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Abnormal Child Behavior in primary school students: A Bayesian network analysis

Le comportement anormal de l'enfant en école primaire : une analyse par réseau bayésien

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ABSTRACT

The Conners Teacher Rating Scale revised: short (CTRS-R: S) is a widely used psychometric instrument to screen for Attention Deficit and Hyperactivity Disorder (ADHD) as well as a broader construct of abnormal child behavior. In this study, we aimed to examine the network structure of abnormal child behavior using the CTRS-R: S in a sample of 525 French-speaking primary school students from Belgium. We employed Bayesian network analysis to estimate both the 28-item network and the network with the 8 items with the highest strength centrality, using the PC algorithm and bootstrapping to estimate the figures. Our study uncovered associations between inattention symptoms and learning disorders, shedding new light on the complexity of abnormal child behavior. We also identified different network structures, revealing a fresh perspective on the underlying mechanisms of these conditions. Our findings, though preliminary, are consistent with previous research and add to the burgeoning literature on Bayesian network analysis in abnormal child behavior research. Overall, our study underscores the complexity of the construct of abnormal child behavior and the importance of considering multiple factors in screening and diagnosis, emphasizing the need for a comprehensive approach to understanding and treating these disorders.

Mots clés :
Analyse par réseau
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RÉSUMÉ

La *Conners Teacher Rating Scale revised short* (CTRS-R: S) est un instrument psychométrique largement utilisé pour dépister le trouble du déficit de l'attention avec ou sans hyperactivité (TDAH), ainsi qu'un construit plus large appelé comportement anormal de l'enfant. Dans cette étude, nous avions pour objectif d'examiner la structure par réseau du comportement anormal de l'enfant en utilisant la CTRS-R: S dans un échantillon de 525 élèves francophones en école primaire en Belgique. Nous avons utilisé l'analyse par réseau bayésien pour estimer à la fois le réseau à 28 items et celui aux 8 items ayant la force de centralité la plus élevée, en utilisant l'algorithme PC et la technique du *bootstrap* pour estimer les figures. Notre étude révèle des associations entre les symptômes d'inattention et les troubles de l'apprentissage, apportant un nouvel éclairage sur la complexité du comportement anormal de l'enfant. Nous avons également identifié différentes structures de réseaux, révélant une perspective nouvelle sur les mécanismes sous-jacents de ces conditions. Nos résultats, bien que préliminaires, sont cohérents avec les recherches précédentes et contribuent à la littérature croissante sur l'analyse par réseau bayésien dans la recherche

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sur les comportements anormaux chez l'enfant. Dans l'ensemble, notre étude souligne la complexité du concept de comportement anormal de l'enfant et l'importance de prendre en compte plusieurs facteurs dans le dépistage et le diagnostic, soulignant ainsi la nécessité d'une approche globale pour comprendre et traiter ces troubles.

Introduction

The Conners Teacher Rating Scale revised short, commonly referred to as the CTRS-R: S, is a psychometric instrument used in clinical settings to screen for Attention Deficit and Hyperactivity Disorder (ADHD) in children and adolescents [1]. Originally developed to help clinicians screen children with ADHD based on the teacher's perception of the child's behavior, this widely used test is clinically relevant given the diagnostic criteria for ADHD in the Diagnostic and Statistical Manual of Mental Disorders 5 (DSM 5) [2]. In addition, the items of the CTRS have been adapted to the school setting: the CTRS-R: S consists of 28 items divided into four subscales, namely opposition (items 2, 6, 10, 15, 20), hyperactivity (3, 7, 11, 17, 21, 24, 27), cognitive problems/attention (4, 8, 13, 18, 22), and ADHD index (1, 5, 9, 12, 14, 16, 19, 23, 25, 26, 28), which was known as hyperactivity index in the old version [1]. Clinicians commonly use this scale to assess the child's behavior in school, measure the extent of the disorder, and determine how to manage the symptomatology. For instance, treatment may differ depending on whether a child exhibits motor behavior or if the child is inattentive [3–5]. Clinical assessment, which remains the cornerstone of diagnosis, along with neuropsychological evaluation, can help guide clinicians in determining the most appropriate management plan for the child.

The CTRS-R: S also contains items related to learning disorders or oppositional defiant disorder (ODD). For this reason, we prefer to use the concept of abnormal child behavior, which is broader than ADHD alone, because relying solely on the ADHD approach could be incorrect and incomplete. This concept of abnormal child behavior is supported by Conners et al. [1,6,7]. Some researchers have used subsets of abnormal child behavior as a proxy for studying the construct. In such cases, Attention deficit hyperactivity disorder (ADHD) has been used as a useful proxy for examining abnormal child behavior: there are several psychometric instruments used for its early detection in children, and these instruments contain items that measure a wider construct than ADHD itself, such as the various versions of the Conners Rating Scale [1].

In recent years, psychometric network theory has been the subject of significant scientific research. This theory proposes that a given mental disorder arises from the interactions between individual symptoms rather than arising from an underlying common cause. A psychopathological network consists of nodes and edges, where nodes represent measurable entities (such as items from psychometric tools) on the scale or a symptom of the psychiatric disorder, and edges represent the connections between nodes [8].

Network analysis provides several ways to interpret the network, its structure and its stability. The relations between symptoms in a psychometric network can be estimated in a number of ways, most commonly as undirected partial correlations [9], but can also be estimated as directed relations using Directed Acyclic Graphs (DAG). CTRS-R: S has been previously analyzed with undirected networks [7]. However, the interpretation of undirected networks is limited [10]. To overcome these limitations, Bayesian networks (BNs) estimate the direction of the effect between nodes. BNs enable the representation of causal relationships among variables by expressing their conditional independence relationships using graphical separation [10–14]. This type of analysis has recently been employed to model causal systems from cross-sectional data and to understand complex psychopathological systems.

In this paper, DAGs are used as a graphical models to elucidate and illustrate the findings from a previous study [7]. By representing the relationships among variables as a DAG, it becomes easier to visualize the plausible causal structure of the system and to identify important variables or nodes that act as key drivers or mediators of the system among the variables. This approach facilitates the interpretation and communication of complex causal relationships, aiding in the understanding and analysis of complex systems.

Network estimation can be used to establish intervention targets on items and symptoms. For instance, items with high centrality in Bayesian Gaussian Graphical Models (BGGM) can be considered as potential targets for intervention. Several authors have opted for Bayesian networks to study the effect of interventions on nodes in the network [15–17]. Furthermore, this supplementary analysis may provide insights to address queries or uncertainties that arose from the initial network analysis of CTRS-R: S.

Few researchers have applied BNs in the field of psychopathology and, to our knowledge, no studies have specifically focused on applying BNs to the construct of abnormal child behavior. With Bayesian networks, the emphasis is on revealing "plausible" causal relationships rather than strict causality. DAGs express independent conditional relationships, deriving from the Pearlian causal inference [13,18]. Given that Bayesian networks primarily consist of directed connections, this allows for the representation of admissible causal relationships. This study aims to explore abnormal child behavior using BNs, acknowledging the complexity of clinical symptoms. Through the examination of symptoms such as inattention, opposition, hyperactivity, and learning difficulties, our objective is to establish potential associations among these symptoms and their connections within the symptom ensemble. This approach provides an overview of complex systems.

This study is organized as follows. First, we will estimate a network with the items of CTRS-R: S. Second, we will analyze the network according to these items. Third, we will estimate a Directed Acyclic graph from the items determined to be important to the network's self-determination [7]. Fourth, we will discuss the results and the implications of this study for future research and highlight its limitations.

Method

Participants

Data from this study were collected on 525 French-speaking Belgian students in primary schools, where teachers completed the CTRS-R: S questionnaire and provided information about the participants' age and sex. Our study protocol was approved by the Ethical Committee of the Centre Hospitalier Universitaire Brugmann (protocol B0772020000052/I/U Modeling of interactions between ADHD symptoms of the CTRS-R: S scale).

Table 1
Twenty-eight items from Conners Teacher Rating Scale revised short (CTRS-R: S) [1,19,20].

Label	Item Text
C1	Inattentive, easily distracted
C2	Defiant
C3	Restless in the "squirmy" sense
C4	Forgets things he/she has already learned
C5	Disturbs other children
C6	Actively defies or refuses to comply with adults' requests
C7	Is always "on the go" or acts as if driven by a motor
C8	Poor in spelling
C9	Cannot remain still
C10	Spiteful or vindictive
C11	Leaves seat in classroom or in other situations in which remaining seated is expected
C12	Fidgets with hands or feet or squirms in seat
C13	Not reading up to par
C14	Short attention span
C15	Argues with adults
C16	Only pays attention to things he/she is really interested in
C17	Has difficulty waiting his/her turn
C18	Lacks interest in schoolwork
C19	Distractibility or attention span a problem
C20	Temper outbursts
C21	Runs about or climbs excessively in situations where it is inappropriate
C22	Poor in arithmetic
C23	Interrupts or intrudes on others (e.g., butts into others' conversations or games)
C24	Has difficulty playing or engaging in leisure activities quietly
C25	Fails to finish things he/she starts
C26	Does not follow through on instructions and fails to finish schoolwork
C27	Excitable, impulsive
C28	Restless, always up and on the go

Measurement

The CTRS-R: S questionnaire (as reported in Table 1) comprises 28 items that are divided into four subcategories: ADHD index, Oppositional, Excitable-impulsive, and Cognitive-Inattentive Problems. Each item is scored on a scale ranging from absent (0), intermediate (1,2) to severe (3). The CTRS-R: S does not include any reverse-scored items [1].

Network analysis

The software R was used for statistical computing (version 3.6.1, open source, available at https://www.r-project.org/). The packages used to carry out the analysis are *bnlearn* version 4.7 [21].

Network structure

Psychometric networks represent the psychological constructs, behaviors, and in the case of the current work, symptoms or items as nodes, while the relations between these variables are represented by edges. There are many ways of constructing psychometric networks, each resulting in different interpretations of what edges mean. Moreover, BN derive their name more from the way in which they are estimated and utilized, rather than solely from Bayesian approach to the estimation of networks.

In this paper, we use Bayesian networks, which represent the probabilistic relations between variables as directed relations. Bayesian networks (BNs) are characterized by the integration of a network structure, typically represented as a directed acyclic graph (DAG), and a probability distribution [10]. The DAG in a Bayesian network (BN) provides a valuable framework for qualitative reasoning on the interconnections between symptoms in exploratory analysis and hypothesis testing. Simultaneously, the

Table 2
High-centrality items from the CTRS-R: S.

N	Item
26	Does not follow through on instructions and fails to finish schoolwork (not due to oppositional behavior or failure to understand instruction)
27	Excitable, impulsive
28	Restless, always up and on the go
1	Inattentive easily distracted
23	Interrupts or intrudes on others (e.g., butts into others conversations or games)
16	Only pays attention to things he/she is really interested in
15	Argues with adults
8	Poor in spelling

probability distributions associated with the symptoms allow for quantifying these relationships in terms of their strength and direction. Specifically, the DAG in a BN represents the set of conditional independence relationships among variables and implies "causal" relationship according to the Pearlian causal inference paradigm. For example, in a simple network with two items, A and B, A≥B indicates that the causal relationship from A to B is the most plausible given the data. The arrows indicate the direction of probabilistic dependence from one node to another. DAGs represent conditional independence relationships that illustrate the joint probability distribution of variables.

Peter & Clark (PC) algorithm

The Inductive Causation (IC) algorithm is a conceptual algorithm and was implemented in the PC algorithm [22,23]. The algorithm starts with a complete and undirected network. In the first step, the algorithm removes independent edges between pairs of nodes that are not dependent on each other. In other words, the algorithm searches for those variables A and B in the set X that are independent given increasingly large sets of nodes S_{AB} (A and B are not part of in S_{AB}). These connections are removed from the network (10,22). In the second step, the algorithm checks whether there is an intermediate element between two unconnected nodes in the path direction. For example, if X and Z are not connected, but X and Z are connected to Y, i.e., X-Y-Z, the algorithm determines the edge direction between X-Z, Y-Z and Y-Z. This suggests that X is dependent on Z given Y. However, it's important to note that in some cases, especially with cross-sectional data, certain edge directions may be unidentifiable. In such instances, the PC algorithm returns a CPDAG containing undirected arcs. The PC algorithm does not provide the estimation of uncertainty. It is recommended to measure the probability of inclusion of edges in the estimated BN [10]. To evaluate network stability, we implemented a bootstrapping technique, generating 200 bootstrap samples from the original dataset, each time resampling and re-estimating the network structure. From these samples, edges were selected if they were present in over 85% of the networks, signifying strong consistency (termed as "strength"). Additionally, we considered edges whose directionality persisted in more than 50% of the networks, referred to as the "minimum direction", as suggested in prior research [24,25]. Therefore, this network produces connectivity reports that are observed in over 85% of the utilized networks. Furthermore, these connections exhibit a distinct directionality (e.g., from node A to node B) that is found in more than half of the networks generated through the bootstrapping procedure [25].

Strength, in and out degrees

In this section, we will examine the strength, in-degrees, and out-degrees of network elements. Table 2 presents the in-degrees and out-degrees of the 28 items. The in-degree corresponds to the count of connections directed towards a node, while the out-degree

Table 3
Twenty-eight items In and Out degree.

Items	In-degree	Out-degree	Items	In-degree	Out-degree
C1	1	2	C15	2	2
C2	0	3	C16	1	0
C3	0	4	C17	1	0
C4	1	3	C18	1	1
C5	2	0	C19	2	0
C6	1	1	C20	1	1
C7	1	2	C21	0	0
C8	1	1	C22	2	0
C9	2	1	C23	0	1
C10	1	0	C24	1	0
C11	1	0	C25	0	1
C12	2	0	C26	2	1
C13	0	1	C27	2	1
C14	2	2	C28	0	2

Table 4
Descriptive statistics.

Items	Valid	Mean	Standard deviation	Items	Valid	Mean	Standard deviation
C1	525	1.12	1.1	C15	525	0.28	0.68
C2	525	0.4	0.81	C16	525	0.49	0.89
C3	525	0.71	0.98	C17	525	0.49	0.89
C4	525	0.68	1.01	C18	525	0.49	0.91
C5	525	0.61	0.9	C19	525	0.57	0.95
C6	525	0.24	0.63	C20	525	0.21	0.61
C7	525	0.43	0.85	C21	525	0.17	0.58
C8	525	0.79	1.11	C22	525	0.59	1.01
C9	525	0.55	0.9	C23	525	0.41	0.8
C10	525	0.24	0.64	C24	525	0.34	0.74
C11	525	0.39	0.78	C25	525	0.43	0.87
C12	525	0.56	0.92	C26	525	0.45	0.89
C13	525	0.59	0.99	C27	525	0.34	0.79
C14	525	0.72	1.01	C28	525	0.4	0.82

represents the count of connections originating from a node [21]. In Table 3, we detail the arc strength and direction estimations obtained utilizing the PC algorithm with an r value of 200 (200 being the number of bootstrap replication). Specifically, Table 3 shows only the edges within the network. The strength metric quantifies the degree of confidence regarding their inclusion in the network (threshold set at >0.85), while the direction metric reflects the level of certainty concerning the specific orientation of the arcs (threshold set at >0.5) [10]. By employing these analyses, we aim to enhance our understanding of network interconnections and the robustness of directional influences within the studied framework.

Results

Data set

In our data set, children were 48.76% female and 51.24% male. Children were 5–12 years old (M = 8.04; SD = 1.98). Descriptive statistics for our data set are shown in Table 4.

This table presents the descriptive statistics per item. The first two rows indicate that there were 525 individuals, and all questions were answered. There were no missing data. Additionally, the table displays the minimum and maximum scores for each item, with scores ranging from 0 (minimum) to 3 (maximum).

Network structure

Fig. 1 illustrates the Directed Acyclic Graph (DAG) of a Bayesian network (BN) constructed using the PC algorithm with 200 bootstrapping iterations for the 28 items of the CTRS-R: S. The arrows between nodes (items) in the DAG represent the plausible causal relationships according to other connections. Item 2 ("Defiant") is a parent node of a chain that includes Item 15 ("Replies, persists with adults"), item 6 ("Actively defies or refuses to comply with adults requests"), and item 10 ("Spiteful or vindictive). Item 21 ("Runs about or climbs excessively in situations where it is inappropriate") is isolated in the network as it lacks connections both to and from other items. It was excluded from the network based on the specified parameters of strength, direction, and bootstrapping. Strong connections exist between item 18 ("Lacks interest in schoolwork") and item 16 ("Only pays attention to things he/she is really interested in"), and between item 7 ("Is always on the go or acts as if driven by a motor") and item 11 ("Leaves seat in classroom or in other situations in which remaining seated is expected"). As an example of a different DAG structure, item 5 ("Disturb other children") is a child node of item 2 ("Defiant") and item 3 ("Restless in the squirmy sense"), which forms a collider structure.

Bayesian network of 28 items from the CTRS-R: S, where nodes represent items and arrows indicate the plausible causal relationship between two nodes given the other connections. This network was learned using the Constraint-Based PC Algorithm.

Eight domain network

In the previous study, eight items with the highest centrality were found, presented in Table 2 [7].

Items are presented in descending order of centrality within each of the eight communities, from the highest to the lowest.

Fig. 2 shows the causal dependence between the most relevant items from CTRS-RS given the other connections. We conducted 200 bootstrapping iterations and generated Fig. 2. Item 8 ("Poor in spelling") appears to be the causal item of the reduced network, but the strongest connection is between item 28 and item 27.

Item 8 ("Poor in spelling") is the parent node in the chain including item 1 ("Inattentive, easily distracted"), item 28 ("Restless, always up and on the go"), item 27 ("Excitable, impulsive"), item 15

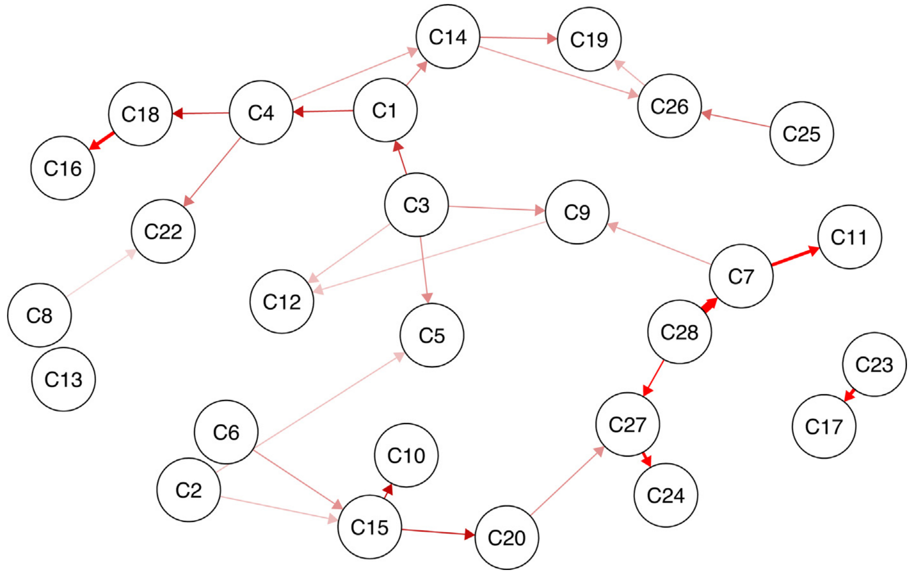

Figure 1. Twenty-eight items CTRS-R: S Bayesian network.

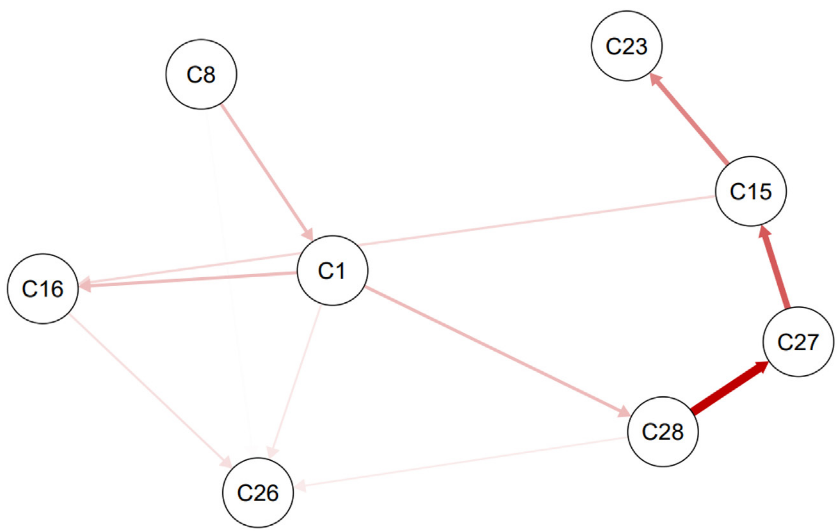

Figure 2. Eight domain items network.

("Replies, persists with adults") and the final item: item 23 ("Interrupts or intrudes others") in this respective order.

In turn, item 26 ("Does not follow instructions all the way through and fails to finish schoolwork") is a child node of item 1 ("Inattentive, easily distracted"), item 16 ("Pays attention only to what really interests them"), and item 28 ("Restless, always on the go").

Bayesian network of eight items from the CTRS-R: S with the highest strength of centrality for the eight communities. This network was learned using the Constraint-Based PC Algorithm.

In and outdegree and Strength network

In this section, we will analyze the in- and out-degrees as presented in Table 3, along with the associated strength and direction values outlined in Table 3, in conjunction with Fig. 1. However, it is important to highlight exceptions for Items 13 ("Not reading up to par") and 21 ("Runs about or climbs excessively in situations where it is inappropriate"). As a result, these items are neither depicted in Fig. 1 nor included in Table 3. This exclusion does not suggest a lack of connections or significance for these items; rather, it indicates that, with a bootstrap of 200, these connections lack the robustness required for representation.

The in-degree counts the connections directed towards each item. Notably, no item exhibits more than two connections, consistent with the observations in Fig. 2. For instance, item 5 ("Disturbs other children") serves as the point of origin for two directed connections, originating from item 2 ("Defiant") and item 3 ("Restless in the squirmy sense"). In contrast, there are more outgoing connections, with item 3 sharing four connections towards other items, thereby possessing the highest out-degree.

All non-null strength values fall within the range of 1 to 0.005, while direction values span from 1 to 0.1, resulting in 332 non-null connections. In Table 4, only "visible" connections from Fig. 1 were retained, employing thresholds of strength >0.85 and direction >0.5. The strength of each arc is determined by its empirical frequency across a collection of networks derived from bootstrap samples, with the results reported in Table 5. Additionally, the algorithm calculates the probability of each arc and the conditional probabilities of each arc's direction given its presence in the

Table 5
Arc strength and direction.

From	To	Strength	Direction	From	To	Strength	Direction
C1	C14	1	0.58	C13	C8	1	0.51
C1	C4	0.99	0.52	C14	C19	1	0.55
C2	C15	1	0.61	C14	C26	0.85	0.53
C2	C5	0.98	0.69	C15	C10	1	0.59
C2	C6	0.96	0.65	C15	C20	0.98	0.54
C3	C1	0.99	0.64	C18	C16	1	0.63
C3	C12	0.99	0.73	C20	C27	0.90	0.57
C3	C5	0.94	0.64	C21	C11	0.88	0.51
C3	C9	1	0.62	C23	C17	1	0.63
C4	C14	0.87	0.59	C26	C19	0.96	0.51
C4	C22	1	0.72	C26	C25	1	0.54
C6	C15	1	0.52	C27	C24	0.99	0.73

graph. The significance threshold is automatically derived from the strength estimates [21]. It is crucial to note that all analyses were conducted using the PC algorithm with a selected *r*-value of 200.

The in-degree corresponds to the count of connections directed towards a node. The out-degree represents the count of connections originating from a node.

The table displays the estimated arc strength and direction of edges for 28 items using the PC algorithm with an *r*-value of 200. The direction metric indicates the confidence level regarding the orientation of the arcs. As outlined in the methodology, thresholds of strength >0.85 and direction >0.5 were utilized.

Discussion

To our knowledge, this study represents the first investigation of abnormal child behavior, as measured by the CTRS-R: S, using Bayesian networks (BNs) to infer a plausible causal structure underlying the scale. Building on previous network analyses of the CTRS-R: S using undirected models, the results of this study provide an important complement to previous research using partial correlation networks [7].

First, the BN of the 28 items of the CTRS-R: S was estimated using the PC algorithm with 200 bootstraps, and several noteworthy connections were identified. For example, Fig. 1 highlights a robust connection between item 16 ("Only pays attention to things he/she is really interested in") and item 18 ("Lacks interest in schoolwork"), with item 18 directed towards item 16. In practice, this connection may raise questions. For instance, a child displaying a lack of interest in school might be more inclined to engage solely with subjects that captivate their attention. Although it seems logical to interpret it in reverse, this proposition remains unverified within this study. One of the reasons for this is that the scale scoring is administered within the school environment, facilitated by teachers' perspectives.

Another noteworthy discovery pertains to item 8 ("Poor in spelling"), which exerts a plausible causal influence on item 22 ("Poor in arithmetic"), given the other interconnected elements within the network. However, it is crucial to acknowledge that these connections should not be interpreted as strictly causal but rather as dependencies based on the other nodes in the network. Other researchers have posited that a more pronounced connection exists between difficulties in arithmetic and spelling rather than between arithmetic skills and reading [26,27]. A study by Morsanyi found evidence suggesting a co-occurrence rate of 46% between mathematical difficulties and challenges in reading/orthography [27]. However, this specific study did not distinguish between dyslexia and dysorthography while arriving at this result. The criterion used for assessing dyslexia and dysorthography was a score lower than 78% in English [27].

Notably, deficits in arithmetic exhibited a higher incidence of co-occurrence with deficits in spelling as opposed to deficits in reading. Furthermore, rates of comorbidity between arithmetic and reading decreased upon the application of more stringent criteria for deficits. Nonetheless, comorbidity rates remained elevated between arithmetic and spelling regardless of the specific deficit criterion employed [27].

The chain connection starting with item 3 ("Restless in the squirmy sense") and including items 9 ("Cannot remain still"), 7 ("Is always on the go or acts as if driven by a motor") and 11 ("Leaves seat in classroom or in other situations in which remaining seated is expected") appear to describe relationships that are clinically logical.

As in other chains, item 2 starts a chain connection including items 15 ("Argues with adults") and 10 ("Spiteful or vindictive"). These items were found in the same community or group of items ("Spiteful or vindictive") identified in a previous study [7].

One node of particular interest is item 3 ("Restless in the squirmy sense"), which is causally linked to four other items. It is possible that these items will diminish as the child develops and the motor presentations subside over time [28] or that they could be targeted by practitioners as part of an effort to reduce the overall network. This process is referred to as the hysteresis concept. As mental illness is a complex construct, symptoms interact with one another and can activate a dormant network. When the symptoms that activate the network disappear, the network may transition to an active stable state or return to a latent position [8].

The choice of the network estimation algorithm and the 200 bootstrap samples aims to retain only the strongest connections; however, certain items and connections are not represented. Some connections are computed, such as those between items 17 and 23 and between items 26 and 25 (refer to Tables 2 and 3), but they are not shown in Fig. 2.

As a reminder, we employed bootstrap resampling with a value of 200, which is relatively high. This choice ensures the retention of the most stable connections, as they were evaluated 200 times. The utilization of a higher bootstrap value enhances the robustness of our findings, offering a more reliable representation of the stability of network connections [25].

The current study has corroborated the existence of negative connections within the Gaussian Graphical Model (GGM) network, as established in the preceding research [7]. Indeed, one of the primary objectives of this study was to assess the network linkage of the earlier investigation. Negative connections within GGM networks can be attributed to two potential explanations: either there is an absence of a direct link between negatively connected items (as exemplified by items 16 and 20), or the negative edge signifies the presence of a collider. A negative edge statistically implies that if a given group of subjects scores high on item X, they are less likely to score high on item Y. However, a negative partial correlation may arise between two nodes X and Y if they are both connected to a third node Z, and the underlying causal structure is $X \rightarrow Z \leftarrow Y$.

The present study has revealed interesting connections between item 8, "Poor in spelling", and the other seven items depicted in Fig. 2. These findings suggest that item 8 may be a plausible causal factor underlying the other items. Previous research has indicated that learning disorders are often comorbid with attention-deficit/hyperactivity disorder (ADHD) and oppositional defiant disorder (ODD) [29]. Some studies have suggested that inattention symptoms could be a consequence of learning difficulties in school rather than the reverse [30]. Furthermore, authors have argued that ADHD behaviors should be considered as a disorder of conduct in the classroom because the child with learning difficulties is excluded from much of the normal classroom activities [30,31]. Although ADHD has been linked to neurological origins, difficulties with learning, inattention, impulsive behavior, and oppositional behavior appear to be part of a continuum of symptoms, forming a spectrum of behavior that varies with external factors and evolves with a child's development. The literature also suggests an inverse relationship between ADHD and spelling ability, with children with a diagnosis of ADHD often exhibiting spelling difficulties [32]. Furthermore, children children with a diagnosis of ADHD without comorbidities may have difficulties performing school tasks such as writing. However, it should be noted that a "thin arrow" may occur after bootstrapping the relation from item 1 to item 8 [33]. That is, in a directed acyclic graph used for predicting directions, a thin edge indicates that the arrowhead is frequently pointed in the opposite direction for a significant minority of the bootstrapped graphs computed during the Bayesian iterative process [33].

Based on this approach, we can envision the implementation of targeted interventions tailored to specific symptom profiles [34].

For instance, if oppositional behaviors or conduct-related symptoms are predominant, a behavioral therapy approach may be particularly relevant [35]. Conversely, if learning difficulties – particularly in reading or mathematics – are more prominent, educational accommodations within the classroom environment could be considered. These may include remedial exercises, task segmentation, the use of clearer visual layouts (e.g., simplified typographies), and structured learning supports adapted to the student's cognitive profile [34,36].

This work highlights the complexity of the construct of abnormal child behavior, emphasizing the significant role that learning difficulties play in the development of inattention and defiance in children.

The results of this study should be interpreted with caution due to several limitations. First, the data in this study were collected from a sample of French-speaking Belgian elementary school students because the goal of this study was to examine a network structure estimated from a non-clinical sample. We do not know if there are children diagnosed and/or treated for ADHD in the observed group. Using a non-clinical, teacher-rated sample limits generalizability to clinical populations. In clinically diagnosed cohorts, symptom severity, comorbidity, and diagnostic awareness may differ substantially, potentially altering symptom profiles and their associations. Moreover, internalizing symptoms might be underreported in non-clinical contexts. Future research including clinically referred samples and multi-informant approaches is needed to assess the robustness of these findings.

The network structure may not replicate in other samples, although our results align with other network studies that used different psychometric instruments [37,38]. Second, the CTRS-R: S was naturally completed by the teacher, which may introduce some bias in the scores depending on the teacher who completed the scale. Third, the relatively recent adoption of directed acyclic graphs as a modeling tool limits our ability to compare our results with previous studies that used different methodologies. Fourth, the choice of the scale itself depends on the investigator, and some items or symptoms of the abnormal child behavior may not be present because of the original scale. Otherwise, the term "abnormal child behavior" should be reconsidered, as the scale predominantly targets external symptoms.

In this type of study, the choice of scale presents a limitation on the construct under investigation. Fifth, it is important to note that the BN approach has its limitations. However, probabilistic dependency cannot confirm temporal precedence in cross-sectional data, although it is consistent with such an interpretation [10]. In future studies, a broader assessment framework should be adopted. This includes the use of comprehensive screening tools incorporating parent ratings, which are essential for capturing cross-contextual symptoms and reducing rater bias. Additionally, the inclusion of a wider range of items beyond DSM-based criteria could allow for the identification of broader, more ecologically valid constructs that better reflect the heterogeneity of real-world presentations.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the first author utilized ChatGPT to check the spelling and grammar of the manuscript. Following the use of this tool/service, the author(s) reviewed and edited the content as necessary and assume(s) full responsibility for the publication's content.

Disclosure of interest

The authors declare that they have no competing interest.

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The Conners scale was referenced in the methodology section and the paper was cited for scientific purposes. The scale can be accessed via the following link: https://www.pediatricenter.com/assets/forms/ConnersTeacherRatingScale.pdf.

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