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# Self-regulation is negatively associated with habit tendencies: A validation of the German Creature of Habit Scale

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ABSTRACT

Adaptive behavior depends on the process of self-regulation. If self-regulation fails, maladaptive behavior may start to predominate, leading to impulsive actions, maladaptive habits, and compulsive behavior patterns. The tendency to develop habitual behavior differs 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). Data of two independent community samples was collected online. Dynamic connections with measures of regulatory control, namely self-regulation, impulsivity, and compulsivity, were analyzed using a network approach. Psychometric analyses were conducted using exploratory and confirmatory factor analyses utilizing a Bayesian lasso procedure. 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. We replicated and validated the two-factorial structure of the COHS. Our findings provide evidence that habitual propensity is interconnected with measures of regulatory control. Information gathered using the COHS could be useful in identifying vulnerabilities and developing tailored therapeutic strategies for psychopathologies associated with deficient regulatory control.

## 1. 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). Therefore, repeated goal-pursuit in stable contexts leads to habit formation (Ouellette & Wood, 1998). Hence, it is important to distinguish between

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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, & Rünger, 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 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, 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 present study had two aims: First, examine associations of self-regulation, impulsivity, and compulsivity with habitual propensity. As outlined above, we expected that self-regulation should be negatively associated with habitual propensity, but also impulsivity and compulsivity. We also expected that it should influence the connection between habitual propensity and impulsivity as well as compulsivity. Second, to assess habitual propensity, we furthermore aimed 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.

## 2. Methods

### 2.1. Study design and sample

#### 2.1.1. 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.

#### 2.1.2. 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 ± 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 ± 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 Technische Universität Dresden approved both study procedures (EK 310082018 and EK 135042018).

### 2.2. 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 German version of 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 German version of the Barratt Impulsiveness Scale-11 (BIS) consists of 30 items and is an instrument assessing *impulsivity as a personality trait* (Patton, Stanford, & Barratt, 1995; Preuss et al., 2003). 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 German version of 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 $\alpha$ between 0.73 and 0.82 (Diehl, Semegon, & Schwarzer, 2006; Luszczynska, Diehl, Gutiérrez-Dona, Kuusinen, & Schwarzer, 2004).

### 2.3. 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).

## 3. Results

### 3.1. 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*: $\phi = 0.18$ [CI 0.06–0.29]; *sample 2*: $\phi = 0.074$ [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).

### 3.2. 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 = .53; *sample 2*: PP p = .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 Fig. 1 for a path diagram of the COHS structure. All factor-loading estimates were significant and appeared to be satisfactory in

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

| | Sample 1 | | Sample 2 | |
|---|---|---|---|---|
| | COHS routine | COHS automaticity | COHS routine | COHS automaticity |
| 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 et al., 2017) routine and automaticity subscales.

magnitude. As expected, the factors were positively correlated to a small extent (*sample 1*: $\phi = 0.069$ [HPD 0.016–0.137]; *sample 2*: $\phi = 0.074$ [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).

### 3.3. 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]).

### 3.4. 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). Fig. 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-

**Table 2**
Parameter estimates of Bayesian Lasso confirmatory factor analysis for samples 1 and 2.

| | Item | Parameter estimates for sample 1. | | | Parameter estimates for sample 2. | | |
|---|---|---|---|---|---|---|---|
| | | λ | HPD | SE | λ | HPD | SE |
| COHS routine | 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 |
| | 27 | 0.87 | 0.68–1.00 | 0.10 | 0.76 | 0.58–0.93 | 0.09 |
| COHS automaticity | 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).

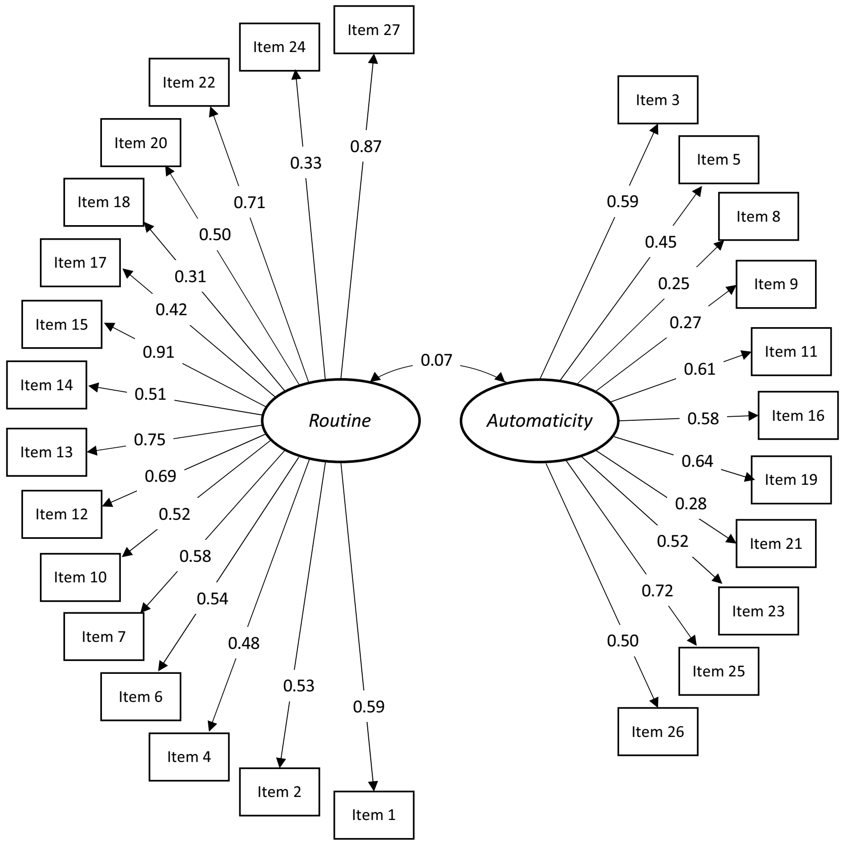


**Fig. 1.** Path diagram of the Creature of Habit Scale (Ersche et al., 2017) Bayesian lasso confirmatory factor analysis results in sample 1, including all items with their respective standardized factor loadings on the subscales as well as the weak correlation between the two subscales.

regulation and impulsivity (*pr* = −0.41). 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 (*pr* = 0.23 and *pr* = 0.14, respectively), as well as to each other (*pr* = 0.14). The connection between automaticity and self-regulation was negative (*pr* = −0.29), as was the connection between routine and impulsivity (*pr* = −0.31). The connection between self-regulation and compulsivity was negative (*pr* = −0.20). See Fig. 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 Fig. 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(*cor* = 0.7) = 0) and closeness (CS(*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(*cor* = 0.7) = 0.283; CS(*cor* = 0.7) = 0.363).

## 4. Discussion

The present study investigated the dynamic associations of self-regulation, impulsivity, compulsivity and habitual propensity. As expected, self-regulation was found to be negatively associated with all other measures of regulatory control. An exception was COHS *routine*, which was connected to self-regulation via impulsivity. COHS *routine* was negatively correlated with impulsivity. Both subscales of the COHS

**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 routine | | COHS automaticity | | Compulsivity | | Impulsivity | | Self-regulation | |
|---|---|---|---|---|---|---|---|---|---|---|
| | tau | p | tau | p | tau | p | tau | p | tau | p |
| COHS routine | 1 | – | | | | | | | | |
| COHS automaticity | 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 et al., 1995) sum score; Self-regulation = sum score Self-Regulation Scale (Diehl et al., 2006).

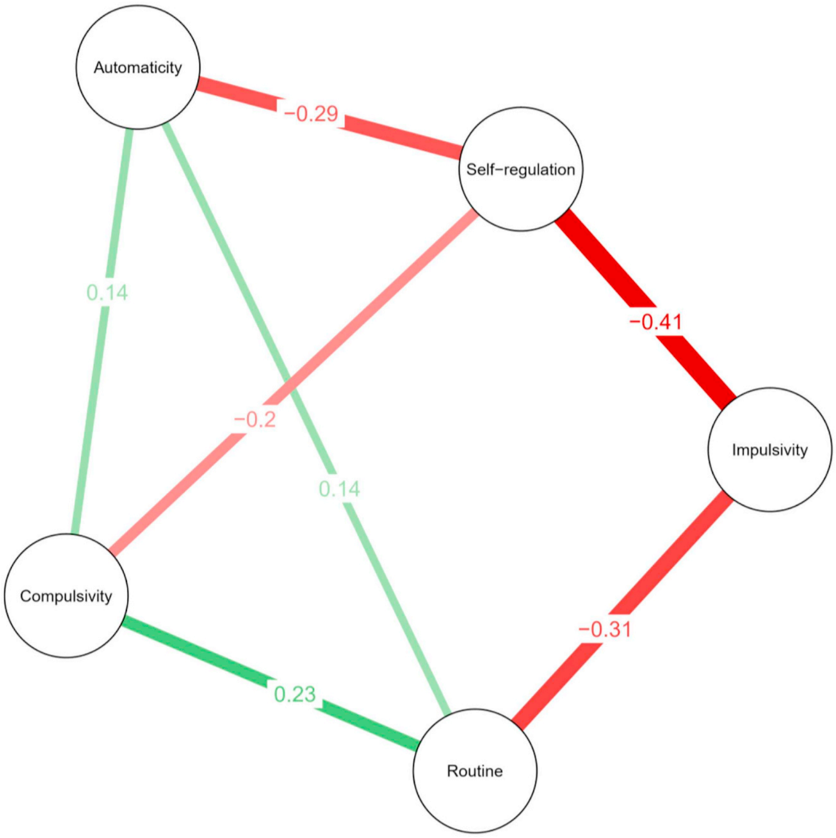


**Fig. 2.** Between-subject graphical lasso network with tuning parameter selected using the extended Bayesian information criterion. Nodes represent the traits impulsivity, compulsivity, self-regulatory capacity as well as tendency for routine and automatic behavior. Edges (connections) can be interpreted as partial correlation coefficients. Red (dashed) lines represent negative edges, green (solid) lines positive edges. Self-regulation = Self-regulation scale (Schwarzer et al., 1999) 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 (Preuss et al., 2003) 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. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

were positively associated with compulsivity. Self-regulation was shown to be the most central node within the network, therefore providing evidence of influence on the connection between all other measures. We also examined the psychometric properties of a German version of the COHS in two independent samples. 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. 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.

### 4.1. 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 the 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 et al., 2016; Gillan & Robbins, 2014). 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 Self-Report Habit Index (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.

### 4.2. 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 influence of extrinsic and not just intrinsic aspects of self-regulation as well as motivational aspects, as described by the self-determination theory (Deci & Ryan, 2008). Additionally, the connection of routine and automaticity to the different components of self-regulation could be of relevance. 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.

### 4.3. 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 heterogenic 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, 2019).

## 5. 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 with 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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## 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.

## CRediT authorship contribution statement

**Rebecca Overmeyer:** Conceptualization, Methodology, Data curation, Formal analysis, Visualization, Writing - original draft. **Sophia Fürtjes:** Conceptualization, Methodology, Data curation, Writing - review & editing. **Karen D. Ersche:** Conceptualization, Methodology, Writing - review & editing. **Stefan Ehrlich:** Conceptualization, Supervision, Funding acquisition, Writing - review & editing. **Tanja Endrass:** Conceptualization, Methodology, Supervision, Funding acquisition, Writing - review & editing.

## Declaration of competing interest

None.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.paid.2020.110029.

## References

Aarts, H., Verplanken, B., & Van Knippenberg, A. (1998). Predicting behavior from actions in the past: Repeated decision making or a matter of habit? *Journal of Applied Social Psychology, 28*(15), 1355–1374.

American Psychiatric Association (2013). Diagnostic and statistical manual of mental disorders. *BMC Medicine, 17*, 133–137.

Baumeister, R. F., & Heatherton, T. F. (1996). Self-regulation failure: An overview. *Psychological Inquiry, 7*(1), 1–15.

Bernaards, C. A., & Jennrich, R. I. (2005). Gradient projection algorithms and software for arbitrary rotation criteria in factor analysis. *Educational and Psychological Measurement, 65*(5), 676–696.

Borsboom, D., & Cramer, A. O. (2013). Network analysis: An integrative approach to the structure of psychopathology. *Annual Review of Clinical Psychology, 9*, 91–121.

Carden, L., & Wood, W. (2018). Habit formation and change. *Current Opinion in Behavioral Sciences, 20*, 117–122.

Carver, C. S., & Scheier, M. F. (1981). *Attention and self-regulation: A control-theory approach to human behavior.* Springer.

Chamberlain, S. R., Stochl, J., Redden, S. A., & Grant, J. E. (2018). Latent traits of impulsivity and compulsivity: Toward dimensional psychiatry. *Psychological Medicine, 48*(5), 810–821.

Chen, J., & Chen, Z. (2008). Extended Bayesian information criteria for model selection with large model spaces. *Biometrika, 95*(3), 759–771.

Claes, L., Nederkoorn, C., Vandereycken, W., Guerrieri, R., & Vertommen, H. (2006). Impulsiveness and lack of inhibitory control in eating disorders. *Eating Behaviors,*

*7*(3), 196–203.
Clark, F. A. (2000). The concepts of habit and routine: A preliminary theoretical synthesis. *Occupational Therapy Journal of Research, 20*(1_suppl), 123S–137S.
Corbit, L. H., Chieng, B. C., & Balleine, B. W. (2014). Effects of repeated cocaine exposure on habit learning and reversal by N-acetylcysteine. *Neuropsychopharmacology, 39*(8), 1893.
Costantini, G., Richetin, J., Preti, E., Casini, E., Epskamp, S., & Perugini, M. (2019). Stability and variability of personality networks. A tutorial on recent developments in network psychometrics. *Personality and Individual Differences, 136*, 68–78.
Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika, 16*(3), 297–334.
Dalley, J. W., Everitt, B. J., & Robbins, T. W. (2011). Impulsivity, compulsivity, and top-down cognitive control. *Neuron, 69*(4), 680–694. https://doi.org/10.1016/j.neuron.2011.01.020.
Danner, U. N., Aarts, H., & de Vries, N. K. (2008). Habit vs. intention in the prediction of future behaviour: The role of frequency, context stability and mental accessibility of past behaviour. *British Journal of Social Psychology, 47*(2), 245–265.
Dayan, P. (2009). Goal-directed control and its antipodes. *Neural Networks, 22*(3), 213–219.
Deci, E. L., & Ryan, R. M. (2008). Self-determination theory: A macrotheory of human motivation, development, and health. *Canadian Psychology, 49*(3), 182–185.
Diehl, M., Semegon, A. B., & Schwarzer, R. (2006). Assessing attention control in goal pursuit: A component of dispositional self-regulation. *Journal of Personality Assessment, 86*(3), 306–317.
Dolan, R. J., & Dayan, P. (2013). Goals and habits in the brain. *Neuron, 80*(2), 312–325.
Endrass, T., & Ullsperger, M. (2014). Specificity of performance monitoring changes in obsessive-compulsive disorder. *Neuroscience & Biobehavioral Reviews, 46*, 124–138.
Epskamp, S., Borsboom, D., & Fried, E. I. (2018). Estimating psychological networks and their accuracy: A tutorial paper. *Behavior Research Methods, 50*(1), 195–212.
Epskamp, S., Cramer, A. O., Waldorp, L. J., Schmittmann, V. D., & Borsboom, D. (2012). qgraph: Network visualizations of relationships in psychometric data. *Journal of Statistical Software, 48*(4), 1–18.
Epskamp, S., & Fried, E. I. (2018). A tutorial on regularized partial correlation networks. *Psychological Methods, 23*(4), 617.
Ersche, K. D., Lim, T. V., Ward, L. H. E., Robbins, T. W., & Stochl, J. (2017). Creature of Habit: A self-report measure of habitual routines and automatic tendencies in everyday life. *Personality and Individual Differences, 116*, 73–85. https://doi.org/10.1016/j.paid.2017.04.024.
Ersche, K. D., Ward, L. H. E., Lim, T. V., Lumsden, R. J., Sawiak, S. J., Robbins, T. W., & Stochl, J. (2019). Impulsivity and compulsivity are differentially associated with automaticity and routine on the Creature of Habit Scale. *Personality and Individual Differences, 150*, 109493.
Evans, J. S. B., & Stanovich, K. E. (2013). Dual-process theories of higher cognition: Advancing the debate. *Perspectives on Psychological Science, 8*(3), 223–241.
Fineberg, N. A., Potenza, M. N., Chamberlain, S. R., Berlin, H. A., Menzies, L., Bechara, A., ... Hollander, E. (2010). Probing compulsive and impulsive behaviors, from animal models to endophenotypes: A narrative review. *Neuropsychopharmacology, 35*(3), 591–604. https://doi.org/10.1038/npp.2009.185.
Finger, H., Goeke, C., Diekamp, D., Standvoß, K., & König, P. (2017). LabVanced: A unified JavaScript framework for online studies. *Paper presented at the International Conference on Computational Social Science (Cologne)*.
Fletcher, T. D. (2010). *Psychometric: Applied psychometric theory*.
Foa, E. B., Huppert, J. D., Leiberg, S., Langner, R., Kichic, R., Hajcak, G., & Salkovskis, P. M. (2002). The Obsessive-Compulsive Inventory: Development and validation of a short version. *Psychological Assessment, 14*(4), 485.
Foygel, R., & Drton, M. (2010). Extended Bayesian information criteria for Gaussian graphical models. *Paper presented at the advances in neural information processing systems*.
Friedman, J., Hastie, T., & Tibshirani, R. (2008). Sparse inverse covariance estimation with the graphical lasso. *Biostatistics, 9*(3), 432–441.
Gagne, P., & Hancock, G. R. (2006). Measurement model quality, sample size, and solution propriety in confirmatory factor models. *Multivariate Behavioral Research, 41*(1), 65–83.
Gillan, C. M., Papmeyer, M., Morein-Zamir, S., Sahakian, B. J., Fineberg, N. A., Robbins, T. W., & de Wit, S. (2011). Disruption in the balance between goal-directed behavior and habit learning in obsessive-compulsive disorder. *American Journal of Psychiatry, 168*(7), 718–726.
Gillan, C. M., & Robbins, T. W. (2014). Goal-directed learning and obsessive–compulsive disorder. *Philosophical Transactions of the Royal Society, B: Biological Sciences, 369*(1655), 20130475.
Gillan, C. M., Robbins, T. W., Sahakian, B. J., van den Heuvel, O. A., & van Wingen, G. (2016). The role of habit in compulsivity. *European Neuropsychopharmacology, 26*(5), 828–840.
Gilpin, A. R. (1993). Table for conversion of Kendall's Tau to Spearman's Rho within the context of measures of magnitude of effect for meta-analysis. *Educational and Psychological Measurement, 53*(1), 87–92.
Gonner, S., Leonhart, R., & Ecker, W. (2007). The German version of the obsessive-compulsive inventory-revised: A brief self-report measure for the multidimensional assessment of obsessive-compulsive symptoms. *Psychotherapie, Psychosomatik, Medizinische Psychologie, 57*(9–10), 395–404. https://doi.org/10.1055/s-2007-970894.
Gönner, S., Leonhart, R., & Ecker, W. (2007). Das Zwangsinventar OCI-R-die deutsche version des obsessive-compulsive inventory-revised. *PPmP-Psychotherapie·Psychosomatik·Medizinische Psychologie, 57*(09/10), 395–404.
Heatherton, T. F. (2011). Neuroscience of self and self-regulation. *Annual Review of Psychology, 62*, 363–390.
Hofmann, W., Schmeichel, B. J., & Baddeley, A. D. (2012). Executive functions and self-regulation. *Trends in Cognitive Sciences, 16*(3), 174–180.
Hogarth, L., Chase, H. W., & Baess, K. (2012). Impaired goal-directed behavioural control in human impulsivity. *The Quarterly Journal of Experimental Psychology, 65*(2), 305–316.
Holgado–Tello, F. P., Chacón–Moscoso, S., Barbero–García, I., & Vila–Abad, E. (2010). Polychoric versus Pearson correlations in exploratory and confirmatory factor analysis of ordinal variables. *Quality & Quantity, 44*(1), 153.
Howell, D. C. (2012). *Statistical methods for psychology.* Cengage Learning.
Jackson, C. H. (2011). Multi-state models for panel data: The msm package for R. *Journal of Statistical Software, 38*(8), 1–29.
Karoly, P. (1993). Mechanisms of self-regulation: A systems view. *Annual Review of Psychology, 44*(1), 23–52.
Kendall, M. G. (1938). A new measure of rank correlation. *Biometrika, 30*(1/2), 81–93.
Lally, P., Van Jaarsveld, C. H., Potts, H. W., & Wardle, J. (2010). How are habits formed: Modelling habit formation in the real world. *European Journal of Social Psychology, 40*(6), 998–1009.
Lange, F., & Dewitte, S. (2019). Cognitive flexibility and pro-environmental behaviour: A multimethod approach. *European Journal of Personality, 33*(4), 488–505.
Lauritzen, S. L. (1996). *Graphical models. Vol. 17*. Clarendon Press.
Lê, S., Josse, J., & Husson, F. (2008). FactoMineR: An R package for multivariate analysis. *Journal of Statistical Software, 25*(1), 1–18.
LimeSurvey Project Team (2015). *LimeSurvey: An open source survey tool.* Germany: LimeSurvey Project Hamburg.
Linnebank, F. E., Kindt, M., & de Wit, S. (2018). Investigating the balance between goal-directed and habitual control in experimental and real-life settings. *Learning & Behavior, 46*(3), 306–319.
Luszczynska, A., Diehl, M., Gutiérrez-Dona, B., Kuusinen, P., & Schwarzer, R. (2004). Measuring one component of dispositional self-regulation: Attention control in goal pursuit. *Personality and Individual Differences, 37*(3), 555–566.
Mardia, K. V. (1970). Measures of multivariate skewness and kurtosis with applications. *Biometrika, 57*(3), 519–530. https://doi.org/10.1093/biomet/57.3.519.
Martin, L. E., & Potts, G. F. (2009). Impulsivity in decision-making: An event-related potential investigation. *Personality and Individual Differences, 46*(3), 303–308.
Martin, A. D., Quinn, K. M., & Park, J. H. (2011). *MCMCpack: Markov chain Monte Carlo in R*.
McDonald, R. P. (2013). *Test theory: A unified treatment.* Psychology Press.
Meade, A. W., & Craig, S. B. (2012). Identifying careless responses in survey data. *Psychological Methods, 17*(3), 437–455. https://doi.org/10.1037/a0028085.
Meule, A. (2013). Impulsivity and overeating: A closer look at the subscales of the Barratt Impulsiveness Scale. *Frontiers in Psychology, 4*, 177.
Orbell, S., & Verplanken, B. (2010). The automatic component of habit in health behavior: Habit as cue-contingent automaticity. *Health Psychology, 29*(4), 374.
Osborne, J. W., & Fitzpatrick, D. C. (2012). Replication Analysis in Exploratory Factor Analysis: What it is and why it makes your analysis better. *Practical Assessment, Research & Evaluation, 17*.
Ouellette, J. A., & Wood, W. (1998). Habit and intention in everyday life: The multiple processes by which past behavior predicts future behavior. *Psychological Bulletin, 124*(1), 54.
Pan, J., Ip, E. H., & Dube, L. (2017). An alternative to post hoc model modification in confirmatory factor analysis: The Bayesian lasso. *Psychological Methods, 22*(4), 687–704. https://doi.org/10.1037/met0000112.
Patton, J. H., Stanford, M. S., & Barratt, E. S. (1995). Factor structure of the Barratt impulsiveness scale. *Journal of Clinical Psychology, 51*(6), 768–774.
Preuss, U., Rujescu, D., Giegling, I., Koller, G., Bottlender, M., Engel, R., ... Soyka, M. (2003). Factor structure and validity of a german version of the barratt impulsiveness scale. *Fortschritte der Neurologie-Psychiatrie, 71*(10), 527–534.
R Core Team (2018). *R: A language and environment for statistical computing. 2012*. Vienna, Austria: R Foundation for Statistical Computing.
Raiche, G. (2010). *nFactors: An R package for parallel analysis and non graphical solutions to the Cattell scree test*.
Revelle, W. (2018). *Psych: Procedures for personality and psychological research.* Evanston: Northwestern University.
Revelle, W., & Zinbarg, R. E. (2009). Coefficients alpha, beta, omega, and the glb: Comments on Sijtsma. *psychometrika, 74*(1), 145.
Ripley, B., Venables, B., Bates, D. M., Hornik, K., Gebhardt, A., Firth, D., & Ripley, M. B. (2013). *Package "mass"*.
Robbins, T., & Costa, R. M. (2017). Habits. *Current Biology, 27*(22), R1200–R1206.
Robbins, T. W., Gillan, C. M., Smith, D. G., de Wit, S., & Ersche, K. D. (2012). Neurocognitive endophenotypes of impulsivity and compulsivity: Towards dimensional psychiatry. *Trends in Cognitive Sciences, 16*(1), 81–91. https://doi.org/10.1016/j.tics.2011.11.009.
Rosval, L., Steiger, H., Bruce, K., Israël, M., Richardson, J., & Aubut, M. (2006). Impulsivity in women with eating disorders: Problem of response inhibition, planning, or attention? *International Journal of Eating Disorders, 39*(7), 590–593.
Ruscio, J. (2018). RGenData: Generates multivariate nonnormal data and determines how many factors to retain. R package version 1.0. https://CRAN.R-project.org/package=RGenData.
Ruscio, J., & Roche, B. (2012). Determining the number of factors to retain in an exploratory factor analysis using comparison data of known factorial structure. *Psychological Assessment, 24*(2), 282.
Schafer, J., Opgen-Rhein, R., Zuber, V., Ahdesmaki, M., Silva, A. P. D., Strimmer, K., & Strimmer, M. K. (2017). *Package "corpcor"*.
Schwabe, L., & Wolf, O. T. (2011). Stress-induced modulation of instrumental behavior: From goal-directed to habitual control of action. *Behavioural Brain Research, 219*(2), 321–328.

Schwarzer, R., Diehl, M., & Schmitz, G. (1999). *Self-regulation scale.* (Retrieved October, 28, 2006).
Stanford, M. S., Mathias, C. W., Dougherty, D. M., Lake, S. L., Anderson, N. E., & Patton, J. H. (2009). Fifty years of the Barratt Impulsiveness Scale: An update and review. *Personality and Individual Differences, 47*(5), 385–395.
Tabachnick, B. G., Fidell, L. S., & Ullman, J. B. (2007). *Using multivariate statistics. Vol. 5*. Boston, MA: Pearson.
Thorndike, E. (1911). *Animal intelligence: Experimental studies Macmillan.* (New York).
Torregrossa, M. M., Quinn, J. J., & Taylor, J. R. (2008). Impulsivity, compulsivity, and habit: The role of orbitofrontal cortex revisited. *Biological Psychiatry, 63*(3), 253–255.
Ullsperger, M., Fischer, A. G., Nigbur, R., & Endrass, T. (2014). Neural mechanisms and temporal dynamics of performance monitoring. *Trends in Cognitive Sciences, 18*(5), 259–267.
Verplanken, B. (2006). Beyond frequency: Habit as mental construct. *British Journal of Social Psychology, 45*(3), 639–656.
Wood, W., Labrecque, J. S., Lin, P.-Y., & Rünger, D. (2014). Habits in dual process models. *Dual process theories of the social mind* (pp. 371–385). .
Wood, W., Quinn, J. M., & Kashy, D. A. (2002). Habits in everyday life: Thought, emotion, and action. *Journal of Personality and Social Psychology, 83*(6), 1281.
Wood, W., & Rünger, D. (2016). Psychology of habit. *Annual Review of Psychology, 67*, 289–314.