P.Grasman@uva.nl (R.P.P.P. Grasman).