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Conceptualising compulsivity through network analysis: A two-sample study

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ABSTRACT

Compulsivity is a transdiagnostic construct crucial to understanding multiple psychiatric conditions and problematic repetitive behaviours. Despite being identified as a clinical- and research-relevant construct, there are limited insights into the internal conceptual structure of compulsivity. To provide a more nuanced understanding of compulsivity, the current study estimated the structure of compulsivity (indexed using the previously validated Cambridge-Chicago Compulsivity Trait Scale, CHI-T) among two large-scale and geographically distinct samples using the network estimation method. The samples consisted of a United Kingdom cohort (n = 122,346, 51.4% female, Mean age = 43.7, SD = 16.5, range = 9–86 years) and a South Africa cohort (n = 2674, 65.6% female, Mean age = 24.6, SD = 8.6, range = 18–65 years). Network community analysis demonstrated that compulsivity was constituted of three interrelated dimensions, namely: perfectionism, cognitive rigidity and reward drive. Further, 'Completion leads to soothing' and 'Difficulty moving from task to task' were identified as core (central nodes) to compulsivity. The dimensional structure and central nodes of compulsivity networks were consistent across the two samples. These findings facilitate the conceptualisation and measurement of compulsivity and may contribute to the early detection and treatment of compulsivity-related disorders.

Compulsivity (i.e., the tendency towards repetitive actions that persist despite such actions are inconsistent with one's overall goal and may bring negative consequences; [1,2]) is a transdiagnostic construct relevant to both clinical and general populations. Psychiatric conditions that prominently feature compulsivity include anorexia nervosa, body dysmorphic disorder, obsessive-compulsive and related disorders (OCRDs) and addictions (i.e., alcohol/substance use disorders and gambling disorder; [3–5]). At a subclinical level, the lifetime prevalence of obsessive-compulsive symptoms was estimated to be 28.2% among the general population (indexed by the Composite International Diagnostic Interview 3.0; [6]). Compulsivity-related problems at both clinical and subclinical levels have been found to be associated with reduced quality of life, reduced well-being and productivity, resulting in considerable health–economic burdens [7–9]. For instance, the annual cost of obsessive-compulsive disorder (OCD) in the US is estimated to be $10.6 billion [10]. The prevalence, health impact and costs of compulsivity-related problems indicate that a thorough understanding of compulsivity is of great research and clinical importance.

Research on compulsivity has bloomed over the last decade. One line of thinking posits that compulsivity may be conceptualised as trait-like tendencies, which are normally distributed in the population and exist before the onset of symptoms [11]. Individuals placed at the severe end

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of the trait spectrum may be at greater risk of developing various compulsivity-related problems/disorders [11–14]. This novel perspective has the potential to identify the at-risk population for preventative and early interventions.

Another theoretical advancement in this emerging field is the paradigm shift towards a transdiagnostic conceptualisation of compulsivity. Traditionally, the conceptualisation of compulsivity was confined to compulsions specifically in OCD (the "archetypal" compulsive condition, [15–17]). More recently, it has been proposed that compulsivity may be viewed as a multi-dimensional transdiagnostic construct [11]. Instead of confining to OCD-specific symptoms (e.g., compulsive checking), the transdiagnostic compulsivity construct covers broad dimensions (e.g., perfectionism) that are shared by disorders outside OCD diagnostic categories. The transdiagnostic conceptualisation of compulsivity is in line with the Research Domain Criteria (RDoC) framework and addresses the issue that OCD-specific symptoms (e.g., compulsive washing, checking, etc.) may not be relevant to other compulsivity-related conditions (e.g., addiction-related disorders, [18]).

Advances in theoretical understanding of the transdiagnostic trait compulsivity construct motivated the development of its measurement tool, namely, the Cambridge-Chicago Compulsivity Trait Scale (CHI-T, [11]). The CHI-T addresses critical issues concerning the use of OCD instruments to measure "compulsivity" (i.e., limited transdiagnostic applicability to other compulsivity-related conditions, [18]). The scale was initially validated in a community sample, with good internal consistency (Cronbach's $\alpha = 0.80$) and excellent convergent validity against gold-standard measures for compulsive symptoms (i.e., Structured Clinical Inventory for Gambling Disorder and Padua inventory, with moderate effect size, [11]). Further validation study using online samples has found that the CHI-T sum score is associated with various problematic behaviours (i.e., problematic internet use, alcohol use, gambling and eating), obsessive-compulsive symptoms, and familial risk of addiction and obsessive-compulsive related disorders [12]. The scale also correlates with cognitive functioning such as rigid response styles [11] and reward-related attentional capture [12]. The psychometric soundness and capability of measuring compulsivity as a transdiagnostic construct make the CHI-T stand out from other scales and is recommended to be used when measuring compulsivity [18].

Despite the theoretical and methodological advancements in conceptualising compulsivity as a transdiagnostic trait, some ambiguities remained pertaining to key aspects of this construct. First, despite being identified as a multi-dimensional construct, the exact number and nature of dimensions comprising compulsivity remain unclear. As a relatively new construct, insights into the dimensional structure of transdiagnostic compulsivity are scarce [18]. Rigorous large-scale validation of the CHI-T using structural equation modelling identified two largely orthogonal subdimensions: (1) Perfectionism and (2) Reward drive [19]. Further exploration into the dimensional structure of transdiagnostic compulsivity may lead to improved models of compulsivity and facilitate more precise understanding of neurobiological and genetic substrates that underpin specific compulsivity dimensions [18].

Second, compulsivity is a complex construct, comprising various components (e.g., dysfunctional beliefs, negative affect, repetitive behaviours, etc.), with some components being potentially more important than others in the maintenance of compulsivity. For instance, dysfunctional beliefs about perfection may trigger negative emotions (e.g., worrying about making mistakes), further contributing to the repeated performing of certain behaviours to soothe the negative emotions (e.g., constantly checking to avoid potential mistakes), thus fostering continued compulsivity. In this case, dysfunctional beliefs about perfection may be at the core of compulsivity. Identifying such components may facilitate the conceptualisation of the construct. Further, interventions targeting core components of compulsivity may provide more efficacious results [20,21].

Traditionally, latent factor models were used to examine the dimensional structure of psychological constructs. However, as such approaches usually involve a predetermined set of factors, the full complexity of relations (e.g., reciprocal interactions of compulsivity components) may be masked [22]. More recently, the network approach was proposed as a promising complementary approach for the conceptualisation of psychological constructs. From the network perspective, compulsivity may be viewed as a network of nodes (e.g., items/components) and edges (pairwise direct relationships) between them, rather than the reflection of one or more latent variables [23]. Within the network, individual compulsivity components may reinforce one another through their putative causal relationships (i.e., $A \rightarrow B$, $A \leftarrow B$, or $A \leftrightarrow B$) and produce the phenomenon (i.e., compulsivity).

Dimensions occur when nodes cluster together due to their strong reciprocal relationships [24]. That is, for example, negative beliefs about perfection could trigger behavioural responses such as performing to the highest standard, resulting in their co-occurrence and constituting the "perfectionism" dimension. This is different from the latent variable perspective, which holds that, for example, a latent "perfectionism" factor causes both negative beliefs about perfection and keeping things to the highest standard (which are independent from each other). The differences in data-generating mechanisms distinguish the network approach from the classic latent factor approach [24]. Arguably, the reciprocal interactions gauged by the network approach are more in line with daily/clinical observations and may offer insights for clinical practice, as one major goal of clinical practices is to break (putative) causal links between components that constitute psychopathological constructs [25].

Network analysis also offers centrality indices (e.g., expected influence) to quantify the relative importance of each component of a given construct. This may help to identify core components that serve to maintain compulsivity. Components with high centrality are most strongly connected to other nodes within the network [21]. Theoretically, activation of central nodes may exert influence on other nodes throughout the network, while deactivation of such nodes may be like "removing a central card in a house of cards, causing the entire deck to collapse" [26], p. 148). This innovative perception of "central nodes" differs from the mainstream latent variable model, which posits that all components of a given construct are "equally central and thus exchangeable" [27], p. 144). It also allows for dynamic modelling of regulatory loops that create a complex network of interactions between the subcomponents of the network, which has important applications in psychiatry [28]. The importance of dynamic modelling is further shown in the fact that central nodes may represent predictors of disorder chronicity, and treatment outcomes [29–31], supporting the clinical utility of identifying central nodes.

Conceptualising psychological constructs as networks introduces a novel framework that not only often better captures their underlying nature but also offers an exploratory approach to uncovering their structures through empirical data [32,33]. Therefore, in order to provide a more refined conceptualisation of compulsivity, the current study examined the structure of the CHI-T scale through the network approach. By analysing the network structure (component level relationships) and centrality estimates, we aimed to understand, within a networking model, 1) the number and characteristics of dimensions constituting compulsivity, and 2) central nodes potentially critical to the maintenance of compulsivity. To ensure the stability and replicability of the findings, we estimated network models based on two large-scale independent samples. Considering the exploratory nature of network psychometrics [33] and the novelty of conceptualising compulsivity from a network perspective, we adopted an exploratory approach. Hence, we did not form hypotheses regarding the most central node or the specific number of dimensions.

1. Method

1.1. Participants

The first sample was based largely in the United Kingdom (UK). The UK sample included 122,346 participants (aged 9–86 years) who engaged in the online Great British Intelligence Test (GBIT), a collaborative citizen science project with BBC2 Horizon [34]. The majority of the participants were members of the general public who reside in the UK. No remuneration / prize draws were offered for involvement.

The second sample was based in South Africa (SA). The SA sample included 2674 participants. Participants were recruited across several online platforms as well as students and staff recruited from four local universities. The data collection took place from March 26th through to October 2020. Entry to a lucky prize draw was offered as an incentive for completing the study (worth 1000 ZAR, [equivalent to ~£50]). Individuals aged 18–65 years with access to the internet were eligible to participate in the study.

All procedures contributing to this work comply with the ethical standards of the relevant national and institutional committees on human experimentation [UK: Imperial College Research Ethics Committee (Approval Number: 17IC4009); SA: Stellenbosch University's Health Research Ethics Committee (Approval Number: N19/07/079)] and with the Helsinki Declaration of 1975, as revised in 2008. Participants in both studies provided written informed consent prior to their participation and completed measures of interest (i.e., demographic questions and the CHI-T Scale) online.

1.2. Measure

1.2.1. Cambridge–Chicago compulsivity trait scale (CHI-T, [11])

The CHI-T is a 15-item transdiagnostic measurement of compulsivity. This self-report scale covers broad aspects of compulsivity, including perfectionism, habitual tendencies, cognitive rigidity, reward-seeking, and intolerance of uncertainty [11,19]. The scale was demonstrated to be psychometrically sound in terms of internal consistency and convergent validity in initial pilot validation [11]. It was then more rigorously validated in an extremely large scale sample [19]. The SA study used an intermediate version of scale, featuring four response options: 1 = "strongly disagree", 2 = "disagree", 3 = "agree", 4 = "strongly agree". The UK study employed a more updated version of the scale, incorporating a neutral option of "neither agree nor disagree". This led to revised scoring options in the UK study, where responses were: 0 = "strongly disagree", 1 = "disagree", 2 = "neither agree nor disagree", 3 = "agree", 4 = "strongly agree". Individual item scores were used for data analysis.

1.3. Statistical analysis

We adopted the analytic procedures (i.e., node redundancy test, network estimation and community analysis) described by [35]. Before estimating the network models, we confirmed that the correlation matrix was positive definite (i.e., nodes were not linear combinations of other nodes), and there were no potentially redundant nodes (pairs of nodes that were highly intercorrelated and correlated to the same degree with other nodes) across two samples. The Hittner method for comparing dependent correlations [36] was adopted for the node redundancy test and was applied via the goldbricker function of the R package "network tools" [37].

Two graphical Gaussian models (GGM) with nonparanormal transformations were estimated, namely, the UK network and the SA network. The nonparanormal transformation procedure was applied to address the normality assumptions for network analysis [38]. Based on simulation studies, a sample size of 600 and above is appropriate for estimating a densely connected GGM model with up to 20 nodes [39]. Thus, the two networks (each with 15 nodes) estimated in the current study are based on samples well above the recommended sample size.

Within each network, CHI-T items were depicted as nodes, and regularised partial correlations between pairs of nodes controlling for all other nodes were depicted as edges [40]. The graphical least absolute shrinkage and selection operator (GLASSO) method was utilised to regularise the presented networks. The regularisation algorithm used a tuning parameter to shrink trivially small correlation coefficients to zero and remove spurious edges from final networks [40,41]. The tuning parameter (λ) value was set to 0.5 to balance the trade-off between sensitivity and specificity [40]. The Fruchterman-Reingold algorithm was used for layout visualisation [42], which placed closely related nodes next to each other. Blue edges represented positive pairwise associations, while red edges represented negative pairwise associations. The magnitudes of pairwise associations (edge weights) were indicated by edge thickness. The network estimation and visualisation were conducted via the R package "bootnet" [43].

To detect potential communities/dimensions within the network, we applied the Walktrap community detection algorithm (partitioning adjacent nodes into clusters using the random walk-based distance measure, for details, see [44] via the R package "igraph" [45]. Simulation studies have shown that the Walktrap community detection algorithm paired with GLASSO method consistently provides the most accurate and least biased results [24,46]. The combination of techniques has comparable or better accuracy than most accurate factor analytic techniques (e.g., parallel analysis) for detecting the number of dimensions within a construct [24,46].

We computed node expected influence (the sum of edge weights, both positive and negative, connected to a certain node, [47] to quantify the relative importance of each node within its respective networks and identify potential central nodes. Nodes with higher expected influence values are more strongly associated with other nodes within the network and considered to be more central/important for maintaining the network system [47]. We plotted the expected influence value of each node within the two estimated networks via the centralityPlot function of the R package "qgraph" [48].

To ensure the accuracy and stability of the estimated networks, we adopted the procedures described in [38]. Specifically, we bootstrapped the 95% confidence intervals (with 1000 bootstrap samples) of each edge within the networks to ensure the accuracy of edge weights. Correlation stability coefficients (CS-coefficient) of edge weights and centrality indices (expected influence) were calculated to examine the stability of edge weights and centrality. According to [38], the optimal value for CS-coefficient is above 0.5. Finally, we performed bootstrapped difference tests for edge weights and centrality indices [38]. The bootstrapped network accuracy and stability estimations were conducted via the R package "bootnet" [43]. The R code can be provided upon reasonable request to the first author.

2. Results

The UK sample included 122,346 participants (51.4% female, Mean age = 43.7, SD = 16.5, range = 9–86 years). The SA sample included 2674 participants (65.6% female, Mean age = 24.6; SD = 8.6, range = 18–65 years). Table 1 displays the descriptive statistics of demographic variables across two samples. It can be seen that the samples were relatively diverse. The descriptive statistics of CHI-T items across two samples are presented in the supplementary materials.

Fig. 1 illustrates the estimated CHI-T network across the UK sample and the SA sample. The UK network was more densely connected (96 remaining edges out of 105 possible edges) than the SA network (80 remaining edges out of 105 possible edges).

When inspecting the community structure of the estimated networks, three identical communities were detected across the two networks. The first community was composed of 5 nodes (i.e., items 1, 2, 3, 11, and 13), capturing the "perfectionism" facet of compulsivity. The second community was composed of 7 nodes (i.e., items 4, 5, 7, 10, 12, 14, and 15),

Table 1
Descriptive statistics of examined variables in the UK sample (n = 122,346) and in the SA sample (n = 2674).

Variable	Mean/*N*	SD/%
UK Sample		
Age	43.7	16.5
Gender		
Female	62,887	51.4
Male	58,728	48.0
Nonbinary/Other	731	0.6
Education Level		
High school and above	114,735	93.8
Ethnicity		
White/Caucasian	108,498	88.7
CHI-T score	35.2	9.0
SA Sample		
Age	24.6	8.6
Gender		
Female	1753	65.6
Male	911	34.1
Nonbinary/Other	10	0.4
Education Level		
High school and above	2670	99.9
Ethnicity		
White/Caucasian	1214	45.4
CHI-T score	41.6	6.0

capturing the "cognitive rigidity" facet of compulsivity. The remaining three nodes (i.e., items 6, 8, and 9) formed the "reward drive" community.

Similarities in edge characteristics were observed across the two samples. In both networks, intra-community edges were generally stronger than inter-community edges. The strongest edges were observed between "Tendency to act on urges" (item 8) and "Doing things that are immediately rewarding" (item 9) across the two samples. Similarly, the strongest inter-community edge was between "Repetition to meet high standards (item 3) and "Difficulty moving from task to task" (item 10). The identical inter-community edges indicated that the three dimensions may directly contribute to one another and form the compulsivity network.

Fig. 2 depicts the expected influence value of each node within the corresponding compulsivity network. The two central nodes that were identified were consistent across samples. Specifically, "Completion leads to soothing" (item 13) and "Difficulty moving from task to task" (item 10) showed the highest expected influence across the two samples, indicating that they were core to the maintenance of the corresponding network.

The bootstrapped confidence intervals of estimated edges across both networks are very narrow, indicating accurate estimation (Figs. S1 & S2). Stability analysis for edge weights and centrality indices showed that both networks have excellent levels of stability for edge weights (CS-coefficient = 0.75) and centrality indices (CS-coefficients = 0.75). Results of bootstrapped difference tests for edge weights and centrality indices are presented in the supplementary materials.

3. Discussion

This is the first network-based study to conceptualise compulsivity, as measured by the CHI-T scale, across two large samples from different geographical and socioeconomic contexts: the UK and SA. In both samples, we found that compulsivity, as operationalized within a network framework, comprised three domains: perfectionism (i.e., have high personal standards and strive to reach those standards), reward drive (i.e., approach tendencies towards immediate gratification and acting on urges, despite negative consequences), and cognitive rigidity (i.e., rigid and repetitive thinking patterns and behaviours). Further, items 'Completion leads to soothing' and 'Difficulty moving from task to task' showed the highest centrality and were identified as central nodes across the two samples. The consistency across the two independent datasets supports the reliability and generalizability of the current findings.

The three-dimensional network structure identified in the current study helps to address the question raised by Hook and colleagues [18], that is, what specific domains underpin the compulsivity construct? The three dimensions (i.e., perfectionism, reward seeking, and cognitive rigidity) we identified mirrored common transdiagnostic processes implicated across compulsivity-related disorders [49–51], supporting

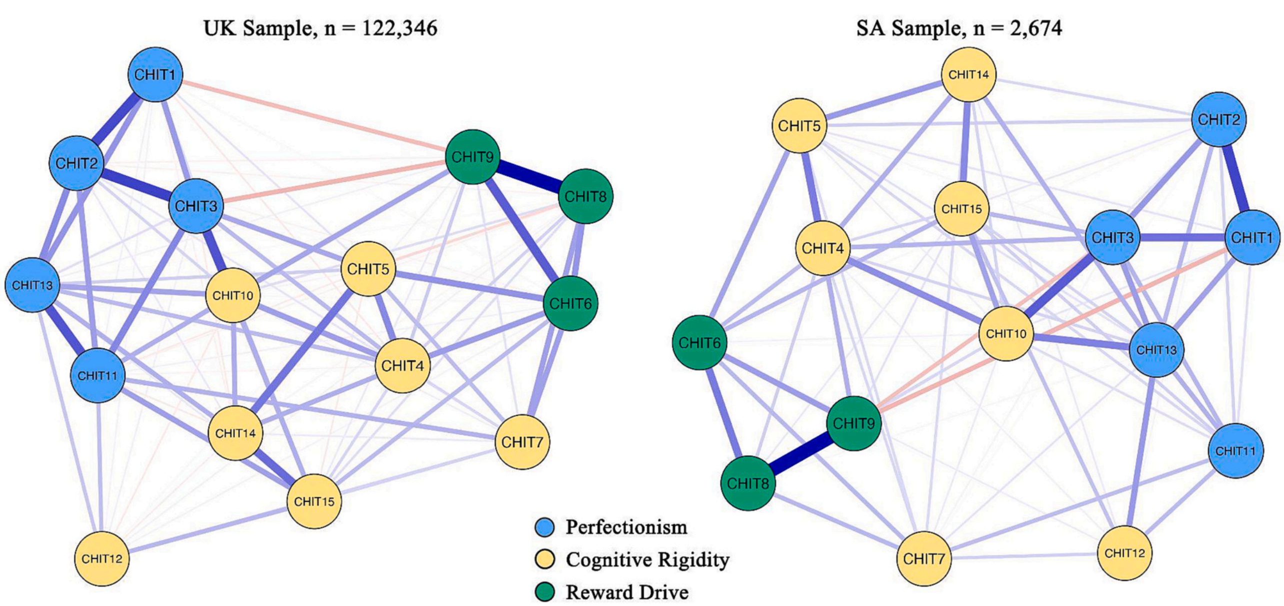

Fig. 1. Networks of the CHI-T in the UK and the SA samples. Nodes represent CHI-T items, and edges represent regularised partial correlations. Blue edges represent positive correlations and red edges represent negative correlations. The thickness of edges represents the strength of correlations. CHIT1, Need for completion; CHIT2, Doing things just right; CHIT3, Repetition to meet high standard; CHIT4, Getting stuck in thoughts; CHIT5, Habit propensity; CHIT6, Addictive propensity; CHIT7, Rigidity; CHIT8, Tendency to act on urges; CHIT9, Doing things that are immediately rewarding; CHIT10, Difficulty moving from task to task; CHIT11, High standards; CHIT12, Scope for improvement / nothing is good enough; CHIT13, Completion leads to soothing; CHIT14, Need for control; CHIT15, Needing to be the best. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

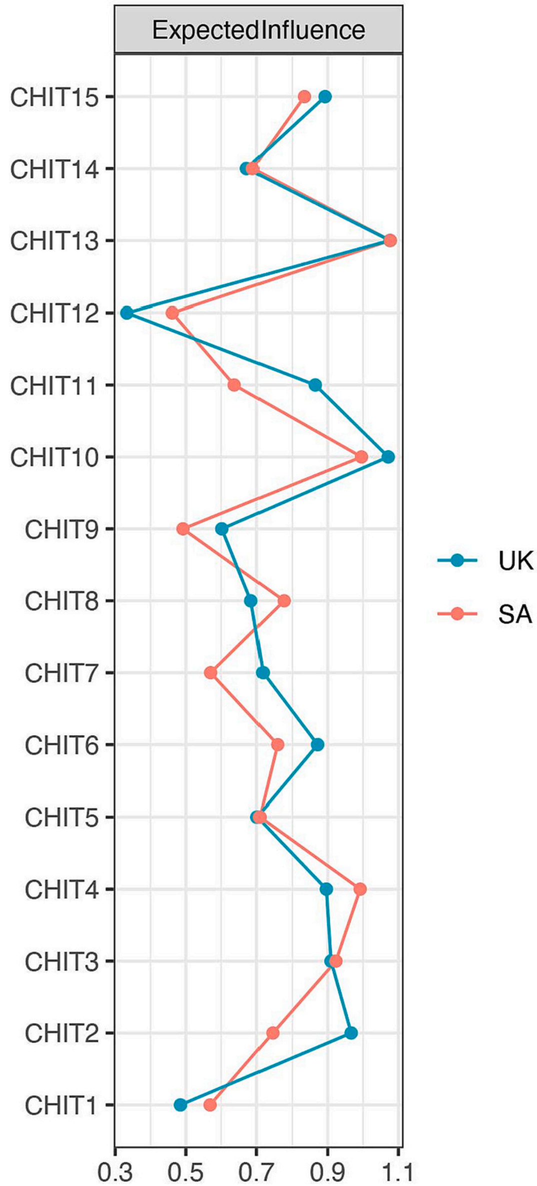

Fig. 2. Node expected influence values for the UK network and the SA network.

the validity of using the CHI-T to measure the transdiagnostic compulsivity construct. It should be noted that the network modelling approach is distinct from what is found using conventional factor analysis, since they are different ways of operationalizing a larger construct, and statistically/procedurally distinct processes. Divergent findings between network community analysis and factor analysis are often reported (e.g., [35,52]). More importantly, the different data generating mechanisms indicate that the results should be interpreted in a substantively different way depending on the framework used. That is, within the network framework, the three dimensions emerge from the putative causal dynamics between individual components, and *constitute* (rather than reflect) the compulsivity construct per se. The two approaches may be complementary to each other as they offer different vantage points.

Similar to existing psychometric network analysis (e.g., [22]), we found particularly strong item-item relations within each dimension. Several notable pathways were identified across the two samples. For instance, we found that "Getting stuck in thoughts" (item 4; cognitive rigidity) and "Difficulty moving from task to task" (item 10; cognitive rigidity) were strongly related to one another. From the network perspective, this may mean that rigid cognitive styles may trigger rigid behavioural patterns; thus, the two features are likely to co-occur. Such potentially causal relationships are frequently observed in both clinical settings and daily lives yet are largely neglected by the traditional latent variable models (by assuming the observed covariance is due to a shared latent mechanism, [53]). Understand how components may trigger and influence one another may help the development of psychological interventions, in which the implied causal links are tackled hierarchically during an intervention [53].

Several inter-dimension pathways were identified, supporting the notion that dimensions of compulsivity may directly interact with one another and contribute to the expression of compulsivity. For instance, we found that "Completion leads to soothing" and "Doing things that are immediately rewarding" are both connected to "Difficulty moving from task to task". These inter-dimension pathways are in line with the work by [54], which suggested that the urge to complete tasks for soothing (a component from the perfectionism dimension) and the urge to obtain immediate rewards (a component from the reward drive dimension) represent high-intensity motivational states, which may narrow individuals' attentional scope [55], preventing individuals from moving from one task to another [54].

Our results suggest that "Completion leads to soothing" may trigger and reinforce dysfunctional beliefs (e.g., things need to be done just right, item 2) and behaviours (e.g., repetition to meet high standards, item 3), thus fostering compulsivity. Meanwhile, "Difficulty moving from task to task" may predispose individuals to repetitive thoughts (item 4) and behaviours (item 3), thereby putatively allowing the emergence/maintenance of compulsivity. Several central nodes have been proposed by previous studies focus on the symptom network structure of OCD, including incompleteness, disturbing thoughts, doubting/checking and negative appraisals of intrusive thoughts [29,56,57]. By identifying "Completion leads to soothing" as a central node, our results supported previous literature on the crucial role of incompleteness. Further, we corroborated earlier findings that identified cognitive flexibility as a core feature shared by OCD spectrum disorders. We expanded upon this understanding by pinpointing the specific component, namely "Difficulty moving from task to task", which may serve as the most potent indicator for transdiagnostic compulsivity [58]. These finding not only expands upon previous studies focused solely on OCD symptoms but also holds broader implications for other disorders characterised by compulsivity (e.g., OCRDs). It is worth stressing again that the two central nodes were closely related to each other, indicating that disruption of the relationship may deactivate resting nodes within the network. Altogether, these results delineate the underlying mechanisms that may serve as the backbone of transdiagnostic compulsivity research in future, within a network approach.

3.1. Implications

The current findings open new avenues for advancement in understanding, assessing and managing compulsivity. From a research perspective, identifying central nodes may provide potential targets for future research to delineate the neurobiological and genetic substrates of compulsivity more precisely. From an assessment perspective, existing research found that central nodes carry more predictive power than peripheral nodes [30,31]. As the compulsivity trait may exist before the onset of compulsivity symptoms, the central nodes we identified may be explored as a potential means of screening people to identify those at risk of developing compulsivity-related problems.

From an intervention perspective, the current findings may offer new insights for developing targeted interventions. Specifically, treatment efforts for compulsivity-related disorders could be dedicated to addressing the underlying latent factors, with the hope that improving the latent factor may lead to reductions in all observable symptoms, whilst in parallel, the network perspective posits that addressing specific constituent components of the construct (i.e., central nodes) may deactivate the entire network, representing the most effective and efficient way for interventions [26]. Given that current treatments for compulsivity-related disorders (e.g., OCRDs) have only been partially successful in addressing the full range of OCRD psychopathology (e.g., for overview, see [8], it may be beneficial to examine the therapeutic value of central nodes (i.e., "Completion leads to soothing" and "Difficulty moving from task to task") identified in the current study. For instance, exposure therapy that precisely target incompleteness [59] may help loosen the pairing of soothing with completion. Further, novel interventions that incorporate task shifting training within naturalistic environments (e.g., through virtual reality), could potentially reduce difficulties in task shifting during real-life situations, and have transdiagnostic benefits for compulsivity-related disorders.

4. Strengths and limitations

To the best of our knowledge, no network-based study in psychopathology to date has adopted a comparable sample size to the one (n = 122,346) employed here. In addition, the network was replicated in two large-scale and geographically distinct samples, with consistent results on dimensional structure and central nodes, supporting the reliability of the findings. Despite these strengths, several limitations should be noted when interpreting the current results. First, the networks were generated from cross-sectional data; thus, the longitudinal trajectories of compulsivity cannot be assumed. Future research should consider investigating the temporal dynamics among CHI-T components and their potential predictive roles in compulsivity-related disorders. Second, both networks relied on data obtained from general population samples, which raises the possibility that the dimensions identified, and the central nodes may vary in clinical samples. Future research should compare CHI-T networks among clinical and non-clinical sub-groups to determine the clinical relevance of these findings. This comparison and verification process may serve as a first step before designing new interventions based on central nodes identified in the current study. Further, the present study did not account for potential confounding effects arising from comorbid disorders. Future research should examine how different comorbidities may influence the network structure and central nodes of the CHI-T. Fourth, it is important to note that different scoring options were employed for the CHI-T in the two samples, which restricts the direct comparison of CHI-T scores across the samples. Nonetheless, the variation in scoring options does not affect the overall validity of the results, as the network findings were consistently replicated across the two samples. Fifth, similar to factor analysis, the estimated networks reflect between-subject effects on a group level, which may not reflect within-person processes. Cross-lagged panel network models may be considered by future studies to separate within- and between-person effects [60]. Sixth, a latent variable-based study has found that sex and ethnicity might impact the structure of CHI-T [19]. Further investigations are necessary to explore potential gender and racial variations in the network structure of CHI-T. Seventh, we did not validate the three dimensions (i.e., perfectionism, cognitive rigidity, and reward drive) against other external measures of these concepts. Future work should address this to provide additional evidence of validity of these dimensions. Lastly, the two samples comprised individuals who reside in countries with Western cultural backgrounds (i.e., the UK and SA). As culturally specific factors may impact individuals' perception and experience of compulsivity [61,62], it may be useful to replicate our findings in countries with different cultural backgrounds (e.g., Asian countries).

5. Conclusions

In conclusion, the current study represents the first attempt to conceptualise compulsivity using a network modelling approach. The consistent results from two large, diverse samples demonstrated that compulsivity may be constituted, within a network framework, by three dimensions: perfectionism, cognitive rigidity, and reward drive. The results also suggest that "Completion leads to soothing" and "Difficulty moving from task to task" may be core to compulsivity and should be evaluated as primary transdiagnostic targets for early detection and intervention. Altogether, these findings may open new avenues for further refinement of the transdiagnostic compulsivity construct, as well as advancements in its assessment, prevention, and treatment.

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Author contributions

C.L. (Chang Liu) and S.R.C. were responsible for the study's concept, design, and data interpretation. C.L. (Chang Liu) conducted the analysis. C.L. (Christine Lochner), P.J.H., and A.H. contributed to the study's design, data collection, curation, and implementation. C.L. (Chang Liu) wrote the first draft of the manuscript, and all authors reviewed and approved the final version of the manuscript.

Declaration of Competing Interest

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Data availability

The data and code that support the findings of this study are available from the corresponding author, C.L., upon reasonable request.

Appendix A. Supplementary data

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