The Role of Self-regulation in the Association between Habitual Propensity with Impulsivity and Compulsivity

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Abstract

Background. Adaptive behavior depends on the process of self-regulation, controlling actions, feelings, or thoughts. If self-regulation fails, maladaptive behavior may start to predominate, leading to impulsive actions, maladaptive habits, and compulsive behavior patterns. Habits are triggered automatically, usually without conscious awareness or deliberate control and make behavior more efficient. The tendency to develop habitual behavior differs substantially between individuals and appears to be associated with different aspects of regulatory control. The present study examined associations of habitual propensity with self-regulation, impulsivity, and compulsivity, elucidating possible underlying functional connections and evaluated the psychometric properties of a German version of the Creature of Habit Scale (COHS). **Methods.** Data of two independent community samples was collected online. Psychometric analyses were conducted using exploratory factor analyses and confirmatory factor analyses utilizing a Bayesian lasso procedure. Dynamic connections with measures of regulatory control, namely self-regulation, impulsivity, and compulsivity were analyzed using a network approach. **Results.** We replicated and validated the two-factorial structure of the COHS. Network analysis revealed that self-regulation was the most central node within the network of dynamic interactions between habitual propensity, impulsivity, and compulsivity. Self-regulation exclusively had negative associations with other measures, an exception being the association with the routine subscale of the COHS, which was an indirect one. **Conclusions.** Our findings provide evidence that habitual propensity is interconnected with measures of regulatory control. Information on habitual behavior gathered using the COHS could be useful in identifying vulnerabilities and developing tailored therapeutic strategies for psychopathologies associated with deficient regulatory control.

Keywords

Questionnaire, Habit, Routine, Automaticity, Self-regulation, Bayesian lasso procedure

Introduction

Habits not only make actions more efficient, but maladaptive habits can make actions dysfunctional. A typical example of such a dysfunctional process is addiction, where individuals lose control over initiation, duration and amount of their habitual drug use (American Psychiatric Association, 2013). These processes presumably depend on the ability to self-regulate, as *self-regulation* refers to the deliberate or automatic use of mechanisms and metaskills for the modulation of behavior, attention, affect or thought (Heatherton, 2011; Karoly, 1993). Understanding these processes and the factors influencing them is of vital importance for developing treatments for habits that have become dysfunctional and harmful and identifying individuals at risk for developing maladaptive habits. The aim of the current study was to validate a German version of the Creature of Habit Scale (COHS), which assesses individual propensity for habit formation (Ersche, Lim, Ward, Robbins, & Stochl, 2017). We assessed its association with internal factors suspected to influence habit propensity, like intrinsic goal-directedness, or self-regulation, while also taking into account personality traits characterized by loss of control over behavior, namely impulsivity and compulsivity (Hofmann, Schmeichel, & Baddeley, 2012; Robbins, Gillan, Smith, de Wit, & Ersche, 2012).

Habits are response patterns individuals exhibit repeatedly in a specific situation (Wood & Rünger, 2016). They allow for highly efficient execution of routine acts, while attention can be focused elsewhere (Wood, Quinn, & Kashy, 2002). Habits are therefore established to reduce the cognitive load of costly behavioral control over *goal-directed behavior* (Ouellette & Wood, 1998). Habitual response patterns are learned by repetition (Lally, Van Jaarsveld, Potts, & Wardle, 2010). After repeated coupling of a stimulus with a specific response pattern and subsequent reinforcement, the stimulus elicits the response pattern automatically (Aarts, Verplanken, & Van Knippenberg, 1998). Long story short, repeated goal-pursuit in stable contexts leads to habit formation (Ouellette & Wood, 1998). Hence, it is important to distinguish between goal-directed and habitual instrumental behavior: Goal-directed behavior is guided by the known association between an action and its consequences, the outcome is motivationally relevant at the time of decision-making (Dolan & Dayan, 2013). An example would be a person's decision to abstain from the usage of plastic bags for the sake of the environment and take reusable ones to the supermarket for grocery shopping. The first few times, conscious control likely needs to be allocated to remember bringing the bags, maybe even forgetting them a few times, and having to return to get them. Habitual behavior, however, is independent from the current motivational value of an outcome and has been shaped by past reinforcement (Thorndike, 1911). Again, our example: After some time, in which a person had already taken the reusable bags with them, they may not even have to consciously remember packing the reusable bags anymore. They just do, just as they would with their wallet and keys. Therefore, goal-directed instrumental control is characterized by active deliberation, high computational cost and adaptive flexibility, while habitual instrumental control is marked by automaticity, computational efficiency and inflexibility (Dayan, 2009). Goals and consequences of repeated goal-directed actions therefore subsequently become less important and the behavior less susceptible to conscious control (Danner, Aarts, & de Vries, 2008; Robbins & Costa, 2017; Verplanken, 2006). This shift from goal-directed to habitual instrumental behavior is influenced by various internal as well as external factors, e.g. high intrinsic goal-directedness, stress, and contact with stimulants (Corbit, Chieng, & Balleine, 2014; Linnebank, Kindt, & de Wit, 2018; Schwabe & Wolf, 2011). There is evidence that habitual behavior partitions into different sub-dimensions: Routines and automatisms are conceptualized as forms of habits that share critical features, but also distinctly differ from each other concerning their function as well as their control over behavior (Ersche et al., 2017; Orbell & Verplanken, 2010). Routines can be characterized as sequential action patterns that are deliberately

executed to make daily life more efficient, and can consciously be amended if no longer appropriate (Clark, 2000). Habitual automatisms, however, can be defined as cue-response associations and are a form of automaticity, but not synonymous (Orbell & Verplanken, 2010). They are insensitive to short-term changes in goals (Wood, Labrecque, Lin, & Rnger, 2014).

The tendency towards developing such habitual behaviors differs substantially between individuals (Lally et al., 2010). Furthermore, excessive habit formation appears to be prominent in mental disorders characterized by deficient goal-directed control over action and response inhibition manifesting in high levels of compulsivity and/or impulsivity (Gillan, Robbins, Sahakian, van den Heuvel, & van Wingen, 2016). Compulsivity describes the failure to stop an ongoing inappropriate behavior, while impulsivity describes the failure to inhibit the initiation of behavior (Robbins et al., 2012). Substance use disorders (SUD), eating disorders, trichotillomania and obsessive-compulsive disorder (OCD) are just a few examples of disorders characterized by deficient goal-directed control, impulsivity and compulsivity (Gillan et al., 2011; Gillan et al., 2016; Hogarth, Chase, & Baess, 2012; Robbins et al., 2012). However, even in healthy samples these connections persist: Compulsivity has been shown to be associated with a preference for strict routines and a higher tendency to form habits (Fineberg et al., 2010). Self-regulatory capacity, as well as impulsivity, have also been associated with habitual behavior (Carden & Wood, 2018; Torregrossa, Quinn, & Taylor, 2008). One could suspect, based on these already established associations, deficient self-regulation to be the cause of healthy habitual behavior becoming problematic. In the case of weak self-regulation, desire may predominate behavior, leading to impulsive actions (Hofmann et al., 2012), and it may also increase the risk of habitual behavior spiraling out of control, leading to compulsive behavior patterns (Gillan & Robbins, 2014). Although habits are regulated by external cues, they require intact self-regulation for an individual to be able to adapt to changing environmental conditions and keep the balance between habitual efficiency and adaptability (Karoly, 1993).

The COHS was developed to measure the tendency towards habitual behavior in daily life and has been shown to efficiently assess the propensity for habitual behavior in English speaking populations, with satisfactory reliability (Ersche et al., 2017). The original version exhibited a two-factorial structure, distinguishing between routine behavior and habitual automatic responses. The scales have been shown to be differentially associated with various measures of personality traits, like anxiety and compulsive as well as impulsive personality traits, goal-pursuit and cognitive flexibility. COHS *Routine* has been shown to be inversely associated with sensation-seeking and impulsivity, COHS *automaticity* to be inversely correlated with goal-pursuit and positively with impulsivity (Ersche et al., 2017; Ersche et al., 2019). Both scales were associated with higher compulsivity as assessed with the obsessive-compulsive inventory (OCI; Foa et al., 2002), a finding which has been replicated (Ersche et al., 2019). They also appear to be negatively associated with measures of cognitive flexibility (Lange & Dewitte, 2019), which supports a possible connection to self-regulation. There is also evidence suggesting that habitual tendencies, as measured by the COHS, explain more variance than the frequency of the behaviors in question (Ersche et al., 2019).

The aim of the present study was to develop and validate a German version of the COHS. To this end, the COHS was translated into German and assessed online in two independent samples. We expected to replicate the two-factorial structure of the questionnaire. Furthermore, we examined associations with self-regulation, impulsivity, and compulsivity. As outlined above, we expected that self-regulation should be negatively associated with habitual propensity, and that it should influence the connection between habitual propensity and impulsivity as well as compulsivity.

Methods

Study design and sample

Sample size estimation. Minimum sample size for factor analysis was estimated based on simulation studies by Gagne and Hancock (2006), who proposed a method that bases sample size estimation on measurement model quality, or reliability, which can both be derived from the number of indicators per factor and the factor loadings of each indicator. Therefore, taking into account the number of indicators per factor ($n = 11$ and $n = 16$, respectively) and the factor loadings of the original questionnaire, we estimated a minimum sample size of $N = 200$.

Sample. The assessment of both samples included the COHS as well as sociodemographic information, including age, education level and native language. All participants were above 18 years of age and were native speakers of German. Data were collected online and participants' identity remained anonymous to the research team.

Sample 1 additionally included measures of obsessive-compulsive and impulsive traits, self-regulatory capacity as well as two control items to check for attention (Meade and Craig (2012)). The order of the questionnaires was randomized across participants. Complete data from 439 individuals were collected online using the internet platform LimeSurvey (LimeSurvey Project Team, 2015). 199 participants were excluded due to either false responding to the control items ($n = 15$), no fluency in German ($n = 5$), the presence of current or past self-reported mental disorders or intake of psychotropic substances within the past 3 months ($n = 133$), or neurological illness with possible influence on mood, cognition and behavior ($n = 46$). The final sample included 240 participants (mean age 26.5 years $\pm$ 8.16 standard deviation (SD), 77.9% female; 83.8% had completed advanced education degrees). Participants could take part in a lottery to win 10 Euro.

Sample 2 comprised data from 602 female individuals was collected online via the crowdsourcing platform clickworker (clickworker® GmbH, Essen, Germany), the study was set up via the online platform Labvanced (Finger, Goeke, Diekamp, Standvoß, & König, 2017). 134 participants were excluded due to current or past self-reported mental health issues. This left a total sample of 468 participants (mean age 29.3 years $\pm$ 7.05 SD, 88.7% had completed advanced education degrees). Participants received a financial compensation of 3.75 Euro for their participation.

The ethics committee at the University Hospital Carl Gustav Carus, Technische Universität Dresden approved both study procedures (EK 310082018 and EK 135042018).

Measures

The COHS (Ersche et al., 2017) assesses the tendency for habitual behavior in various situations in daily life on 27 items. The original version of the COHS was shown to exhibit a two-factorial structure, with factors termed *routine* (16 items) and *automaticity* (11 items). Reliability has been shown to be satisfactory for both scales (COHS *routine*: Cronbach's $\alpha = 0.89$, McDonald's $\omega = 0.92$; COHS *automaticity*: Cronbach's $\alpha = 0.91$, McDonald's $\omega = 0.86$). The COHS was translated into German and back into English by psychologists who were bilingual speakers of German and English. The retranslated version were compared to the original questionnaire. Differing items were discussed and adapted (see Supplement I).

The OCI, consisting of 18 items, was used to assess *obsessive-compulsive symptoms* using a sum score (Foa et al., 2002; Gonner, Leonhart, & Ecker, 2007). Internal consistency has been shown to be satisfactory with Cronbach's $\alpha = 0.85$ (Gonner et al., 2007). The Barratt Impulsiveness Scale-11 (BIS) consists of 30 items and is an instrument assessing *impulsivity as a personality trait* (Patton, Stanford, & Barratt, 1995). High impulsivity is characterized by rash, imprudent actions without consideration of possible negative consequences and is operationalized using a sum score. Internal consistency has been shown to be satisfactory with Cronbach's $\alpha = 0.83$ (Stanford et al., 2009). The Self-Regulation Scale (SRS) consists of 10 items and assesses the *self-regulatory capacity* for sustaining an action even if there are influences interfering with motivation and attention (Schwarzer, Diehl, & Schmitz, 1999). High self-regulatory capacity is associated with goal-directed behavior and perceived self-efficacy. Internal consistency has been shown to be satisfactory with Cronbach's α between 0.73 and 0.82 (Diehl, Semegon, & Schwarzer, 2006; Luszczynska, Diehl, Gutiérrez-Dona, Kuusinen, & Schwarzer, 2004).

Data Analysis

To validate the German version of the COHS in each sample, we first performed exploratory factor analysis (EFA) with oblique rotation (oblimin). Analysis was conducted on a polychoric correlation matrix owing to non-normality of the data (Holgado-Tello, Chacón-Moscoso, Barbero-García, & Vila-Abad, 2010), as assessed by Mardia's test (Mardia, 1970). To extract the number of factors or components, the following techniques were used due to their comparably high accuracy rate (Ruscio & Roche, 2012): parallel analysis for component extraction (PA), minimum average partial procedure (MAP), optimal coordinates (OC), acceleration factor (AF) and comparison data (CD). To validate the factorial structure, we performed a confirmatory factor analysis (CFA) using a Bayesian least absolute shrinkage and selection operator (lasso) to reduce the inverse covariance matrix, based on the procedure described by Pan, Ip, and Dube (2017). This procedure has the advantage of allowing the residuals to be correlated, after latent factors have been included in the model, thus providing a better tradeoff between fit and model complexity, an identifiable model, valid estimates of standard errors, and producing reliable results even in smaller samples. We additionally performed CFA without Bayesian lasso. Reliability was assessed using McDonald's omega and Cronbach's alpha (Cronbach, 1951; McDonald, 2013; Revelle & Zinbarg, 2009). Convergent and discriminant validity were examined using Kendall's tau (Kendall, 1938) correlations with measures of personality traits that have been linked to the individual propensity to habitual behavior. Kendall's tau has been shown to be a better estimate of the correlation in the population, if the data is distributed non-normally (Howell, 2012). To analyze the dynamic connections between the assessed personality traits, we used a network approach and estimated a standardized Gaussian Graphical Model (GGM) using the graphical lasso as a regularization method, the tuning parameter was selected according to the Extended Bayesian information criterion (Chen & Chen, 2008; Foygel & Drton, 2010; Friedman, Hastie, & Tibshirani, 2008; Lauritzen, 1996). Analysis was performed based on polychoric correlations (Epskamp & Fried, 2018). Edge weight, or correlation accuracy and stability of node centrality indices as measures of node importance were assessed using bootstrapping (see Epskamp, Borsboom, & Fried, 2018).

All analyses were carried out with R (R Core Team, 2018), using the packages psych, corpcor, GPArotation, nFactors, RGenData, FactoMineR, MASS, MCMCpack, msm, psychometric, qgraph and bootnet (Bernaards & Jennrich, 2005; Epskamp et al., 2018; Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012; Fletcher, 2010; Jackson, 2011; Lê, Josse, & Husson, 2008; Martin, Quinn, & Park, 2011; Raiche, 2010; Revelle, 2018; Ripley et al., 2013; Ruscio, 2018; Schafer et al., 2017). The Bayesian lasso CFA procedure was carried out using scripts provided by Pan et al. (2017).

Results

Exploratory factor analysis

Assumptions for EFA were met (see Supplement II). An initial analysis was conducted to extract the number of factors to retain. For sample 1, PA extracted two components, OC extracted four factors, MAP and CD extracted two, AF extracted one. We analyzed the data using four and two factors. Compared to the two-factor solution, the four-factor solution yielded more cross loadings and did not seem to adhere to meaningful constructs (see table 1, Supplement II). For sample 2, results were ambiguous as well: PA extracted two components, OC and CD extracted three factors, MAP and AF extracted two. We calculated results for the three- and the two-factor solution. The three-factor solution reproduced the *routine* scale, but split up the *automaticity* scale into two factors. As most of the items from the two *automaticity* factors had substantial cross-loadings, the split into two separate constructs did not appear meaningful (see table 2, Supplement II). Due to the more convincing results from the two-factor solutions, two factors were retained in the analysis. Table 1 shows the factor loadings after rotation. The clustering of the items replicated the factors from the original COHS *routine* and *automaticity* factors. Factors were correlated (*sample 1*: $\varphi = 0.18$ [CI 0.06 - 0.29]; *sample 2*: $\varphi = 0.074$ [CI 0.027 - 0.122]). All squared differences between factor loadings of the two samples were below 0.03, suggesting strong replication (Osborne & Fitzpatrick, 2012).

Bayesian lasso Confirmatory Factor Analysis

A CFA using a Bayesian lasso to reduce the inverse covariance matrix (Pan et al., 2017) was conducted in both samples. Goodness of Fit for the proposed model was tested via posterior predictive (PP) p-value (*sample 1*: PP $p = 0.53$; *sample 2*: PP $p = 0.48$) and the proposed two-factor model considered plausible, because the estimates were not far from 0.50. The Bayesian estimates of the unknown parameters in the factor-loading matrix (λ), their corresponding Highest Posterior Density Intervals (HPD) and standard errors (SE) are presented in table 2. See figure 1 for a path diagram of the COHS structure. All factor-loading estimates were significant and appeared to be satisfactory in magnitude. As expected, the factors were positively correlated to a small extent (*sample 1*: $\varphi = 0.069$ [HPD 0.016 - 0.137]; *sample 2*: $\varphi = 0.074$ [HPD 0.027 - 0.122]). The current analysis revealed 2.14 % ($n = 15$) and 6.27% ($n = 44$) of significant residual covariances within the two samples, respectively. In Bayesian lasso CFA, not every residual covariance has to be equal to zero, but the amount of significant residual covariance should be smaller than 10%. See Supplement III for results from CFA without Bayesian lasso (tables 3-6) as well as the standardized residual covariance matrix (table 7) and the polychoric correlation matrix from sample 1 (table 8).

Reliability

McDonald's omega and Cronbach's alpha suggested satisfactory reliability for COHS *routine* (*sample 1*: $\alpha = 0.85$ [CI 0.82 - 0.88], $\omega = 0.86$ [CI 0.83 - 0.88]; *sample 2*: $\alpha = 0.84$ [CI 0.82 - 0.86], $\omega = 0.84$ [CI 0.82 - 0.87]), as well as COHS *automaticity* (*sample 1*: $\alpha = 0.85$ [CI 0.82 - 0.88], $\omega = 0.86$ [CI 0.83 - 0.88]; *sample 2*: $\alpha = 0.83$ [CI 0.80 - 0.85], $\omega = 0.83$ [CI 0.81 - 0.86]).

Validity and network dynamics

The validity of the COHS subscales was examined in sample 1 and is displayed in table 3. Correlations were small to moderate in magnitude, even when considering the different metric of the tau statistic

(Gilpin, 1993). Figure 2 depicts the network model we used to evaluate the dynamic connections between self-reported measures of routine, habit automaticity, impulsivity, compulsivity, and self-regulation in sample 1. The edge weights (i.e. connections between nodes) can be interpreted as partial correlations, controlled for the presence of all other variables in the network (Borsboom & Cramer, 2013). The strongest connection was the negative association between self-regulation and impulsivity. Interestingly, the direct connections between impulsivity and automaticity as well as self-regulation and routine did not meet the threshold for relevance, leaving shortest indirect connections via self-regulation and impulsivity, respectively. Both routine and automaticity were positively connected to compulsivity, as well as to each other. The connection between self-regulation and compulsivity was negative. See figure 2 in Supplement IV for bootstrap-estimated accuracy of edge weights. Self-regulation appeared to be the most central node, as it had the highest values for node strength, closeness and expected influence, which quantify how well a node is directly as well as indirectly connected to other nodes (Epskamp et al., 2018). See figure 1 and table 9 in Supplement IV for a visualization of the z-standardized and the raw values of centrality indices of the GGM. The correlation stability coefficient (CS) quantifies the maximum proportion of cases that can be dropped while maintaining a correlation of higher than 0.7 (Epskamp et al., 2018). The CS indicated that betweenness ($CS(\text{cor} = 0.7) = 0$) and closeness ($CS(\text{cor} = 0.7) = 0.129$) were not stable under bootstrap subsetting cases and have to be interpreted with caution. Node strength and edges performed better ($CS(\text{cor} = 0.7) = 0.283$; $CS(\text{cor} = 0.7) = 0.363$).

Discussion

The present study investigated the psychometric properties of a German version of the COHS in two independent samples as well as dynamic associations with aspects of regulatory control. We replicated and validated the two-factorial structure of the original version in both samples, using EFA and CFA analyses. All items consistently loaded on the expected factor. Both factors were weakly correlated, as expected. The subscales were associated differentially with measures of regulatory control, providing further evidence that both scales display different aspects of habitual behavior and are relevant in behavioral regulation. Inside the network, both subscales were positively associated with compulsivity. Only COHS *automaticity* was found to be negatively correlated with self-regulation, while COHS *routine* was negatively correlated with impulsivity and connected to self-regulation via impulsivity. Results therefore show that the German version of the COHS, with its distinction between routine behavior and automatic behavior, is a reliable, valid, and useful instrument.

Habit and behavioral regulation

Dynamic interactions between psychological constructs are important when considering individual differences and can be conceptualized within network analyses (Costantini et al., 2019). Our results suggest that habitual propensity, regarding routine as well as automaticity, is intertwined with compulsivity, impulsivity, and self-regulation in a network of behavioral regulation, with evidence that self-regulation is the most influential node. Self-regulation controls how strongly desire and impulsive action dominate behavior (Hofmann et al., 2012). The ability to self-regulate also influences habitual behavior, with the aim of preventing it to spiral out of control and fuel compulsive behavior patterns (Gillan & Robbins, 2014). It appears that although habits are regulated by external cues, they require intact self-regulation to enable adaptation to changing environments and maintain the balance between efficiency and adaptability. Interestingly, the link between self-regulation and COHS *routine* was

an indirect one, indicating that routines are less dependent on self-regulation than automaticity. However, these connections may also go in the reverse direction. For example, high impulsivity may lead to less effective self-regulation, leading to less control over automaticity.

Self-regulation comprises three main components: monitoring if there is a need to self-regulate, motivation for self-regulation and self-regulatory capacity (Baumeister & Heatherton, 1996; Carver & Scheier, 1981). The SRS used in this study to examine self-regulation assesses one specific component of self-regulation: attention control in goal pursuit, which is also described as self-regulatory capacity (Diehl et al., 2006). Habitual routines and automatic behaviors are often uncoupled from attentional processes and do not require conscious control to be executed (Evans & Stanovich, 2013). Conscious regulation becomes necessary, if the behavior is no longer consistent with goals. If self-regulation is weak, the behavior may continue regardless (Wood et al., 2002). Individuals with low self-regulatory capacity may therefore run at risk of their habits to get out of control. In this regard it comes as little surprise that it has been suggested that obsessive-compulsive disorders may be associated with excessive habit formation, and compulsivity described as a transdiagnostic trait, characterized by an imbalance between goal-directed and habit-learning systems (Gillan & Robbins, 2014; Gillan et al., 2016). This also translates to subclinical samples (Chamberlain, Stochl, Redden, & Grant, 2018). The connection to impulsivity, however, seems more complex. The COHS subscales were not associated with impulsivity in the same way. COHS *routine* was shown to be negatively associated with impulsivity. It seems likely that individuals with a propensity to form routines also tend to have a consistent lifestyle, plan aspects of daily life very carefully, and do not often act out of the spur of the moment tend to be less impulsive. These tendencies appear to describe the opposite of impulsivity, which is often characterized as the tendency to act prematurely without foresight (Dalley, Everitt, & Robbins, 2011; Patton et al., 1995). On the other hand, COHS *automaticity* is only indirectly linked to impulsivity, via self-regulation. Automaticity describes cue-response associations that occur without having to focus on the task at hand, allowing the individual to think about other things. It requires conscious self-regulation to override an automatic response, which relies on detection of a need to regulate and then attentional deployment. Habit automaticity has been associated with attention in the past using other measures, e.g. the SRHI correlated with attentional bias to smoking cues in current smokers (Orbell & Verplanken, 2010). Interesting, with respect to the COHS *automaticity* subscale, is the strong focus on eating-related items, especially in the context of an indirect connection to impulsivity. Impulsivity has consistently been related to various measures associated with overeating or binge eating, in clinical as well as healthy samples (Claes, Nederkoorn, Vandereycken, Guerrieri, & Vertommen, 2006; Meule, 2013; Rosval et al., 2006). This potential association between COHS *automaticity* and overeating or binge eating could result from high levels of impulsivity interfering with self-regulation. This could be of interest in future studies examining eating disorders.

Outlook for further research

As the COHS is a new instrument, its usefulness needs to be further evaluated in empirical studies, specifically regarding populations in which habitual tendencies are deemed dysfunctional and self-regulation is deficient, e.g. highly compulsive and impulsive populations. Also of interest would be to examine the connection of routine and automaticity to the different components of self-regulation. For example, self-regulation critically depends on monitoring for the need to adapt a behavior, also called performance monitoring (Ullsperger, Fischer, Nigbur, & Endrass, 2014). Changes in brain activity associated with performance monitoring have been reported for both highly compulsive but also impulsive individuals (e.g. Endrass & Ullsperger, 2014; Martin & Potts, 2009). To summarize, research connecting

self-report to experimental designs, as well as studies aiming elucidate connections to daily life using ecological momentary assessment is warranted.

Limitations

Limitations of the current study include the relatively small sample size of the first sample, and the restriction to female gender in the second sample. Also, not all items might be optimal for the subscales. Some items consistently exhibited low factor loadings ($\lambda \approx 0.30$; relevant for items 18 and 24 on the routine subscale, 8 and 21 on the automaticity subscale), and it could be discussed if they measure aspects not directly related to the latent variables and if they are statistically meaningful (Tabachnick, Fidell, & Ullman, 2007). These items should be further evaluated in larger and more heterogeneous samples. Further, as most of the correlations with other measures of personality were small to moderate in magnitude, results on network dynamics as well as convergent and discriminant validity should be interpreted with caution. Replication of these results in healthy as well as clinical populations might shed some light on the consistency of the structure of these associations. However, consistent replication of the factor structure in two independent samples should be considered strong evidence for the model and psychometric quality of the COHS. Additionally, our findings regarding the associations with impulsivity and compulsivity are in line with previous findings, suggesting reliable results (Ersche et al., 2017; Ersche et al., 2019).

Conclusions

The German version of the COHS appears to be a reliable and valid measure of daily behavior related to habitual routines and automatic behavior. As the COHS subscales cover different aspects of habit propensity, it is not surprising that they appear to differ in their associations to self-regulation, impulsivity and compulsivity. The central role of self-regulation in these dynamic interactions suggests that in pathological conditions with maladaptive habitual behaviors (e.g. smoking), treatments should target self-regulation. Information on habitual behavior gathered using the COHS could be useful in identifying vulnerable individuals and developing tailored therapeutic strategies for certain psychopathologies.

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Conflicts of interest

None.

Ethical standards

The authors assert that all procedures contributing to this work comply with the ethical standards of the relevant national and institutional committees on human experimentation and with the Helsinki Declaration of 1975, as revised in 2008.

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Tables

Table 1

Oblimin rotated standardized loadings (pattern matrix) based upon polychoric correlation matrix for samples 1 and 2.

	Sample 1		Sample 2	
	<i>COHS routine</i>	<i>COHS automaticity</i>	<i>COHS routine</i>	<i>COHS automaticity</i>
Item 01	0.54	0.03	0.57	-0.01
Item 02	0.41	0.00	0.57	0.02
Item 04	0.53	-0.06	0.49	-0.11
Item 06	0.42	0.23	0.39	0.13
Item 07	0.69	-0.08	0.64	-0.12
Item 10	0.50	0.22	0.43	0.22
Item 12	0.66	-0.12	0.66	-0.01
Item 13	0.62	0.02	0.59	0.12
Item 14	0.58	-0.09	0.51	0.01
Item 15	0.85	-0.06	0.83	-0.05
Item 17	0.45	0.08	0.52	0.13
Item 18	0.30	0.08	0.35	0.02
Item 20	0.51	0.04	0.50	-0.04
Item 22	0.68	0.11	0.57	0.03
Item 24	0.26	0.16	0.32	0.16
Item 27	0.72	0.07	0.69	0.03
Item 03	-0.06	0.74	0.04	0.59
Item 05	-0.03	0.57	-0.09	0.59
Item 08	0.02	0.34	0.05	0.40
Item 09	0.04	0.49	0.03	0.57
Item 11	0.00	0.75	0.02	0.73
Item 16	0.07	0.65	0.16	0.58
Item 19	-0.04	0.75	-0.10	0.72
Item 21	0.20	0.33	0.13	0.34
Item 23	0.00	0.65	0.05	0.56
Item 25	0.03	0.88	-0.02	0.84
Item 26	0.00	0.71	0.03	0.53

Note. COHS routine and COHS automaticity = Creature of Habit Scale (Ersche, Lim, Ward, Robbins, & Stochl, 2017) routine and automaticity subscales.

Table 2

		Parameter Estimates for sample 1.					Parameter Estimates for sample 2.				
	Item	λ	HPD		SE		λ	HPD		SE	
COHS <i>routine</i>	1	0.59*					0.48*				
	2	0.53	0.34	- 0.72	0.10		0.63	0.47	- 0.82	0.09	
	4	0.48	0.32	- 0.68	0.09		0.45	0.29	- 0.60	0.08	
	6	0.54	0.36	- 0.74	0.10		0.44	0.26	- 0.61	0.09	
	7	0.58	0.38	- 0.77	0.10		0.56	0.40	- 0.71	0.08	
	10	0.52	0.35	- 0.69	0.09		0.37	0.25	- 0.51	0.06	
	12	0.69	0.51	- 0.86	0.09		0.67	0.52	- 0.84	0.08	
	13	0.75	0.55	- 0.97	0.11		0.71	0.53	- 0.90	0.10	
	14	0.51	0.34	- 0.68	0.09		0.54	0.38	- 0.68	0.08	
	15	0.91	0.71	- 1.00	0.11		0.87	0.70	- 1.00	0.10	
	17	0.42	0.28	- 0.59	0.09		0.52	0.36	- 0.68	0.08	
	18	0.31	0.15	- 0.50	0.09		0.31	0.16	- 0.45	0.07	
	20	0.50	0.36	- 0.66	0.08		0.45	0.31	- 0.59	0.07	
	22	0.71	0.53	- 0.89	0.10		0.56	0.41	- 0.72	0.08	
	24	0.33	0.16	- 0.50	0.09		0.31	0.18	- 0.43	0.06	
COHS <i>automaticity</i>	27	0.87	0.68	- 1.00	0.10		0.76	0.58	- 0.93	0.09	
	3	0.59*					0.62*				
	5	0.45	0.32	- 0.61	0.07		0.48	0.35	- 0.61	0.07	
	8	0.25	0.11	- 0.38	0.07		0.29	0.19	- 0.42	0.06	
	9	0.27	0.13	- 0.43	0.07		0.42	0.26	- 0.59	0.08	
	11	0.61	0.49	- 0.72	0.06		0.62	0.48	- 0.76	0.07	
	16	0.58	0.45	- 0.71	0.07		0.51	0.36	- 0.65	0.07	
	19	0.64	0.46	- 0.84	0.10		0.64	0.47	- 0.83	0.09	
	21	0.28	0.09	- 0.48	0.09		0.25	0.10	- 0.38	0.07	
	23	0.52	0.35	- 0.69	0.09		0.44	0.29	- 0.58	0.07	
	25	0.72	0.59	- 0.87	0.08		0.73	0.57	- 0.92	0.08	
	26	0.50	0.38	- 0.62	0.06		0.41	0.30	- 0.54	0.06	

Note. λ = Standardized factor loadings; HPD = Highest Posterior Density Intervals, characterize uncertainty associated with estimated parameter; SE = standard error; the items with asterisks were fixed to identify the scale of the latent factor; COHS routine and COHS automaticity = Creature of Habit Scale routine and automaticity subscales (Ersche et al., 2017).

Table 3

Kendall's tau correlations and their respective *p*-value between the two subscales of the COHS and measures of compulsive and impulsive personality traits as well as self-regulatory capacity calculated for sample 1 (n = 240).

	COHS <i>routine</i>	<i>p</i>	COHS <i>automaticity</i>	<i>p</i>	Compulsivity	<i>p</i>	Impulsivity	<i>p</i>	Self-regulation	<i>p</i>
COHS <i>routine</i>	1	-								
COHS <i>automaticity</i>	0.15	0.001	1	-						
Compulsivity	0.22	0.001	0.20	0.001	1	-				
Impulsivity	-0.16	0.001	0.10	0.020	0.03	0.489	1	-		
Self-regulation	-0.11	0.019	-0.28	0.001	-0.22	0.001	-0.29	0.001	1	-

Note. COHS routine and COHS automaticity = Creature of Habit Scale (Ersche et al., 2017) routine and automaticity subscale scores; Compulsivity = Obsessive-Compulsive Inventory-Revised (Gönner, Leonhart, & Ecker, 2007) sum score; Impulsivity = Barratt Impulsiveness Scale-11 (Patton, Stanford, & Barratt, 1995) sum score; Self-regulation = sum score Self-Regulation Scale (Diehl, Semegon, & Schwarzer, 2006).

Figures

Figure 1. Path diagram of the Creature of Habit Scale (Ersche et al., 2017) results in sample 1, including all items with their respective standardized factor loadings on the subscales as well as the weak correlation between the two subscales.

Figure 2. Between-subject graphical lasso network with tuning parameter selected using the extended Bayesian information criterion. Nodes represent the traits impulsivity, compulsivity, self-regulatory capacity as well as tendency for routine and automatic behavior. Edges (connections) can be interpreted as partial correlation coefficients. Red (dashed) lines represent negative edges, green (solid) lines positive edges. Self-regulation = Self-regulation scale (Diehl et al., 2006) sum score, Routine = Creature of Habit Scale (Ersche et al., 2017) routine subscale sum score, Compulsivity = Obsessive-Compulsive Inventory (Gönner et al., 2007) sum score, Impulsivity = Barratt Impulsiveness Scale (Patton et al., 1995) sum score, Automaticity = Creature of Habit Scale (Ersche et al., 2017) automaticity subscale sum score. See the online article for the color version of this figure.

Supplement

I. Creature of Habit Scale

Creature of Habit Scale – English

Here are some statements relating to behaviors, feeling, or preferences that some people may have. Please indicate the extent to which you agree with each statement with regard to yourself. Please answer honestly, as there are no right or wrong answers.

1. I like to park my car or bike always in the same place.				
☐ strongly disagree	☐ mildly disagree	☐ undecided	☐ mildly agree	☐ strongly agree
2. I generally cook with the same spices/flavourings.				
☐ strongly disagree	☐ mildly disagree	☐ undecided	☐ mildly agree	☐ strongly agree
3. When walking past a plate of sweets or biscuits, I can't resist taking one.				
☐ strongly disagree	☐ mildly disagree	☐ undecided	☐ mildly agree	☐ strongly agree
4. I tend to go to bed at roughly the same time every night.				
☐ strongly disagree	☐ mildly disagree	☐ undecided	☐ mildly agree	☐ strongly agree
5. I often take a snack while on the go (e.g. when driving, walking down the street, or surfing the web).				
☐ strongly disagree	☐ mildly disagree	☐ undecided	☐ mildly agree	☐ strongly agree
6. I quite happily work within my comfort zone rather than challenging myself, if I don't have to.				
☐ strongly disagree	☐ mildly disagree	☐ undecided	☐ mildly agree	☐ strongly agree
7. I tend to do things in the same order every morning (e.g. get up, go to the toilet, have a coffee...).				
☐ strongly disagree	☐ mildly disagree	☐ undecided	☐ mildly agree	☐ strongly agree
8. Eating crisps or biscuits straight out of the packet is typical of me.				
☐ strongly disagree	☐ mildly disagree	☐ undecided	☐ mildly agree	☐ strongly agree
9. Whenever I go into the kitchen, I typically look in the fridge.				
☐ strongly disagree	☐ mildly disagree	☐ undecided	☐ mildly agree	☐ strongly agree
10. I always try to get the same seat in places such as on the bus, in the cinema, or in church.				
☐ strongly disagree	☐ mildly disagree	☐ undecided	☐ mildly agree	☐ strongly agree
11. I often find myself finishing off a packet of biscuits just because it is lying there.				
☐ strongly disagree	☐ mildly disagree	☐ undecided	☐ mildly agree	☐ strongly agree
12. I normally buy the same foods from the same grocery store.				
☐ strongly disagree	☐ mildly disagree	☐ undecided	☐ mildly agree	☐ strongly agree
13. I rely on what is tried and tested rather than exploring something new.				
☐ strongly disagree	☐ mildly disagree	☐ undecided	☐ mildly agree	☐ strongly agree
14. I generally eat the same things for breakfast every day.				
☐ strongly disagree	☐ mildly disagree	☐ undecided	☐ mildly agree	☐ strongly agree
15. I tend to like routine.				
☐ strongly disagree	☐ mildly disagree	☐ undecided	☐ mildly agree	☐ strongly agree

16. I usually treat myself to a snack at the end of the workday.				
☐ strongly disagree	☐ mildly disagree	☐ undecided	☐ mildly agree	☐ strongly agree
17. In a restaurant, I tend to order dishes that I am familiar with.				
☐ strongly disagree	☐ mildly disagree	☐ undecided	☐ mildly agree	☐ strongly agree
18. I am one of those people who get really annoyed by last minute cancellations.				
☐ strongly disagree	☐ mildly disagree	☐ undecided	☐ mildly agree	☐ strongly agree
19. I often find myself eating without being aware of it.				
☐ strongly disagree	☐ mildly disagree	☐ undecided	☐ mildly agree	☐ strongly agree
20. I usually sit at the same place at the dinner table.				
☐ strongly disagree	☐ mildly disagree	☐ undecided	☐ mildly agree	☐ strongly agree
21. I often find myself running on 'autopilot', and then wonder why I ended up in a particular place or doing something that I did not intend to do.				
☐ strongly disagree	☐ mildly disagree	☐ undecided	☐ mildly agree	☐ strongly agree
22. I always follow a certain order when preparing a meal.				
☐ strongly disagree	☐ mildly disagree	☐ undecided	☐ mildly agree	☐ strongly agree
23. Television makes me particularly prone to uncontrolled eating.				
☐ strongly disagree	☐ mildly disagree	☐ undecided	☐ mildly agree	☐ strongly agree
24. I tend to stick with the version of the software package that I am familiar with for as long as I can.				
☐ strongly disagree	☐ mildly disagree	☐ undecided	☐ mildly agree	☐ strongly agree
25. I often find myself opening up the cabinet to take a snack.				
☐ strongly disagree	☐ mildly disagree	☐ undecided	☐ mildly agree	☐ strongly agree
26. I am prone to eating more when I feel stressed.				
☐ strongly disagree	☐ mildly disagree	☐ undecided	☐ mildly agree	☐ strongly agree
27. I find comfort in regularity.				
☐ strongly disagree	☐ mildly disagree	☐ undecided	☐ mildly agree	☐ strongly agree

Creature of Habit Scale – German

Die „Gewohnheitstier“ Skala

Hier sind einige Aussagen im Zusammenhang mit Verhalten, Gefühlen, oder Vorlieben, die manche Menschen haben können.

Bitte geben Sie an, in welchem Ausmaß die Aussagen auf Sie zutreffen. Bitte antworten Sie ehrlich, da es keine richtigen oder falschen Antworten gibt.

1. Ich stelle mein Auto oder Fahrrad gerne immer an derselben Stelle ab.				
☐ lehne ich stark ab	☐ lehne ich eher ab	☐ unentschieden	☐ stimme ich eher zu	☐ stimme ich stark zu
2. Im Allgemeinen koche ich mit denselben Gewürzen/Aromen.				
☐ lehne ich stark ab	☐ lehne ich eher ab	☐ unentschieden	☐ stimme ich eher zu	☐ stimme ich stark zu
3. Wenn ich an einem Teller mit Süßigkeiten oder Keksen vorbeilaufe, kann ich nicht widerstehen etwas zu nehmen.				
☐ lehne ich stark ab	☐ lehne ich eher ab	☐ unentschieden	☐ stimme ich eher zu	☐ stimme ich stark zu
4. Ich neige dazu, jeden Abend ungefähr um dieselbe Uhrzeit ins Bett zu gehen.				
☐ lehne ich stark ab	☐ lehne ich eher ab	☐ unentschieden	☐ stimme ich eher zu	☐ stimme ich stark zu
5. Ich esse oft eine Kleinigkeit, während ich unterwegs bin (z.B. während ich Auto fahre, auf der Straße laufe, oder im Internet surfe).				
☐ lehne ich stark ab	☐ lehne ich eher ab	☐ unentschieden	☐ stimme ich eher zu	☐ stimme ich stark zu
6. Ich arbeite lieber innerhalb meiner Komfortzone, als dass ich mich einer Herausforderung stelle, wenn ich nicht muss.				
☐ lehne ich stark ab	☐ lehne ich eher ab	☐ unentschieden	☐ stimme ich eher zu	☐ stimme ich stark zu
7. Ich neige dazu, jeden Morgen die Dinge in der gleichen Reihenfolge zu tun (z.B. aufstehen, zur Toilette gehen, Kaffee trinken...).				
☐ lehne ich stark ab	☐ lehne ich eher ab	☐ unentschieden	☐ stimme ich eher zu	☐ stimme ich stark zu
8. Chips oder Kekse direkt aus der Packung zu essen, ist typisch für mich.				
☐ lehne ich stark ab	☐ lehne ich eher ab	☐ unentschieden	☐ stimme ich eher zu	☐ stimme ich stark zu
9. Wenn ich in die Küche gehe, schaue ich normalerweise erst einmal in den Kühlschrank.				
☐ lehne ich stark ab	☐ lehne ich eher ab	☐ unentschieden	☐ stimme ich eher zu	☐ stimme ich stark zu
10. Ich versuche an Orten, wie dem Bus, dem Kino oder der Kirche, immer den gleichen Platz zu bekommen.				
☐ lehne ich stark ab	☐ lehne ich eher ab	☐ unentschieden	☐ stimme ich eher zu	☐ stimme ich stark zu
11. Ich ertappe mich oft dabei, wie ich eine Packung Kekse leer esse, nur weil sie da liegt.				
☐ lehne ich stark ab	☐ lehne ich eher ab	☐ unentschieden	☐ stimme ich eher zu	☐ stimme ich stark zu
12. Ich kaufe normalerweise die gleichen Lebensmittel in dem gleichen Laden.				
☐ lehne ich stark ab	☐ lehne ich eher ab	☐ unentschieden	☐ stimme ich eher zu	☐ stimme ich stark zu
13. Ich verlasse mich eher auf das, was erprobt und bewährt ist, als etwas Neues auszuprobieren.				
☐ lehne ich stark ab	☐ lehne ich eher ab	☐ unentschieden	☐ stimme ich eher zu	☐ stimme ich stark zu
14. Im Allgemeinen esse ich jeden Tag dieselben Dinge zum Frühstück.				
☐ lehne ich stark ab	☐ lehne ich eher ab	☐ unentschieden	☐ stimme ich eher zu	☐ stimme ich stark zu

15. Ich neige dazu, Routinen zu mögen.				
☐ lehne ich stark ab	☐ lehne ich eher ab	☐ unentschieden	☐ stimme ich eher zu	☐ stimme ich stark zu
16. Am Ende eines Arbeitstages gönne ich mir üblicherweise etwas zu Naschen.				
☐ lehne ich stark ab	☐ lehne ich eher ab	☐ unentschieden	☐ stimme ich eher zu	☐ stimme ich stark zu
17. Ich neige dazu, in einem Restaurant Gerichte zu bestellen, die ich schon kenne.				
☐ lehne ich stark ab	☐ lehne ich eher ab	☐ unentschieden	☐ stimme ich eher zu	☐ stimme ich stark zu
18. Ich gehöre zu den Menschen, die von Absagen in letzter Minute richtig genervt sind.				
☐ lehne ich stark ab	☐ lehne ich eher ab	☐ unentschieden	☐ stimme ich eher zu	☐ stimme ich stark zu
19. Ich ertappe mich oft beim Essen, ohne mir dessen bewusst zu sein.				
☐ lehne ich stark ab	☐ lehne ich eher ab	☐ unentschieden	☐ stimme ich eher zu	☐ stimme ich stark zu
20. Am Esstisch sitze ich normalerweise immer am gleichen Platz.				
☐ lehne ich stark ab	☐ lehne ich eher ab	☐ unentschieden	☐ stimme ich eher zu	☐ stimme ich stark zu
21. Ich merke oft, dass ich wie auf Autopilot laufe und wundere mich dann, warum ich an einem bestimmten Ort gelandet bin oder etwas tue, das ich nicht beabsichtigt hatte.				
☐ lehne ich stark ab	☐ lehne ich eher ab	☐ unentschieden	☐ stimme ich eher zu	☐ stimme ich stark zu
22. Ich folge immer dem gleichen Ablauf, wenn ich eine Mahlzeit vorbereite.				
☐ lehne ich stark ab	☐ lehne ich eher ab	☐ unentschieden	☐ stimme ich eher zu	☐ stimme ich stark zu
23. Fernsehen macht mich besonders anfällig für unkontrolliertes Essen.				
☐ lehne ich stark ab	☐ lehne ich eher ab	☐ unentschieden	☐ stimme ich eher zu	☐ stimme ich stark zu
24. Ich bevorzuge es, so lange wie möglich bei der gleichen Version eines Software-Pakets zu bleiben, mit der ich schon vertraut bin.				
☐ lehne ich stark ab	☐ lehne ich eher ab	☐ unentschieden	☐ stimme ich eher zu	☐ stimme ich stark zu
25. Ich ertappe mich häufig dabei, wie ich die Schranktür öffne, um mir etwas zum Naschen zu nehmen.				
☐ lehne ich stark ab	☐ lehne ich eher ab	☐ unentschieden	☐ stimme ich eher zu	☐ stimme ich stark zu
26. Ich bin anfällig dafür, mehr zu essen, wenn ich gestresst bin.				
☐ lehne ich stark ab	☐ lehne ich eher ab	☐ unentschieden	☐ stimme ich eher zu	☐ stimme ich stark zu
27. Ich fühle mich wohl, wenn alles regelmäßig abläuft.				
☐ lehne ich stark ab	☐ lehne ich eher ab	☐ unentschieden	☐ stimme ich eher zu	☐ stimme ich stark zu

II. Exploratory Factor Analysis for samples 1 and 2, with alternative factor solutions

All analyses were carried out with R (R Core Team, 2018), using the package psych, corpcor, GPArotation, nFactors, RGenData, FactoMineR, MASS, msm, and psychometric (Bernaards & Jennrich, 2005; Fletcher, 2010; Lê, Josse, & Husson, 2008; Raiche, 2010; Revelle, 2018; Ripley et al., 2013; Schafer et al., 2017) as well as a KMO function (Trujillo-Ortiz, Hernandez-Walls, Castro-Perez, Barba-Rojo, & Otero-Limon, 2006).

Assumptions. The Kaiser-Meyer-Olkin measure (KMO) verified the sampling adequacy which is classified as 'great' according to Kaiser (1974): KMO = .82 in sample 1 and KMO = .87 in sample 2. All KMO values for individual items were > .64 in sample 1 and >.75 in sample 2, which is above the acceptable limit of .60. Bartlett's test of sphericity (sample 1: $X^2(351) = 2237, p < .001$; sample 2: $X^2(351) = 4554, p < .001$) indicated that correlations between items were sufficiently large for factor analysis.

Table 1

Oblimin rotated standardized loadings (pattern matrix) of four-factor solution based upon polychoric correlation matrix for sample 1.

	COHS 1	COHS 2	COHS 3	COHS 4
Item 01	-0.05	0.48	0.06	0.20
Item 02	0.04	0.20	0.29	-0.07
Item 04	0.04	0.65	-0.12	0.01
Item 06	0.09	0.09	0.44	0.17
Item 07	0.04	0.84	-0.11	-0.02
Item 10	0.08	0.37	0.17	0.27
Item 12	-0.06	0.52	0.23	-0.04
Item 13	-0.04	0.04	0.83	-0.04
Item 14	0.09	0.46	0.23	-0.22
Item 15	0.03	0.70	0.27	-0.05
Item 17	0.01	0.05	0.56	0.05
Item 18	0.05	0.11	0.26	0.03
Item 20	0.11	0.32	0.29	-0.10
Item 22	-0.07	0.57	0.16	0.38
Item 24	0.11	-0.01	0.37	0.03
Item 27	0.03	0.43	0.40	0.07
Item 03	0.86	0.06	-0.12	-0.09
Item 05	0.46	-0.05	0.03	0.16
Item 08	0.43	-0.14	0.24	-0.18
Item 09	0.19	0.06	-0.06	0.47
Item 11	0.78	0.04	-0.03	0.02
Item 16	0.73	0.13	-0.03	-0.06
Item 19	0.40	-0.10	0.01	0.60
Item 21	-0.01	0.20	-0.06	0.62
Item 23	0.43	-0.08	0.08	0.33
Item 25	0.78	-0.04	0.11	0.15
Item 26	0.56	-0.14	0.19	0.19

Note. COHS 1 - 4 = Creature of Habit Scale (Ersche, Lim, Ward, Robbins, & Stochl, 2017) factors.

Table 2

Oblimin rotated standardized loadings (pattern matrix) of three-factor solution based upon polychoric correlation matrix for sample 2.

	COHS 1	COHS 2	COHS 3
Item 01	0.57	-0.01	0.01
Item 02	0.57	0.10	-0.09
Item 04	0.49	-0.01	-0.11
Item 06	0.39	0.10	0.07
Item 07	0.63	0.02	-0.18
Item 10	0.43	-0.04	0.36
Item 12	0.65	0.07	0.09
Item 13	0.59	0.07	0.09
Item 14	0.51	0.03	-0.04
Item 15	0.82	-0.03	-0.01
Item 17	0.52	0.15	-0.01
Item 18	0.34	0.10	-0.01
Item 20	0.50	-0.02	-0.01
Item 22	0.58	-0.15	0.25
Item 24	0.31	0.17	0.01
Item 27	0.69	0.01	0.05
Item 03	0.03	0.79	-0.19
Item 05	-0.08	0.50	0.15
Item 08	0.05	0.45	-0.04
Item 09	0.03	0.30	0.39
Item 11	0.02	0.62	0.20
Item 16	0.16	0.61	0.01
Item 19	-0.10	0.33	0.59
Item 21	0.14	-0.05	0.55
Item 23	0.05	0.18	0.54
Item 25	-0.02	0.74	0.20
Item 26	0.03	0.36	0.25

Note. COHS 1 - 3 = Creature of Habit Scale (Ersche et al., 2017) factors.

III. Confirmatory Factor Analysis without Bayesian Lasso for samples 1 and 2

All analyses were carried out with R (R Core Team, 2018), using the package lavaan (Rosseel, 2012).

Table 3

Standardized factor loadings (λ) for sample 1 based on polychoric correlations and estimated using diagonally weighted least squares; CI = confidence interval; SE = standard error; the items with asterisks were fixed to identify the scale of the latent factor; all loadings were significant.

	Item	λ	CI		SE	
COHS routine	1	0.56*	0.47	-	0.66	0.05
	2	0.43	0.33	-	0.54	0.06
	4	0.50	0.40	-	0.61	0.05
	6	0.52	0.42	-	0.62	0.05
	7	0.65	0.57	-	0.73	0.04
	10	0.60	0.49	-	0.70	0.05
	12	0.62	0.53	-	0.71	0.05
	13	0.65	0.57	-	0.73	0.04
	14	0.54	0.44	-	0.64	0.05
	15	0.82	0.77	-	0.88	0.03
	17	0.50	0.40	-	0.60	0.05
	18	0.34	0.21	-	0.47	0.07
	20	0.54	0.44	-	0.64	0.05
	22	0.72	0.64	-	0.79	0.04
	24	0.34	0.23	-	0.46	0.06
	27	0.74	0.66	-	0.81	0.04
COHS automaticity	3	0.74*	0.68	-	0.81	0.03
	5	0.56	0.46	-	0.66	0.05
	8	0.37	0.25	-	0.49	0.06
	9	0.52	0.41	-	0.62	0.05
	11	0.78	0.71	-	0.85	0.04
	16	0.67	0.58	-	0.75	0.04
	19	0.73	0.66	-	0.81	0.04
	21	0.44	0.33	-	0.56	0.06
	23	0.64	0.55	-	0.73	0.05
	25	0.88	0.83	-	0.93	0.03
	26	0.69	0.62	-	0.76	0.04

Note. COHS = Creature of Habit Scale (Ersche et al., 2017)

Table 4

Standardized factor loadings (λ) for sample 2 based on polychoric correlations and estimated using diagonally weighted least squares; CI = confidence interval; SE = standard error; the items with asterisks were fixed to identify the scale of the latent factor; all loadings were significant.

	Item	λ	CI		SE
COHS routine	1	0.56*	0.49 - 0.63		0.04
	2	0.60	0.53 - 0.66		0.03
	4	0.44	0.37 - 0.52		0.04
	6	0.44	0.37 - 0.52		0.04
	7	0.58	0.51 - 0.65		0.03
	10	0.52	0.45 - 0.60		0.04
	12	0.65	0.59 - 0.71		0.03
	13	0.65	0.59 - 0.71		0.03
	14	0.50	0.43 - 0.57		0.04
	15	0.80	0.76 - 0.84		0.02
	17	0.58	0.51 - 0.64		0.03
	18	0.35	0.27 - 0.44		0.04
	20	0.48	0.40 - 0.56		0.04
	22	0.58	0.52 - 0.65		0.04
	24	0.39	0.30 - 0.47		0.04
	27	0.70	0.65 - 0.76		0.03
COHS automaticity	3	0.61*	0.55 - 0.68		0.03
	5	0.53	0.46 - 0.61		0.04
	8	0.43	0.35 - 0.51		0.04
	9	0.57	0.50 - 0.64		0.04
	11	0.74	0.69 - 0.79		0.03
	16	0.64	0.58 - 0.71		0.03
	19	0.68	0.62 - 0.74		0.03
	21	0.42	0.34 - 0.51		0.04
	23	0.59	0.52 - 0.66		0.04
	25	0.83	0.79 - 0.87		0.02
	26	0.54	0.47 - 0.62		0.04

Note. COHS = Creature of Habit Scale (Ersche et al., 2017)

Table 5

Covariance (cov) between the two factors COHS routine and automaticity of CFA in sample 1 and 2.

	cov	<i>p</i>	CI	SE
Sample 1	0.10	0.000	0.05 – 0.16	0.03
Sample 2	0.10	0.000	0.07 – 0.14	0.02

Note. COHS = Creature of Habit Scale (Ersche et al., 2017)

Table 6

Additional model parameters and fit indices of CFA in sample 1 and 2.

	RMSEA	SRMR	CFI	$\chi^2_{robust} (df)$	p_{boot}	χ^2_{robust} / df
Sample 1	0.066 [CI 0.059 – 0.074]	0.083	0.962	622.43 (323)	0.02	1.93
Sample 2	0.062 [CI 0.057 – 0.066]	0.069	0.957	830.29 (323)	0.02	2.57

Note. CFA = Confirmatory factor analysis; RMSEA = Root Mean Square Error of Approximation; CI = Confidence Interval; TLI = Tucker-Lewis Index; SRMR = Standardized Root Mean Square Residual; p_{boot} = bootstrapped p-value of χ^2 Test; *df* = degrees of freedom.

Table 7

Standardized residual covariance matrix sample 1.

Item	1	2	4	6	7	10	12	13	14	15	17	18	20	22	24	27	3	5	8	9	11	16	19	21	23	25	26
1	0.000																										
2	0.109	0.000																									
4	0.041	-0.002	0.000																								
6	-0.102	0.046	-0.073	0.000																							
7	0.002	-0.059	0.193	-0.063	0.000																						
10	0.187	-0.091	-0.028	-0.001	-0.040	0.000																					
12	0.058	0.138	0.102	-0.170	0.005	-0.070	0.000																				
13	-0.153	0.015	-0.144	0.153	-0.152	-0.076	0.040	0.000																			
14	-0.162	0.030	0.042	-0.149	0.074	-0.156	0.116	0.032	0.000																		
15	-0.006	-0.092	0.034	-0.068	0.099	-0.065	0.021	-0.017	0.096	0.000																	
17	-0.101	0.033	-0.156	-0.024	-0.120	-0.053	-0.005	0.193	0.067	-0.041	0.000																
18	-0.017	-0.008	0.000	0.035	-0.025	-0.078	-0.078	0.039	-0.096	-0.053	0.097	0.000															
20	0.169	0.044	-0.033	-0.061	-0.053	0.077	-0.002	-0.005	-0.031	-0.047	0.000	0.076	0.000														
22	-0.029	-0.052	-0.024	-0.033	0.066	0.000	0.032	-0.088	-0.024	-0.033	-0.023	-0.004	-0.102	0.000													
24	-0.059	-0.009	-0.035	-0.062	-0.164	0.104	-0.108	0.096	0.031	-0.121	0.033	0.018	0.014	0.016	0.000												
27	-0.092	-0.056	-0.020	0.036	-0.030	-0.088	-0.063	0.015	-0.043	0.045	-0.062	0.010	0.010	0.048	0.046	0.000											
3	-0.077	-0.014	-0.034	0.054	-0.051	0.017	-0.098	-0.125	-0.049	-0.093	-0.014	-0.044	-0.023	-0.044	0.053	-0.011	0.000										
5	-0.017	0.004	-0.007	0.211	-0.067	0.057	-0.145	-0.018	-0.158	-0.078	-0.042	-0.026	-0.054	-0.005	0.017	-0.021	0.009	0.000									
8	-0.046	0.100	-0.103	0.147	-0.113	0.007	-0.098	0.048	0.056	0.023	0.122	0.080	0.137	-0.124	0.093	-0.009	-0.002	0.105	0.000								
9	0.097	0.092	-0.129	0.189	-0.047	0.293	-0.064	-0.062	-0.124	-0.086	0.112	0.061	0.042	0.094	-0.003	-0.001	-0.122	0.107	0.097	0.000							
11	0.036	-0.025	-0.048	0.116	-0.093	0.126	-0.044	-0.071	-0.073	-0.083	-0.061	0.051	0.080	-0.006	0.016	-0.051	0.098	0.017	0.104	-0.120	0.000						
16	-0.137	-0.064	0.025	0.061	0.086	0.147	-0.135	-0.016	0.060	0.033	0.097	0.133	-0.009	0.046	0.059	0.024	0.070	-0.016	-0.044	-0.108	0.008	0.000					
19	-0.038	-0.122	-0.024	0.156	-0.136	0.128	-0.166	-0.055	-0.168	-0.135	0.073	0.073	-0.135	0.118	0.101	-0.052	-0.025	-0.035	-0.155	0.097	-0.078	-0.049	0.000				
21	0.155	-0.025	0.089	0.142	0.097	0.179	0.067	0.053	0.042	0.094	0.109	-0.017	0.037	0.319	-0.016	0.063	-0.166	0.049	-0.138	0.129	-0.036	-0.151	0.174	0.000			
23	0.025	-0.013	-0.123	0.083	-0.161	0.106	-0.091	-0.024	-0.050	-0.038	-0.088	-0.016	-0.048	0.113	0.030	0.063	-0.119	-0.022	-0.014	0.025	-0.029	-0.016	0.072	-0.009	0.000		
25	-0.022	-0.035	-0.063	0.132	-0.077	0.130	-0.105	-0.004	-0.064	-0.088	0.037	0.041	0.043	0.040	0.169	0.087	0.008	-0.010	-0.044	-0.016	-0.046	0.042	-0.012	-0.114	0.027	0.000	
26	0.062	0.040	-0.059	0.127	-0.110	0.117	-0.135	0.060	-0.137	-0.098	0.083	0.043	-0.034	0.049	0.118	0.051	0.006	-0.033	-0.074	-0.074	-0.005	-0.056	0.072	-0.166	0.068	0.020	0.000

Table 8

Polychoric correlation matrix sample 1.

Item	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
1	1																										
2	0.35	1																									
3	0.02	0.06	1																								
4	0.32	0.22	0.06	1																							
5	0.06	0.06	0.42	0.06	1																						
6	0.19	0.27	0.15	0.19	0.28	1																					
7	0.36	0.22	0.07	0.52	0.02	0.27	1																				
8	0.00	0.14	0.27	-0.06	0.31	0.20	-0.05	1																			
9	0.17	0.15	0.26	-0.07	0.39	0.25	0.03	0.29	1																		
10	0.52	0.17	0.13	0.27	0.14	0.31	0.35	0.06	0.37	1																	
11	0.14	0.06	0.68	0.05	0.45	0.22	0.03	0.39	0.28	0.24	1																
12	0.40	0.40	0.01	0.41	-0.06	0.15	0.40	-0.04	0.01	0.30	0.07	1															
13	0.21	0.30	-0.01	0.18	0.07	0.49	0.27	0.11	0.02	0.31	0.05	0.44	1														
14	0.14	0.26	0.05	0.31	-0.08	0.13	0.42	0.10	-0.06	0.17	0.03	0.45	0.38	1													
15	0.46	0.26	0.06	0.45	0.03	0.36	0.63	0.10	0.02	0.43	0.07	0.53	0.52	0.54	1												
16	-0.05	0.01	0.56	0.11	0.35	0.15	0.19	0.20	0.24	0.24	0.53	-0.03	0.09	0.15	0.17	1											
17	0.18	0.25	0.08	0.10	0.03	0.24	0.20	0.17	0.17	0.24	0.03	0.30	0.52	0.34	0.37	0.18	1										
18	0.17	0.14	0.02	0.17	0.02	0.21	0.19	0.11	0.10	0.12	0.12	0.13	0.26	0.09	0.23	0.19	0.27	1									
19	0.06	-0.04	0.52	0.07	0.37	0.25	-0.02	0.12	0.47	0.24	0.49	-0.06	0.06	-0.07	0.01	0.44	0.16	0.13	1								
20	0.47	0.28	0.07	0.24	0.02	0.22	0.29	0.19	0.11	0.40	0.18	0.33	0.34	0.26	0.40	0.08	0.27	0.26	-0.04	1							
21	0.22	0.02	0.16	0.14	0.30	0.20	0.17	0.03	0.36	0.24	0.31	0.13	0.12	0.10	0.18	0.14	0.16	0.02	0.50	0.10	1						
22	0.37	0.26	0.09	0.34	0.09	0.34	0.53	-0.06	0.18	0.43	0.13	0.47	0.38	0.36	0.56	0.16	0.33	0.24	0.25	0.28	0.40	1					
23	0.11	0.05	0.36	-0.04	0.33	0.16	-0.06	0.22	0.35	0.20	0.47	0.01	0.08	0.03	0.09	0.41	-0.01	0.04	0.54	0.04	0.27	0.23	1				
24	0.13	0.14	0.12	0.14	0.06	0.12	0.06	0.12	0.04	0.31	0.08	0.10	0.32	0.22	0.16	0.12	0.20	0.13	0.16	0.20	0.02	0.26	0.08	1			
25	0.10	0.06	0.66	0.05	0.48	0.24	0.06	0.28	0.44	0.26	0.64	0.03	0.14	0.05	0.09	0.63	0.15	0.11	0.63	0.16	0.28	0.20	0.59	0.24	1		
26	0.16	0.11	0.52	0.03	0.35	0.22	0.00	0.18	0.28	0.22	0.53	-0.03	0.17	-0.05	0.04	0.40	0.17	0.10	0.58	0.06	0.14	0.17	0.51	0.18	0.63	1	
27	0.32	0.26	0.02	0.35	0.08	0.42	0.44	0.06	0.09	0.35	0.09	0.39	0.49	0.35	0.65	0.14	0.30	0.26	0.08	0.40	0.14	0.58	0.18	0.30	0.25	0.18	1

IV. Network Analysis

The Analyses were done using a Gaussian Graphical Model with graphical lasso and extended Bayesian information criterion in sample 1. All analyses were carried out with R (R Core Team, 2018), using the packages qgraph and bootnet (Epskamp, Borsboom, & Fried, 2018; Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012).

Figure 1. The z-standardized centrality coefficient estimates. Self-regulation = Self-regulation scale sum score, Routine = Creature of Habit Scale (Ersche et al., 2017) routine subscale sum score, Compulsivity = Obsessive-Compulsive Inventory (Gönner, Leonhart, & Ecker, 2007) sum score, Impulsivity = Barratt Impulsiveness Scale (Patton, Stanford, & Barratt, 1995) sum score, Automaticity = Creature of Habit Scale (Ersche et al., 2017) automaticity subscale sum score.

Table 9

Raw scores of centrality indices of the GGM in sample 1.

	Routine	Automaticity	Compulsivity	Impulsivity	Self-regulation
Node strength	0.683	0.569	0.575	0.719	0.891
Closeness	0.049	0.043	0.042	0.052	0.060
Betweenness	0	0	0	2	4
Expected Influence	0.058	-0.001	0.176	-0.719	-0.891

Note. Self-regulation = Self-regulation scale (Diehl, Semegon, & Schwarzer, 2006) sum score, Routine = Creature of Habit Scale (Ersche et al., 2017) routine subscale sum score, Compulsivity = Obsessive-Compulsive Inventory (Gönner et al., 2007) sum score, Impulsivity = Barratt Impulsiveness Scale (Patton et al., 1995) sum score, Automaticity = Creature of Habit Scale (Ersche et al., 2017) automaticity subscale sum score.

Figure 2. Bootstrapped confidence intervals of estimated edge-weights for the estimated network. The red line indicates the sample values and the gray area the bootstrapped confidence intervals. Each dot represents one edge of the network, ordered from the edge with the highest edge-weight to the edge with the lowest edge-weight. Self-regulation = Self-regulation scale (Diehl et al., 2006) sum score, Routine = Creature of Habit Scale (Ersche et al., 2017) routine subscale sum score, Compulsivity = Obsessive-Compulsive Inventory (Gönner et al., 2007) sum score, Impulsivity = Barratt Impulsiveness Scale (Patton et al., 1995) sum score, Automaticity = Creature of Habit Scale (Ersche et al., 2017) automaticity subscale sum score.

Figure 3. The average correlations between centrality indices of bootstrapped networks (sampled with cases dropped) and the original sample. Lines = means of estimated network centrality indices, areas = range from 2.5th quantile to the 97.5th quantile.

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