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Unpacking the overlap between Autism and ADHD in adults: A multi-method approach



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ABSTRACT

The overlap between Autism and Attention-Deficit Hyperactivity Disorder (ADHD) is widely observed in clinical settings, with growing interest in their co-occurrence in neurodiversity research. Until relatively recently, however, concurrent diagnoses of Autism and ADHD were not possible. This has limited the scope for large-scale research on their cross-condition associations, further stymied by a dearth of open science practices in the neurodiversity field. Additionally, almost all previous research linking Autism and ADHD has focused on children and adolescents, despite them being lifelong conditions. Tackling these limitations in previous research, 5504 adults – including a nationally representative sample of the UK (Study 1; $n = 504$) and a large pre-registered study (Study 2; $n = 5000$) – completed well-established self-report measures of Autism and ADHD traits. A series of network analyses unpacked the associations between Autism and ADHD at the individual trait level. Low inter-item connectivity was consistently found between conditions, supporting the distinction between Autism and ADHD as separable constructs. Subjective social enjoyment and hyperactivity-impulsivity traits were most condition-specific to Autism and ADHD, respectively. Traits related to attention control showed the greatest Bridge Expected Influence across conditions, revealing a potential transdiagnostic process underlying the overlap between Autism and ADHD. To investigate this further at the cognitive level, participants completed a large, well-powered, and pre-registered study measuring the relative contributions of Autism and ADHD traits to attention control (Study 3; $n = 500$). We detected age- and sex-related effects, however, attention control did not account for the covariance between Autism and ADHD traits. We situate our findings and discuss future directions in the cognitive science of Autism, ADHD, and neurodiversity, noting how our open datasets may be used in future research.

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1. Introduction

Two of the most common neurodevelopmental conditions – Autism Spectrum Disorder (hereafter Autism), characterised by social communication difficulties and repetitive and restrictive behaviours, and Attention-Deficit Hyperactivity Disorder (ADHD), characterised by hyperactivity, inattention, and impulsivity – collectively affect ~6–14% of the population (Francés et al., 2022). The conditions share many characteristics (e.g., Panagiotidi et al., 2019; Ronald et al., 2008), however, co-occurring diagnoses of Autism and ADHD have only been permissible since 2013 (DSM-5; American Psychiatric Association [APA], 2013; see Thapar et al., 2017). Further, even where dual diagnosis has been possible, studies on Autism have often excluded those with ADHD and vice versa (Bora & Pantelis, 2016; Leitner, 2014). Research, therefore, has typically focused on each condition separately (e.g., Livingston et al., 2022; Riglin et al., 2022; Taylor et al., 2021), without fully investigating the transdiagnostic processes which may underpin their similarities and co-occurrence.

Research that has explored Autism and ADHD traits concurrently has typically focused on clinical, atypical, and/or child and youth samples (e.g., Cooper et al., 2014; Hayashi et al., 2022; Kotte et al., 2013; Krakowski et al., 2022; Ronald et al., 2010, 2014; Stergiakouli et al., 2015; van der Meer et al., 2017), with limited application for the wider adult population (but see Hargitai et al., 2023). However, with increasing awareness and clinical understanding of neurodiversity, more adults are seeking support for neurodevelopmental conditions later in life (Huang et al., 2020; Russell et al., 2022). Despite the urgent need to understand the overlap between Autism and ADHD to help support this fast-growing and under-researched population, there remains a striking paucity of cross-condition neurodevelopmental research in adults. To address this gap in the literature, the current study aims to utilise adult samples from the general population to conduct large-scale trait analyses.

Substantial evidence shows that Autism and ADHD can be conceptualised and measured as quantitative traits in the general population (see Happé & Frith, 2020, 2021; Lundström et al., 2012; Stanton et al., 2020), which can help to overcome clinic bias when relying on diagnosed samples alone. The trait approach also captures detailed characteristics and underlying processes that facilitate understanding of the overlap between different forms of neurodivergence. Further, in line with the concept of neurodiversity, utilising large general population samples increases statistical power and retains a level of detail that is otherwise lost through research based on traditional classification approaches (Lyll, 2023). Leveraging the trait approach in the current research will thus ensure that the nuanced and fine-grained relationships between Autism and ADHD can be investigated.

A popular data modelling technique for investigating psychological traits and their inter-relationships is network analysis. It identifies the unique relationships between traits, whilst accounting for all other traits in the network (Epskamp et al., 2018). Whilst increasingly used to investigate Autism and ADHD traits individually (Briganti et al., 2020; Cuve et al., 2022; Goh et al., 2020; Kim et al., 2015; Martel et al., 2016; Montazeri

et al., 2020; Preszler & Burns, 2019; Ruzzano et al., 2015; Silk et al., 2019; Waldren et al., 2022; Williams et al., 2021; Yang et al., 2022; Zhou et al., 2019), network analysis has seldom been used to investigate the links between these conditions. This is despite its well-known capacity to capture cross-condition associations (i.e., bridge centralities; Jones et al., 2021). Recent research (Farhat et al., 2022) has successfully used network analysis to investigate cross-condition links between Autism and ADHD traits in a large general population youth cohort (6–17 years old), finding evidence for some transdiagnostic links between Autism and ADHD, but generally low cross-condition connectivity (i.e., in support of a distinction between the conditions). Whilst these findings are limited to young populations, they demonstrate the utility of network analysis for investigating the co-occurrence of neurodevelopmental conditions and neurodiversity more generally. The current study aims to extend this previous work, by investigating the links between Autism and ADHD traits in large samples of adults.

In addition to under-investigating the co-occurrence of Autism and ADHD, most cross-condition neurodiversity research has not considered socio-demographic factors (e.g., Panagiotidi et al., 2019). Yet, sex (e.g., Arnett et al., 2015; Begeer et al., 2013; Fedele et al., 2012; Hull et al., 2017; Mandy et al., 2012; Mowlem, Rosenqvist, et al., 2019; Mowlem, Agnew-Blais, et al., 2019; Murray et al., 2019; Wood-Downie et al., 2021), age (e.g., Faraone et al., 2009; Mason et al., 2021; Oerbeck et al., 2019; Stewart et al., 2018; Wallace et al., 2016), intelligence (e.g., Bussing et al., 2012; Pastura et al., 2009), and co-occurring mental health conditions (e.g., D'Agati et al., 2019; Hunsche et al., 2022; Reale et al., 2017; Vannucchi et al., 2014), have all been linked to the manifestation of Autism and/or ADHD, and therefore should be considered when studying their overlap. Addressing this limitation in previous research, the current study will, for the first time, employ network comparisons to investigate if socio-demographic factors influence the connectivity between Autism and ADHD traits.

1.1. The current study

Overall, there has been a surprising lack of research investigating the links between Autism and ADHD traits, particularly in adults. The current study aimed to address existing knowledge gaps across three studies. First, using an existing, nationally representative sample ($n = 504$), Study 1 utilised network analysis to elucidate the links between self-reported Autism and ADHD traits, with a focus on understanding which traits are most likely to reflect transdiagnostic features linking the two conditions. Second, to address potential limitations in Study 1, Study 2 was a pre-registered replication and extension with a much larger sample ($n = 5000$), more robust network estimation, and network comparisons (to explore the influence of socio-demographic factors). Whilst the use of self-report data in Studies 1 and 2 provided initial insights into the potential transdiagnostic and cognitive links between Autism and ADHD, any associations identified would need to be further tested at the cognitive level. Therefore, drawing on the results of Studies 1 and 2, Study 3 ($n = 500$) investigated the links between Autism and ADHD traits using an experimental cognitive task. This allowed us to determine

if the transdiagnostic features inferred from self-report data were also found using psychometrically robust cognitive experimentation.

2. Network analysis: Studies 1 and 2

We report how we determined our sample size, all data exclusions, all inclusion/exclusion criteria, whether inclusion/exclusion criteria were established prior to data analysis, all manipulations, and all measures in the study.

2.1. Participants, measures, and procedure

Ethical clearance was granted by the local ethics committee and all participants gave informed consent prior to study completion. In Study 1, 504 English-speaking adults from the United Kingdom (UK) were recruited through the online platform, *Prolific*. The sample was nationally representative of the UK population, cross-stratified by age ($M = 45.03$ years, $SD = 15.41$ years, $Range = 18–79$ years) and sex (50.99% female, 49.01% male) according to [Office for National Statistics \(2020\)](#) data. Whilst this sample size was sufficient for commonly used network regularisation techniques, the reliability of specific edges would be improved through conducting an unregularised network analysis in a larger sample ([Epskamp et al., 2017, 2018; Isvoranu & Epskamp, 2021](#)). This was undertaken in Study 2, where 5000 English-speaking adults from the UK and United States (US) were recruited. The sample was aged between 18 and 89 years ($M = 39.19$, $SD = 13.40$), with an even split across sex (50.36% female, 49.60% male, .04% non-binary). Study 2 was pre-registered (<https://aspredicted.org/4pk9q.pdf>) prior to data collection, specifying the sample size, exclusion criteria, measures, and fundamental parameters of the analyses. Across both studies, 74 additional participants were excluded for failing a simple attention check embedded into the measure (e.g., “Please select ‘Slightly Agree’ to show that you are reading the questions.”).

In both Study 1 and 2, participants completed Autism and ADHD trait measures in a counter-balanced order. The 28-item Autism-Spectrum Quotient (AQ28; <https://doi.org/10.1007/s10803-010-1073-0>; [Hoekstra et al., 2011](#)) was used to measure Autism traits due to its demonstrated suitability for capturing the Autism phenotype across both males and females ([Grove et al., 2018](#)) and for open-science research (i.e., it is freely available). Using a 4-point scale (1 = *Definitely Agree*, 4 = *Definitely Disagree*), participants rated their level of (dis)agreement with 28 statements capturing Autism traits (e.g., “I prefer to do things with others rather than on my own.”). Reverse-phrased items were recoded so that higher scores endorsed the Autism trait for each item, generating an overall score between 28 (few Autism traits) and 112 (many Autism traits).

The 18-item Adult ADHD Self-Report Scale (ASRS; <https://doi.org/10.1017/S0033291704002892>; [Kessler et al., 2005](#)) was administered to measure ADHD traits due to its high classification accuracy (96.2%; [Kessler et al., 2005](#)) and suitability for open-science research. Using a 5-point scale (0 = *Never*, 4 = *Very Often*), participants rated their ADHD traits (e.g., “How often do you interrupt others when they are busy?”), generating an overall score between 0 (no ADHD traits) and 72 (many ADHD traits).

All participants answered socio-demographic questions regarding their sex, age (years), and level of educational attainment (0 = No qualifications, 8 = Doctorate; [UNESCO Institute for Statistics, 2012](#)). In Study 2, participants additionally reported if they had any mental health conditions (see [Supplementary Materials S.M.1.](#)).

2.2. Analysis and results

All analyses were performed using R (v 4.1.1; [R Core Team, 2022](#)). The data and analysis code are provided as [Supplementary Materials](#). Data from both studies were analysed using the same procedure, except where explicitly stated. The Autism (AQ28) and ADHD (ASRS) trait measures had good internal reliability in both datasets, and we found correlations that were expected in line with previous research: a moderate positive correlation between Autism and ADHD traits and a higher level of Autism traits in male versus female participants (see [Table 1](#)).

2.2.1. Network estimation

Across networks, each node (represented as a circle) depicts an Autism or ADHD trait, as measured through each item in the AQ28 and ASRS (see [Fig. 1](#)). Each edge (represented as a connecting line between two nodes) depicts the strength (thickness) and valence (colour) of the association between two nodes when accounting for all other nodes in the network ([Epskamp & Fried, 2018](#)). Only meaningful associations (any edges with non-zero weightings) were retained in the network. By using this approach, the links between specific traits, the connectivity across the whole network, and the links within and between each condition, were explored.

In Study 1, the network was constructed using an EBIC-glasso regularised algorithm ([Epskamp et al., 2012, 2018](#)) using partial correlations and an absolute least weight shrinkage

Table 1 – Correlation and reliability statistics for Study 1 and Study 2.

Measure	Study 1					Reliability	
	Correlation					α	ω
	1.	2.	3.	4.	5.		
1. Autism	–					.84	.85
2. ADHD	.30***	–				.90	.90
3. Sex	.13**	–.09	–			–	–
4. Age	–.04	–.23***	.01	–		–	–
5. Education	–.09*	–.05	.03	–.11*	–	–	–
Measure	Study 2					Reliability	
	Correlation					α	ω
	1.	2.	3.	4.	5.		
1. Autism	–					.84	.85
2. ADHD	.34***	–				.90	.91
3. Sex	.09***	–.12***	–			–	–
4. Age	–.02	–.23***	.13***	–		–	–
5. Education	–.05***	–.04*	.02	–.03*	–	–	–

Note. Study 1 ($n = 504$), Study 2 ($n = 4996$). Sex and education associations were calculated using point-biserial and Spearman's rank correlations, respectively. Significance is indicated as * $p < .05$, ** $p < .01$, *** $p < .001$.

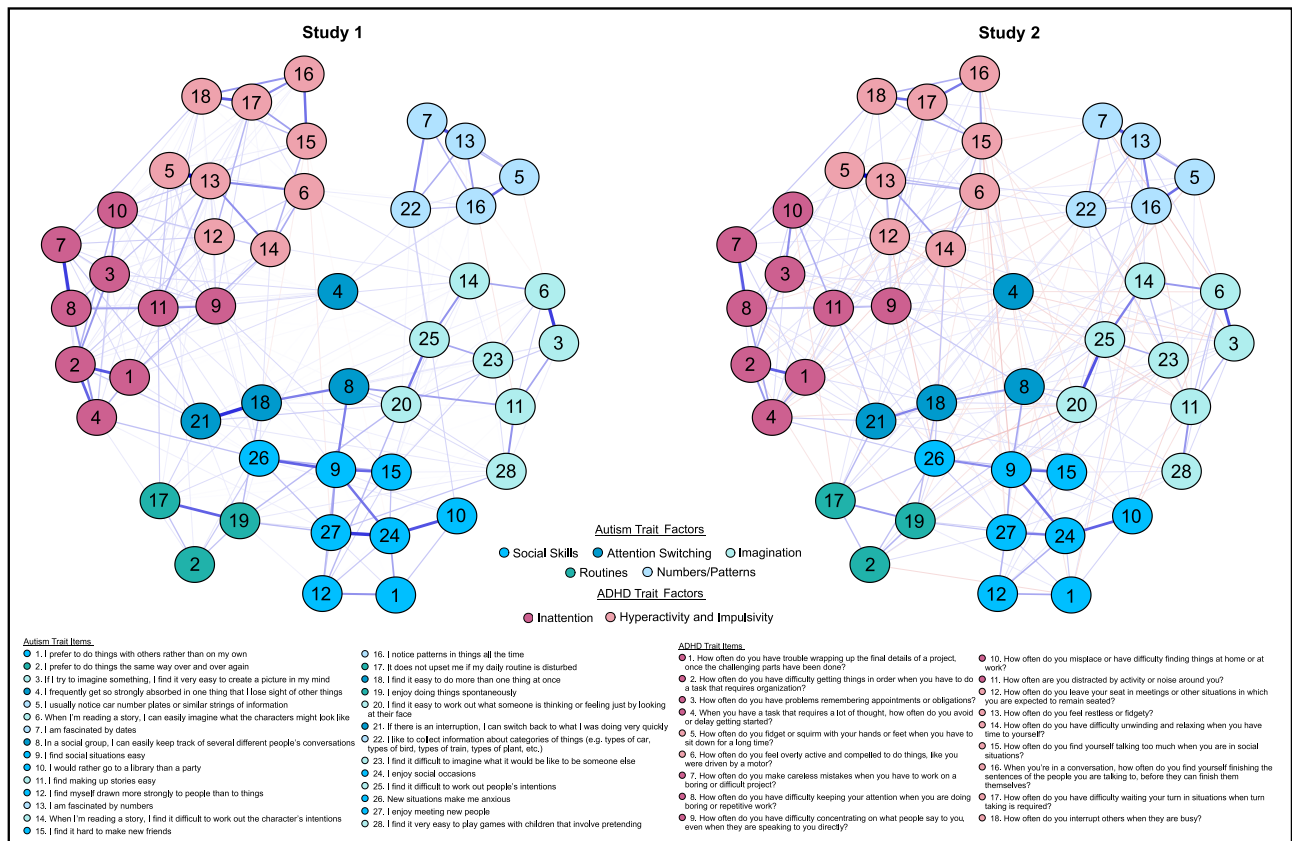


Fig. 1 – Network analysis results for Study 1 and Study 2. Note. Nodes (circles) are shaded according to the factor structure within each measure (Autism factors in blue/green, ADHD factors in pink). Nodes contain their item number, and the corresponding trait statement can be found at the bottom of the figure. Edge associations (connecting lines) are described by their width (thicker lines indicate stronger associations) and colour (blue lines indicate positive and red lines indicate negative associations).

penalty to avoid including spurious associations. In Study 2, networks were created using *ggmModSelect* (Epskamp et al., 2012; Isvoranu & Epskamp, 2021), whereby different edge combinations were iteratively tested until an optimal model fit was identified.

As shown in Fig. 1, network density ranged from 24.25 to 24.73% across Study 1 and Study 2, with 251 and 256 edges out of a possible 1035 retained in the final networks, respectively (Study 1: 245/251 edges were positive, $M = .07$ Range = $-.04$ to $.40$; Study 2: 212/256 edges were positive, $M = .08$, Range = $-.12$ to $.53$). Non-parametric bootstrapping suggested the edge weight estimates of both networks had acceptable levels of stability (Epskamp et al., 2018; see Supplementary Materials S.M.2.).

2.2.2. Edge weights

Across both studies, traits were more densely and strongly connected to traits from the same condition (Table 2; see also Supplementary Materials S.M.3.). This pattern of results suggests there is greater distinction between Autism and ADHD traits than overlap, supporting the separability and diagnostic distinction of the two conditions.

At the individual trait-level, the strongest links between Autism and ADHD traits in Study 1 were between: Autism item

26 “New situations make me anxious” and ADHD item 4 “When you have a task that requires a lot of thought, how often do you avoid or delay getting started?” ($b = .10$); Autism item 21 “If there is an interruption, I [cannot] switch back to what I was doing very quickly” and ADHD item 2 “How often do you have difficulty getting things in order when you have to do a task that requires organisation?” ($b = .09$); and Autism item 21 and ADHD item 11 “How often do you get distracted by activity or noise around you?” ($b = .08$).

In Study 2, the strongest links between Autism and ADHD traits were between: Autism item 21 and ADHD item 11 ($b = .13$); Autism item 8 “In a social group, I [cannot] easily keep track of several different people's conversations” and ADHD item 9 “How often do you have difficulty concentrating on what people say to you, even when they are speaking to you directly?” ($b = .12$); and Autism item 26 and ADHD item 14 “How often do you have difficulty unwinding and relaxing when you have time to yourself?” ($b = .12$). Strong links between Autism items 21 and 26 and ADHD item 11 appeared consistently across Study 1 and Study 2.

¹ Reverse scored items have been rephrased to reflect the meaning of a high score. E.g., “I find it easy to do more than one thing at once” has been rephrased to “I find it [difficult] to do more than one thing at once”.

Table 2 – Within- and between-condition global edge weights for Study 1 and Study 2.

		Study 1						
Edges	Density	Range (b)	Comparison (p)					
			1.	2.	3.			
1. Autism–Autism	119/378 (31.48%)	-.04 .33	–					
2. ADHD–ADHD	89/153 (58.17%)	.00 .40	.45			–		
3. Autism–ADHD	43/504 (8.53%)	-.03 .10	<.001			<.001 –		
Kruskal Wallis			$\chi^2(2) = 19.90,$ $p < .001$					
		Study 2						
Edges	Density	Range (b)	Comparison (p)					
			1.	2.	3.			
1. Autism–Autism	126/378 (33.33%)	-.12 .36	–					
2. ADHD–ADHD	69/153 (45.10%)	-.08 .53	.09			–		
3. Autism–ADHD	61/504 (12.10%)	-.11 .13	<.001			<.001 –		
Kruskal Wallis			$\chi^2(2) = 37.02,$ $p < .001$					

Note. 'Density' shows the number of significant edges compared to the number of potential edges (percentage density in parentheses) for Autism–Autism connections, ADHD–ADHD connections, and between Autism–ADHD connections. 'Range' shows the edge weight range for each association type. 'Comparison' depicts pairwise Wilcoxon test results for overall edge strength between groups, following a significant difference in edge weights identified using Kruskal–Wallis (in line with Farhat et al., 2022).

2.2.3. Network centrality

Centrality measures were used to explore the ways in which a node is connected to the wider network. *One-step Expected Influence* (EI) is the summed absolute weight of a node's edges across the whole network, reflecting how strongly that node (trait) is connected to all other nodes (traits) in the network (Opsahl et al., 2010). *One-step Bridge Expected Influence* (Bridge-EI), on the other hand, focuses specifically on a node's connections to nodes in the other condition (e.g., how strongly connected an Autism trait is to all ADHD traits, and vice-versa; Jones et al., 2021). By contrasting these EI and Bridge-EI values, we uncovered which traits appear most strongly condition-specific (i.e., demonstrating stronger connectivity to traits in their own condition than the opposing condition). More importantly, this revealed which traits show the strongest transdiagnostic properties (i.e., demonstrating stronger connections to traits in the opposing condition than to their own).²

² Additional centrality measures, such as closeness, betweenness, and their bridge counterparts, can further elucidate the associations between traits (Opsahl et al., 2010). As their validity has recently been questioned (Hallquist et al., 2021), we have not made any inferences on the basis of these metrics but report them in the [Supplementary Materials \(S.M.4.\)](#) for the interested reader.

Encompassing 75% of the nodes identified in the top transdiagnostic edge weights, Autism items 9, 24, and 27, and ADHD items 2, 13, and 17 showed greatest condition specificity, with greater EI than Bridge-EI z-scores across both datasets. These Autism traits arguably tap into subjective social enjoyment, whilst the ADHD traits reflect general hyperactivity-impulsivity. More interestingly, Autism trait items 4, 21, and 26, and ADHD trait items 4, 9, and 11 consistently showed high transdiagnostic properties, with greater Bridge-EI than EI z-scores across both datasets (Table 3 and Fig. 2). These bridge Autism items appear to reflect atypicalities with sustained attention (item 4; “I frequently get so strongly absorbed in one thing that I lose sight of other things”); and attentional disengagement (item 21: “If there is an interruption, I [cannot] switch back to what I was doing very quickly”). That is, atypicalities with maintaining focus and with shifting focus from one stimulus to another. The bridge ADHD items concern selective attention (item 9: “How often do you have difficulty concentrating on what people say to you, even when they are speaking to you directly?”) and attention inhibition (item 11: “How often are you distracted by activity or noise around you?”). That is, atypicalities with attending to important and relevant information and preventing distracting stimuli from interfering with attention. Together, these four aspects of attention (i.e., sustained attention, attentional disengagement, selective attention, attention inhibition) are widely thought to fall under the overarching umbrella of ‘attention control’, that is, the ability to attend and maintain focus to the appropriate stimuli without interference or distraction (e.g., Taylor et al., 2016).

2.2.4. Socio-demographic network comparisons

Network comparisons were possible due to the large sample size in Study 2. Such analyses permit testing of whether the relationships between Autism and ADHD traits change as a function of socio-demographic factors. To this end, the dataset was split into two groups per factor: sex (female, male), age (young, old, based on the sample median of 35 years), education (no degree, degree or above), and mental health condition status (none, 1+) and a network was estimated for each group. The two networks for each socio-demographic factor were compared using the Network Comparison permutation tests with Bonferroni correction (van Borkulo et al., 2022). Changes in the connectivity across the whole network and in the centrality of the specific transdiagnostic traits identified in the prior analyses (i.e., Autism items 4, 21, and 26, and ADHD items 4, 9, and 11; see Table 3) were inspected.

Mean Autism trait scores significantly differed by group for sex, education, and mental health networks, whilst mean ADHD trait scores significantly differed by group for sex, age, and mental health networks (Table 4). The network connectivity between traits remained very similar across networks, with the greatest change in connectivity found as a function of education and mental health status. The only significant increase in the strength of connections between Autism and ADHD traits was found in participants with a university degree compared to those without a university degree (Table 5). No change in centrality across network comparisons was observed for the six transdiagnostic traits of interest (see above [Network Centrality 2.2.3.](#); Table 5).

Table 3 – Interpretation of the top within- and between-condition nodes.

Within-Condition Nodes			
	Node Items	Main Construct	Transdiagnostic Construct
Autism	9. I find social situations easy 24. I enjoy social occasions 27. I enjoy meeting new people	Subjective Social Enjoyment	NA
ADHD	2. How often do you have difficulty getting things in order when you have to do a task that requires organization? 13. How often do you feel restless or fidgety? 17. How often do you have difficulty waiting your turn in situations when turn taking is required?	Hyperactivity-Impulsivity	
Between-Condition Bridge Nodes			
	Node Items	Main Construct	Transdiagnostic Construct
Autism	4. I frequently get so strongly absorbed in one thing that I lose sight of other things 21. If there is an interruption, I [cannot] switch back to what I was doing very quickly 26. New situations make me anxious	Attentional Disengagement, Sustained Attention	Attention Control
ADHD	4. When you have a task that requires a lot of thought, how often do you avoid or delay getting started? 9. How often do you have difficulty concentrating on what people say to you, even when they are speaking to you directly? 11. How often are you distracted by activity or noise around you?	Selective Attention, Inhibition	

Note. Traits are reported with their corresponding item measure number. The ‘Main Construct’ column contains a suggested interpretation that unifies the top nodes within each condition, and the ‘Transdiagnostic Construct’ column contains a suggested interpretation that links the Autism and ADHD top nodes.

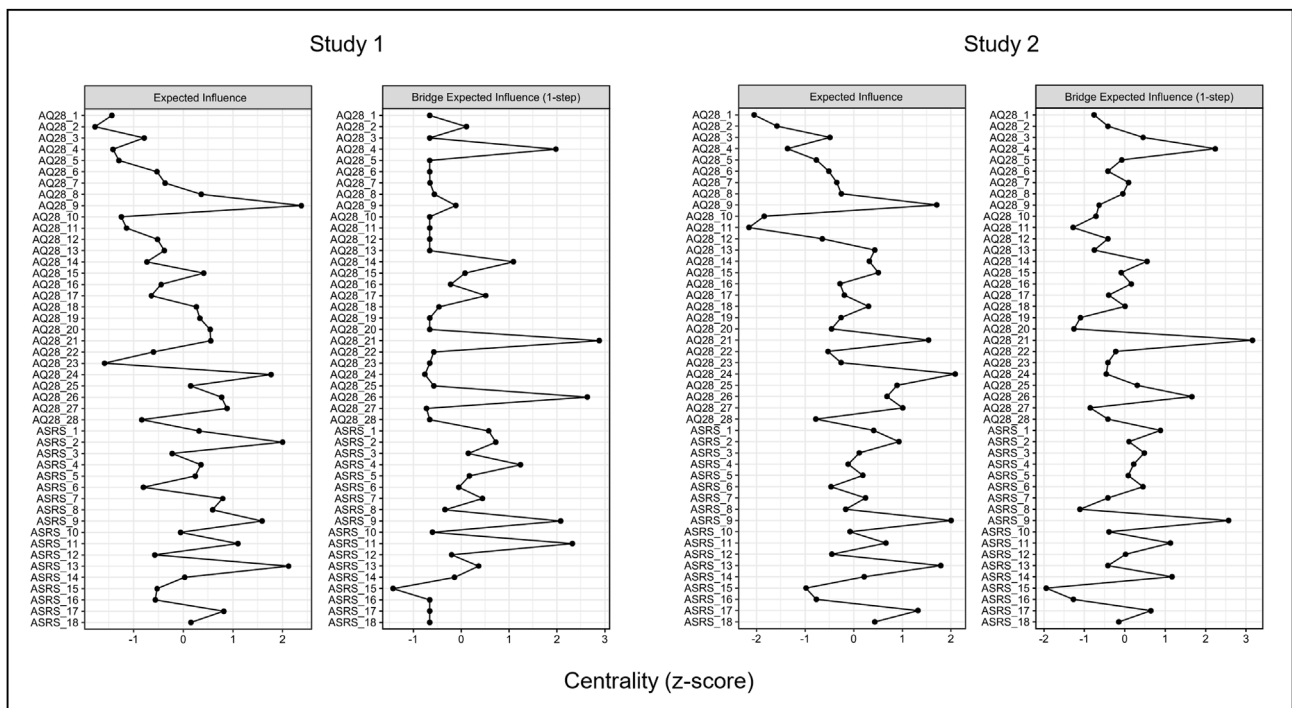


Fig. 2 – Expected Influence and Bridge Expected Influence Centrality for Study 1 and Study 2. Note. Standardised 1-Step Expected Influence and 1-Step Bridge Expected Influence for each node in Study 1 and 2. Case-drop bootstrapping suggested centrality estimates across both networks showed acceptable levels of stability (Epskamp et al., 2018; see Supplementary Materials S.M.5.).

Table 4 – Socio-demographic network descriptive statistics.

Network		n	Autism traits	ADHD traits
Sex	Male	2480	67.16 (10.52), 35–112	27.97 (11.49), 0–71
	Female	2518	65.25 (10.68), 31–109	30.66 (11.16), 0–72
			t(4996) = 6.37, p < .001, d = .18	t(4985.9) = -8.41, p < .001, d = -.24
Age	Young	2377	66.29 (10.14), 31–112	31.35 (11.70), 0–72
	Old	2623	66.11 (11.08), 34–109	27.50 (10.81), 0–71
			t(4997.5) = -.58, p = .56, d = -.02	t(4845.7) = -12.06, p < .001, d = -.34
Education	No Degree	2172	66.63 (10.42), 35–109	29.61 (11.53), 0–70
	Degree +	2826	65.87 (10.80), 31–112	29.11 (11.31), 0–72
			t(4748.8) = 2.54, p = .011, d = .07	t(4624.7) = 1.54, p = .12, d = .04
Mental health	None	3108	64.64 (10.06), 31–102	26.83 (10.56), 0–72
	1+ Condition	1892	68.75 (11.08), 36–112	33.44 (11.54), 1–72
			t(3698.9) = -13.15, p < .001, d = -.39	t(3722.6) = -20.27, p < .001, d = -.60

Note. Sample size (n), Autism (AQ28) and ADHD (ASRS) trait scores (M, (SD), Range), and Welch's t-test comparisons for Autism and ADHD traits are reported. Sex networks were created using sex at birth (female, male), removing two non-binary responses in line with the Study's pre-registration. Age networks were created using the whole sample median age (35 years). Education networks were created using university degree status, two participants were removed for ambiguous responses. Mental health networks were created based on participants reporting at least one clinically diagnosed mental health condition.

2.2.5. Redundant nodes

During network estimation, it is important to identify nodes with high similarity, known as redundant nodes, which may bias subsequent results (Christensen et al., 2020; Hallquist et al., 2021). Given the use of partial correlations in our network estimation, we followed the redundant node procedure outlined in Williams et al. (2021). We identified any node pairs with a high partial correlation ($r_p > .4$) and assessed the degree of similarity in their remaining partial correlations across the network (weighted Topological Overlap, wTO; Gysi et al., 2018; Zhang & Horvath, 2005). Two node-pairs were potentially redundant (Study 1: AQ28 item 3—item 6, $r_p = .40$, wTO = .29; ASRS item 5—item 13, $r_p = .48$, wTO = .36; Study 2: ASRS item 5—item 13, $r_p = .53$, wTO = .52) and were summed

into 1-item objects, respectively. All analyses were computed using the full 46- and reduced 44-item datasets, with negligible differences in results. We have reported findings from the full 46-item dataset above, with the equivalent redundant node analyses reported in the Supplementary Materials (S.M.6.).

2.3. Interim discussion

Studies 1 and 2 used powerful network analyses to investigate the relationship between Autism and ADHD traits in adulthood. The consistent results across studies, despite large differences in sample size and analysis techniques, suggest that the arising findings are likely to be robust. These results

Table 5 – Network comparison permutation tests by socio-demographic factors.

Network		Density (%)				Difference	
		Total	Autism	ADHD	Bridge	Strength	Edge
Sex	Male	19.32	24.87	37.91	9.52	.27	.12
	Female	19.52	26.72	39.22	8.13		
Age	Young	19.23	25.40	37.91	8.93	.15	.13
	Old	19.52	26.98	37.25	8.53		
Education	No Degree	17.68	23.81	36.60	7.34	2.20*	.14
	Degree +	22.03	30.42	40.52	10.12		
Mental health	No Condition	21.16	26.98	41.18	10.71	.92	.13
	1+ Condition	17.10	24.60	33.33	6.55		

Network	Change in Bridge Expected Influence					
	AQ28-4	AQ28-21	AQ28-26	ASRS-4	ASRS-9	ASRS-11
Sex	.05	.00	-.03	.07	.00	.00
Age	.00	-.02	-.10	.03	.06	.00
Education	-.05	-.05	.05	-.02	.04	.00
Mental health	.08	.00	.06	.01	-.06	.00

Note. Edge Density (%) are reported for total network, Autism–Autism (Autism), ADHD–ADHD (ADHD) and Autism–ADHD (Bridge) edges. The difference in global edge strength (Strength), the maximum difference in edge weight (Edge), and the difference in 1-step Bridge Expected Influence for the 6 identified transdiagnostic nodes are presented using 90 permutations. *Indicates p < .05. Sex networks were created using sex at birth (female, male), two non-binary responses were removed from analyses. Age networks were created using the whole sample median age (35 years). Education networks were created using university degree status, two participants were removed for ambiguous responses. Mental health networks were created based on participants reporting at least one clinically diagnosed mental health condition.

support the distinction between Autism and ADHD as separable constructs, in view of the significantly stronger and more densely connected links between traits of the same condition than between Autism and ADHD traits. The three Autism traits found to be most connected to other Autism traits – and thus likely reflecting condition-specific characteristics – referred to social enjoyment and the experienced difficulty of social situations. The three ADHD traits most connected to other ADHD traits reflected more general hyperactivity-impulsivity characteristics. These findings generally align with existing theory and research, reflecting key characteristics of each condition as they appear in the DSM-5 criteria (e.g., APA, 2013; Beck et al., 2020; Colomer et al., 2017; Ronald et al., 2014).

Critically, certain traits did show greater connectivity to traits in the opposing condition than to their own, supporting the presence of transdiagnostic links between Autism and ADHD. The Autism traits with the greatest links to ADHD traits reflected attentional disengagement (Georgiou et al., 2005) and sustained attention (Esterman & Rothlein, 2019; Fortenbaugh et al., 2017), whereas the ADHD traits with the greatest links to Autism traits reflected selective attention (Kotlyusov et al., 2023) and attention inhibition (Howard et al., 2014). These four aspects of attention are widely thought to collectively feed into the broader construct of attention control. Attention control concerns the ability to maintain attention on the required task while also responding to external stimuli, feedback, and continual behaviour correction. Successful attention control, therefore, requires the appropriate functioning of selective attention, to filter out irrelevant information in a task and focus on the important stimuli; inhibition, to suppress interference from irrelevant internal and external stimuli; sustained attention, to keep attention focused on the required task; and attentional disengagement, to detach focus and re-orient focus to the appropriate stimulus in light of changing task criteria (Burgoyne et al., 2023; Draheim et al., 2021; Taylor et al., 2016).

As attention control best encapsulated the latent cognitive construct underlying the Autism and ADHD bridge items, our findings indicate that attention control is likely to be a key cognitive transdiagnostic feature of Autism and ADHD. These findings, whilst novel, do align with the overlapping diagnostic features of Autism and ADHD (APA, 2013; Hendry et al., 2020). For example, attention control differences could underlie both the hypersensitivity to sensory input, as well as the increased attention given to restricted and highly focused interests in Autism (e.g., Crasta et al., 2023; Faja & Darling, 2019). Meanwhile, attention inhibition is a key diagnostic criterion for ADHD (APA, 2013) and challenges with selective attention can underpin many inattentive characteristics observed in ADHD (e.g., Collis et al., 2022; MacLennan et al., 2022; Strömberg et al., 2022).

Because attention control processes are highly intertwined, it is possible that difficulties in one component – at the cognitive level – may not straightforwardly explain any attention problems that are behaviourally or diagnostically observed. Indeed, researchers have struggled to separate attention control components in experimental designs, with the same methods being used to measure different attention control components. For example, the classic Stroop task has

been used to measure inhibition (Bélanger et al., 2010), attentional disengagement (Wilson & Wallis, 2013), and overarching attention control (Kotlyusov et al., 2023); whilst the same attention control components have been measured using multiple experimental designs (e.g., selective attention has been measured using both the classic Simon and Flanker tasks; Kawai et al., 2012; McDermott et al., 2017; Stoet, 2017). Therefore, it is plausible that difficulties in any of the attention control mechanisms could lead to qualitatively similar behavioural characteristics (see Draheim et al., 2021, 2022; Pak et al., 2023, for discussion on how attention control can influence behaviour). Based on Studies 1 and 2, we propose that attention control is likely to be a key transdiagnostic cognitive construct linking Autism and ADHD, but certain attention difficulties may still be condition-specific. This warrants additional investigation, necessitating careful measurement of attention control and its subcomponents, directly at the cognitive level. More specifically, the findings pertaining to attention control in Studies 1 and 2 are novel, with potential implications for future research and the real world, however, they are limited by the inferences that can be made from self-report data alone. Addressing this, we designed a third study using experimental measures of attention control. This allowed us to directly determine the nature of the unique links between Autism, ADHD, and attention control, via cognitive level data.

Measuring attention control, however, is itself not trivial, with many longstanding measures criticised for their poor psychometric properties and lack of domain generality (Burgoyne et al., 2023; Draheim et al., 2021). Particularly critical for our research study, many popular measures of attention control have especially been criticised for their poor reliability in capturing individual differences. This is thought to stem from the widespread use of response time difference scores, which minimise between-subject variability to facilitate between-condition comparisons (Draheim et al., 2019; Hedge et al., 2018; Rouder & Haaf, 2019). To overcome these limitations, Study 3 utilised a recently developed measure of attention control, the Three-Minute Squared Tasks (Burgoyne et al., 2023). This consists of three adapted versions of the classical Stroop, Flanker, and Simon paradigms, and has been well-validated to capture attention control as a latent construct in both online and lab-based samples. Critically, the Three-Minute Squared Tasks are a highly reliable measure for capturing individual differences in attention control, thereby facilitating our study on Autism- and ADHD-related differences in attention control. Altogether, Study 3 was designed to be one of the largest studies on Autism- and ADHD-related attention control processes to date using optimal instruments.

3. Study 3

3.1. Participants, measures, and procedure

The study was pre-registered (<https://aspredicted.org/ii95x.pdf>), ethical clearance was granted by the local ethics committee, and all participants gave consent prior to study completion. Five-hundred participants from Study 2 were re-

recruited through Prolific to form a sample that was broadly representative of the UK population (age: $M = 45.80$ years, $SD = 15.61$ years, $Range = 19–86$ years, sex: 50.80% female, 49.20% male). This sample maintained a comparable distribution of AQ28 and ($M = 65.84$, $SD = 11.28$, $\alpha = .86$, ω_1 Factor = .87) and ASRS ($M = 27.93$, $SD = 11.30$, $\alpha = .91$, ω_1 Factor = .91) scores to the sample in Study 2, and identified the same top transdiagnostic nodes (see [Supplementary Materials S.M.7.](#) for further details).

Participants completed the Three-Minute Squared Tasks (<https://doi.org/10.5281/zenodo.8313315>; Burgoyne et al., 2023; Licalde & Burgoyne, 2023) via Gorilla (www.gorilla.sc; Anwyl-Irvine et al., 2019). This consisted of three adapted versions of classical attention tasks (Stroop, Simon, and Flanker; see Fig. 3 and Burgoyne et al., 2023 for full details). Following the original procedure (Burgoyne et al., 2023), participants completed a 30-second practice, followed by a 90-second experiment period for each task. Trials within each task were presented in a pseudo-randomised order, and performance scores in each task were standardised. Standardised scores were then averaged to create a composite measure of attention performance for multiple regression analyses, but were also considered as individual indicators of an attention control factor in latent variable analyses. Autism, ADHD, and socio-demographic data were drawn from the Study 2 dataset.

3.2. Analysis and results

All analyses were performed using R (v 4.1.1; R Core Team, 2022). In line with Burgoyne et al. (2023), participants' performance scores were removed for each task if they scored below chance (7.33% of all data). A two-pass outlier exclusion procedure was then performed, whereby data points that exceeded 3.5 SDs from the sample mean were removed (.20%). This was performed twice, with sample mean and SD recalculated for each iteration. Mean attention control was correlated with sex, age, education, both ADHD trait factors and the 'Routines' Autism trait factor. Multiple regression analyses showed that Autism traits were predicted by sex, ADHD traits were predicted by age, and mean attention control was predicted by sex, age, and education (see [Supplementary Materials S.M.8.](#) for further details).

Bi-directional relationships between Autism, ADHD, and attention control were explored using the following latent variable analyses. First, the Autism and ADHD trait factor structures stipulated during measure development (Hoekstra et al., 2011; Kessler et al., 2005) were confirmed to still be applicable to the current sample (Autism trait factor structure: $\chi^2(340, N = 500) = 1072.88$, $p < .001$, CFI = .97, TLI = .97, RMSEA = .07; ADHD trait factor structure: $\chi^2(134, N = 500) = 669.17$, $p < .001$, CFI = .97, TLI = .97, RMSEA = .09; see [Supplementary Materials S.M.9.](#) for factor loadings). Second, a CFA was specified to explore the latent correlations between Autism, ADHD, and attention control. Within this model ($\chi^2(1099, N = 403) = 3417.52$, $p < .001$, CFI = .95, TLI = .94, RMSEA = .07), significant correlations were observed between attention control and both ADHD trait factors (Inattention: $r = .12$, $p = .038$; Hyperactivity-Impulsivity $r = .14$, $p = .012$; see [Supplementary Materials S.M.10.](#) for further details).

Third, we specified a Structural Equation Model (SEM) where Autism and ADHD traits (in addition to sex, age, and education) were allowed to predict attention control (Fig. 4A). Accounting for Autism and ADHD did not significantly improve the model fit ($\Delta\chi^2(7) = 4.69$, $p = .70$), and no significant associations between attention control with either Autism or ADHD traits were observed. These findings suggest that the unique variance in attention control could not be explained by Autism or ADHD traits.

Fourth, we specified an alternative SEM, where attention control, age, sex, and education, were allowed to predict Autism and ADHD traits (Fig. 4B). Model fit was not improved by accounting for attention control ($\Delta\chi^2(7) = 4.99$, $p = .66$), and no significant associations between Autism and ADHD traits with attention control were observed. Furthermore, there was no meaningful change in the latent correlations between Autism and ADHD traits after accounting for attention control (see [Supplementary Materials S.M.11.](#)). Taken together, these findings suggest that attention control may not underpin the relationship between Autism and ADHD traits.

Finally, informed by the transdiagnostic items identified in Study 1 and Study 2, a follow-up SEM was performed. Namely, attention control, age, sex, and education were specified to predict a 'transdiagnostic' factor, containing the six items identified in Study 1 and Study 2. Whilst the 6 items loaded well onto the transdiagnostic factor (see [Supplementary Materials S.M.9.](#)), supporting their representation of the overlap between Autism and ADHD, attention control did not predict this new factor (Fig. 4C).

Collectively, these results suggest that attention control may have some role in linking Autism and ADHD, as it correlates with specific factors within each condition. However, these associations were not retained after accounting for socio-demographic variables, suggesting much of the transdiagnostic pattern previously observed between the conditions remains to be characterized by other potential constructs.

4. General discussion

The current study investigated the links between Autism and ADHD traits in adulthood using a multi-method approach. Across nationally representative and large general population samples, Studies 1 and 2 found that Autism and ADHD traits were most connected to traits from within their own condition. Critically, however, strong associations between attention-related Autism and ADHD traits were also found, suggesting that these traits may be transdiagnostic features across the two conditions. Based on these findings from the network analyses, we proposed that attention control may be a key cognitive mechanism that underpins the overlap between Autism and ADHD. To test this at the cognitive level, we re-recruited a large sub-sample of Study 2 participants to complete a well validated measure of attention control (Study 3). Our experimental findings diverged from the inferences made via the self-report data and network analyses. Namely, whilst mean attention control correlated with both ADHD trait factors and the 'Routines' Autism trait factor, neither Autism nor ADHD were uniquely linked to latent

The figure displays three distinct task trials on a black background. Each trial includes a title, a progress bar for 'TIME', a 'SCORE' indicator (0), and a 'Begin practice' button.

- STROOP SQUARED:** The instruction is 'WORD IS IN BLUE COLOR'. The target stimulus is the word 'RED' in blue text. Two response options are shown: 'RED' (labeled 'WRONG ANSWER' with a red 'X') and 'BLUE' (labeled 'CORRECT ANSWER' with a green checkmark).
- SIMON SQUARED:** The instruction is 'ARROW IS POINTING LEFT'. The target stimulus is a white arrow pointing left. Two response options are shown: 'RIGHT' (labeled 'WRONG ANSWER' with a red 'X') and 'LEFT' (labeled 'CORRECT ANSWER' with a green checkmark).
- FLANKER SQUARED:** The instruction is 'OUTSIDE ARROWS ARE POINTING LEFT'. The target stimulus consists of five blue arrows pointing left. Two response options are shown: 'WRONG: INSIDE ARROW IS POINTING RIGHT' (labeled 'WRONG ANSWER' with a red 'X') and 'CORRECT: INSIDE ARROW IS POINTING LEFT' (labeled 'CORRECT ANSWER' with a green checkmark).

Fig. 3 – Example trials from the Three-Minute Squared Tasks. Note. Image taken from [Burgoyne et al. \(2023\)](#). In Stroop Squared, participants were tasked with selecting the response option whose semantic meaning matched the colour of the target stimulus. In Simon Squared, participants were tasked with selecting the response option that indicated the direction that the target arrow was pointing. In Flanker Squared, participants were tasked with selecting the response option with the central arrow pointing in the same direction as the flanking arrows in the target stimulus. For further details, see [Burgoyne et al. \(2023\)](#).

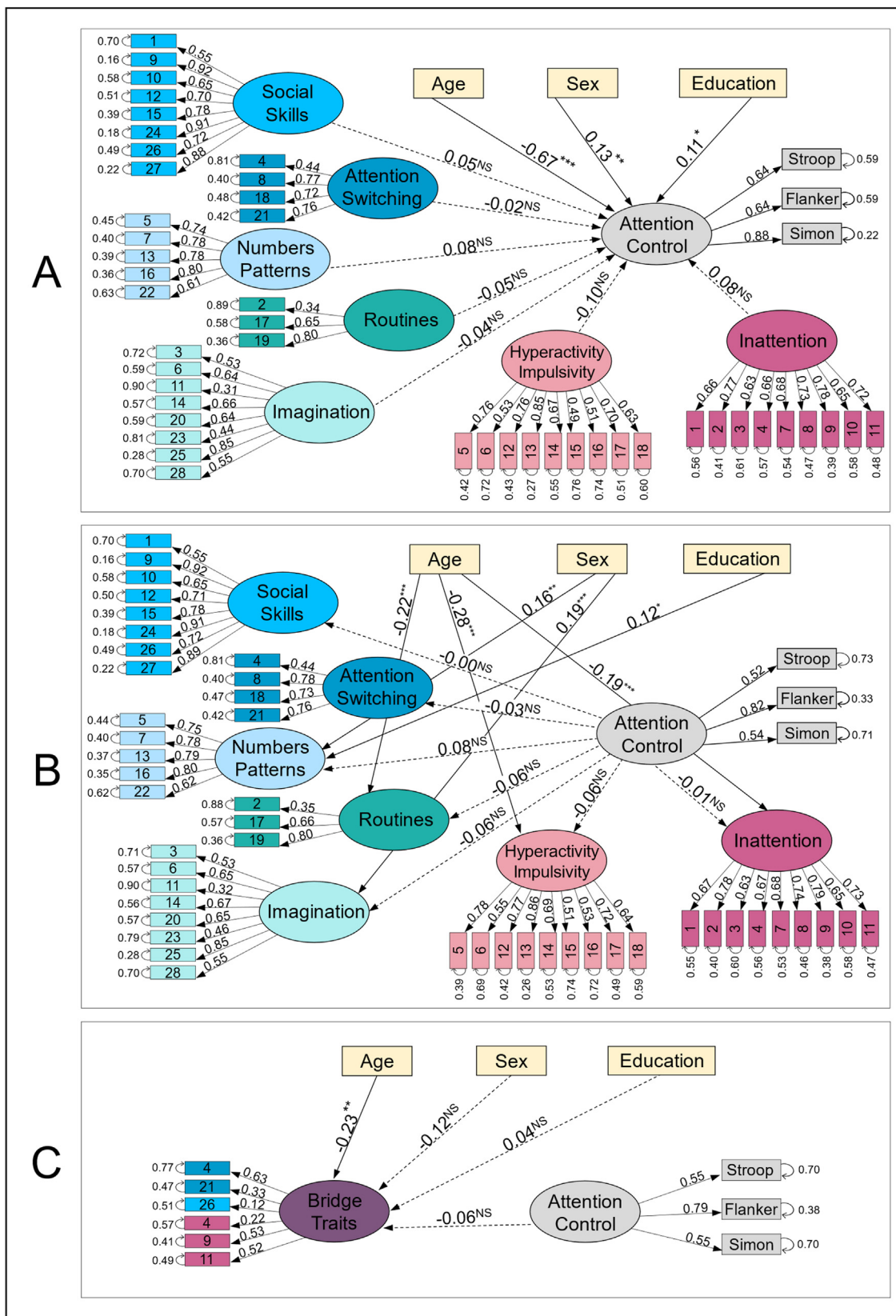


Fig. 4 – SEMs exploring the links between Autism, ADHD, and Attention Control. Note. Regression coefficient significance is indicated as ^{NS} $p > .05$, $*p < .05$, $p < .01$, $***p < .001$. A.) Autism and ADHD trait factors predicting Attention Control. All factor loadings are significant to $p < .001$. B.) Attention Control predicting Autism and ADHD trait factors. All factor loadings are significant to $p < .001$. Only significant socio-demographic regression paths are retained in the figure for readability. C.) Attention Control predicting the Transdiagnostic Trait factor informed by items from Study 1 and Study 2. Autism and ADHD trait factors have been removed for readability. For full details about each model see [Supplementary Materials S.M.11](#).**

attention control whilst accounting for socio-demographic variables.

Both network analyses (Studies 1 and 2) found greater distinction than overlap between Autism and ADHD traits. To our knowledge, this is the first study to investigate Autism and ADHD traits in adulthood using a network analysis approach, and the first study to show this pattern of results in a large, well-powered sample. The results also support the network analysis findings of [Farhat et al. \(2022\)](#) in a study of children and adolescents, where strikingly similar within- and between-condition network edge densities were observed (Total = 30%, Autism–Autism = 42%, ADHD–ADHD = 64%, Autism–ADHD = 10%). Together, these studies very clearly align with existing research and the view of Autism and ADHD as distinct conditions with unique behavioural phenotypes (e.g., [Ronald et al., 2014](#); [Thapar et al., 2017](#)). Additionally, the consistency in results across both youth and adult cohorts suggests the reciprocal relationship between Autism and ADHD traits may generally be stable over development (but see [Shakeshaft et al., 2023](#)), although additional longitudinal network modelling across development would be of great interest in future research.

The characteristics most specific to Autism and ADHD were subjective social enjoyment and hyperactivity-impulsivity, respectively. Whilst in keeping with existing research and current understanding of Autism and ADHD (e.g., [APA, 2013](#); [Beck et al., 2020](#); [Colomer et al., 2017](#)), these findings provide evidence for the condition-specificity of certain traits – especially because network analyses revealed these links whilst statistically accounting for the cross-condition relationships. For example, that hyperactivity-impulsivity ADHD traits were least likely to be linked with Autism strongly supports the complete absence of these characteristics in Autism diagnostic criteria (DSM-5; [APA, 2013](#)) and suggests that where these are present in Autism, they are most likely due to co-occurring ADHD. More broadly, the current results, when situated within the trend towards more general neurodevelopmental clinical support over condition-specific tailored interventions, may highlight characteristics for which the classical, more condition-specific approach is still required (see also, [Sonuga-Barke & Thapar, 2021](#)).

When examining the commonalities across traits linking Autism and ADHD, attention control clearly emerged as a potential transdiagnostic process linking the two conditions. Indeed, this is the first study to reveal the potential importance of considering attention control in Autism–ADHD transdiagnostic research endeavours in adults. More generally, these findings reiterate the need for clinical consideration of Autism when assessing for ADHD and vice versa ([Bora & Pantelis, 2016](#); [Leitner, 2014](#)), to facilitate differential diagnosis, avoid mis-diagnosis, and where necessary, make a dual diagnosis. Our results suggest that careful consideration of self-reported attention control challenges, specifically, may be useful for improving diagnostic precision.

Interestingly, however, we found a conceptually opposing pattern of results in Study 3. The reasons why neither Autism nor ADHD were uniquely linked to attention control needs closer inspection. First, it is possible that the online Three-Minute Squared Tasks of attention control were not as

sensitive to quantifying individual differences as they were designed to be ([Burgoyne et al., 2023](#)). However, socio-demographic differences in performance were robustly identifiable (e.g., with age and sex), strongly supporting the measures' ability to accurately capture individual differences. Second, it was possible that online data collection might have deteriorated the data quality to the extent that we were unable to detect the associations we expected based on the Study 1 and 2 network analyses. Yet, data exclusion rates, whilst marginally higher than the original study, were also well within acceptable limits, suggesting that administering the study online did not harm data quality (see also, [Krendl et al., 2023](#) for a recent discussion on online testing). That the attention control measures had excellent psychometric properties further reinforces this interpretation. Third, it could be argued that there was insufficient variation in Autism and ADHD traits in the sample recruited to complete Study 3, such that we were unable to detect the associations between Autism, ADHD, and attention control. However, the study design guarded against this. That is, participant demographics were broadly representative of the UK population, with Autism and ADHD trait scores being normally distributed, similar to the larger Study 2, and showing the expected and significant associations with socio-demographic factors (see [Supplementary Materials S.M.7](#); as reported in [Bálint et al., 2009](#); [Baron-Cohen et al., 2001](#); [Oerbeck et al., 2019](#)). Altogether, it seems highly unlikely that the pattern of results in Study 3 simply stemmed from problems with the attention control tasks or wider methodological flaws with online data collection or the study design.

Therefore, putting aside those aforementioned basic explanations for understanding the disparity between the network analyses (Study 1 and 2) and cognitive experiments (Study 3), our findings raise more fundamental questions about what we know about cognition in Autism and ADHD (and how it should be measured). Based on our results, it could be argued that previous research on attention atypicalities have been overstated in these conditions. Indeed, there is a body of research that has found relatively weak or no links between Autism and attention control in adults, although this has mainly been focused on socially relevant attention processes (e.g., [Fletcher-Watson et al., 2008](#); [Grubb et al., 2013](#)). Where previous research has reported attention control atypicalities in autistic people (see [Keehn et al., 2013](#)), it has usually been found in small samples and using measures that were arguably not designed to reliably capture individual differences (see [Burgoyne et al., 2023](#); [Hedge et al., 2018](#) for discussion on the Reliability Paradox). This, in turn, may have inflated the putative evidence for attention difficulties in autistic people, and our findings point towards a need for a closer inspection of the link between Autism and attention control, both theoretically and with better powered empirical studies using appropriate measures. For example, a more finely-grained investigation into the influence of specific mental health conditions (e.g., [De Geus et al., 2007](#); [Keller et al., 2019](#); [Reinholdt-Dunne et al., 2013](#)) and general cognitive ability (e.g., [Hambrick et al., 2019](#); [Heitz et al., 2005](#); [Schweizer et al., 2005](#)) may be warranted, given their associations with attention control.

Irrespective of Autism traits, one could expect that ADHD traits would be much more clearly associated with poor attention control, given the centrality of atypical attention to the ADHD diagnostic criteria (e.g., Banich et al., 2009; Salmi et al., 2018). Interestingly, the evidence base for this widely-held assumption is limited and equivocal (e.g., Pelletier et al., 2016; Roberts et al., 2017, 2018). For example, with particular relevance to the current study, research has found disparities between the self-reported experiences and objective task performance of children and adults with ADHD (e.g., Du Rietz et al., 2016; Manor et al., 2012). This suggests our current results may be explained by the inconsistencies between participant's subjective experience of their attention differences and their objective performance on attention control tasks.

More widely, research indicates that self-reported characteristics can be a poor index of objective performance across a range of experimental cognitive measures (Buchanan, 2016; Murphy & Lilienfeld, 2019). This may be due to self-report and cognitive measures capturing different timeframes of behaviour (e.g., days versus seconds), leading to asymmetry and inconstancy when comparing these approaches (e.g., Brunswik symmetry; Kretzschmar et al., 2018; Süß et al., 1996). Our study, extending this work, raises further questions about the challenges of using self-report measures for making inferences about cognitive and behavioural processes. This might be especially challenging within neurodiversity and clinical research, where this approach is widely adopted to overcome practical challenges with data collection (i.e., questionnaires are more readily administered than cognitive tasks).

Nevertheless, self-report data is likely more akin to real world lived experiences, so may better reflect the challenges experienced in daily life over and above objective performance in arguably artificial cognitive tasks (see Dang et al., 2020). Our study highlights that accurately capturing behavioural and cognitive performance may be a particular challenge for studying Autism, ADHD, and neurodiversity more generally, outlining an important avenue to follow in future research. For example, this might be achieved through combining these approaches, in addition to multi-informant and clinical assessments.

In summary, our research paints an interesting and complex picture of the links between Autism and ADHD traits in adulthood. We found support for the distinction between Autism and ADHD as separable constructs, but also report evidence showing an overlap in Autism and ADHD traits in terms of attention control processes (Studies 1 and 2). This pattern of results was clear, but only found in the self-report data, with a markedly different result when conducting an investigation at the cognitive level using up-to-date tasks (Study 3). Moving forward, it is clear that further, systematic work is needed to better understand the links between Autism and ADHD in adults at different levels of explanation. To this end, we suggest that routinely including both self-report and cognitive measures might prove to be important and help to advance our current (limited) understanding of neurodiversity. The fast-growing range of short, psychometrically robust online tasks will support this type of future research (see also, Livingston et al., 2019; Burgoyne et al., 2023) and, by

making the large datasets and analysis code from the current research openly accessible, we hope to facilitate future investigations into Autism and ADHD in adulthood.

Open practices

The studies in this article earned Open Data, Open Material and Preregistered badges for transparent practices. The links to the pre-registered studies are available at: <https://aspredicted.org/4pk9q.pdf> and <https://aspredicted.org/ii95x.pdf> and the links to the archived data and materials are available at: <https://zenodo.org/records/8313315> and https://github.com/Lucy-Wal/Autism_ADHD_Adults.

CRedit authorship contribution statement

Lucy H. Waldren: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing, Project administration. **Florence Y.N. Leung:** Formal analysis, Investigation, Writing – review & editing, Methodology. **Luca D. Hargitai:** Investigation, Writing – review & editing. **Alexander P. Burgoyne:** Methodology, Software, Writing – review & editing. **Van Rynald T. Licalalde:** Methodology, Software, Writing – review & editing. **Lucy A. Livingston:** Conceptualization, Funding acquisition, Resources, Supervision, Writing – review & editing. **Punit Shah:** Conceptualization, Data curation, Funding acquisition, Investigation, Project administration, Resources, Supervision, Writing – original draft, Writing – review & editing.

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Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.cortex.2023.12.016>.

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