

Using Network Analysis to Improve Understanding and Utility of the 10-item Autism-Spectrum Quotient (AQ10)

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Abstract

The 10-item Autism-Spectrum Quotient (AQ10) is a measure of autistic traits used in research and clinical practice. Recently, the AQ10 has garnered critical attention, with research questioning its psychometric properties and clinical cut-off value. To help inform the utility of the measure, we conducted the first network analysis of the AQ10, with a view to gain a better understanding of its individual items. Using a large dataset of 6595 participants who had completed the AQ10, we found strongest inter-subscale connections between communication, imagination, and socially relevant items. The nodes with greatest centrality concerned theory of mind differences. Together, these findings align with cognitive explanations of autism and provide clues about which AQ10 items show greatest utility for informing autism-related clinical practice.

Introduction

The 10-item Autism-Spectrum Quotient (AQ10; Allison *et al.*, 2012) is a popular measure of autistic traits used internationally in research (e.g., Taylor *et al.*, 2021) and clinical practice (e.g., Weir *et al.*, 2020). Recently, however, the AQ10 has attracted scrutiny, with research challenging its validity and utility. First, research has reported psychometric concerns with the measure, notably in studies published in *Experimental Results*. Taylor *et al.* (2020) found the AQ10 had low inter-item correlations and internal consistency, which also suggested that it was tapping into a myriad of constructs. Following Taylor *et al.*, Bertrams (2021) found the AQ10 had low internal consistency and homogeneity, but that changing its scoring system from a 4- to 6-point response scale marginally improved its psychometric properties. Second, the AQ10's cut-off – indicative of a clinically significant level of autistic traits – has been incorrectly applied. Waldren *et al.* (2021) recently reported that the National Institute for Health and Care Excellence (NICE) had, for almost a decade, recommended the incorrect AQ10 cut-off value to screen for autism (≥ 7 instead of ≥ 6 , based on Allison *et al.*, 2012). This error has generated confusion amongst researchers and clinicians who administer the AQ10 in their work, with evidence of several studies (e.g., Payne *et al.*, 2020; Rahman *et al.*, 2021) using the incorrect cut-off value (see Waldren *et al.*, 2022).

NICE have now corrected their guidance (NICE, 2021), and Bertram's 6-point response scale has potential to improve the AQ10, together helping to improve the measure's psychometric validity and utility. This is critical given that the AQ10 is deeply entrenched in both research and clinical practice. Adding to this research, the current study aims to further investigate the AQ10, towards providing users with insights about the utility of its individual items. Previous research on the AQ10 has focussed on overall AQ10 scores, where the measure is administered as a standalone instrument. In practice, however, certain AQ10 items

are used as tools to structure clinical interviews, and inform referrals and clinical formulation, rather than all items being administered rigidly and treated equally (NICE, 2021; Weir *et al.*, 2020). Whilst this flexible use of the AQ10 can itself be problematic, it reflects the concerns with the utility of overall AQ10 scores (e.g., Ashwood *et al.*, 2016) and, equally, points toward the benefit of an individualised approach in time-limited clinical sessions. For example, alongside total AQ10 scores, zooming in on items most relevant to an individual's profile might help inform further assessments and/or interventions. The potential utility of item-specific use of the AQ10 has, however, not been well investigated.

We propose that a closer inspection and better understanding of the individual items in the AQ10 – specifically the interrelationships between them – will speak to enhancing the utility of the measure. To this end, network analysis offers a powerful tool to examine the unique relationships between items and the influence each item has over the larger network. A network consists of nodes (i.e., circles), which represent the individual items in the network, and edges (i.e., connecting lines), which represent the unique conditional relationship between two nodes when accounting for all other relationships in the network. Using this approach, the strongest/weakest connections between AQ10 items can be identified and the relative importance of each AQ10 item for the network examined (Borsboom *et al.*, 2021; Epskamp *et al.*, 2018; Hevey *et al.*, 2018). To our knowledge, this will be the very first network analysis of AQ10 data, which follows increasing and innovative use of this approach for understanding neurodivergent traits (e.g., Farhat *et al.*, 2021).

Methods

Ethical approval was granted by the local ethics committee (Project code: 19-025).

Utilising open-access data from Gollwitzer *et al.* (2019), the current dataset included

binarized AQ10 item responses from 6595 non-clinical participants (AQ10: $M = 3.01$, $SD = 1.71$). We maintained binarized scoring to reflect the scoring system used most widely in clinical settings (see Allison *et al.*, 2012). Analyses were performed in R 4.1.3 (R Core Team, 2022).

To investigate the interrelationships and influence of each item within the AQ10, a weighted, non-directional network was created, whereby each node represents one AQ10 item, and each edge represents the unique conditional relationship between two items (*IsingFit*, van Borkulo *et al.*, 2016). Logistic regression was used to assess the association between AQ10 items and LASSO regularisation was implemented to ensure only significant associations were retained in the final model (Barber & Drton, 2015; Epskamp *et al.*, 2018).

Non-parametric bootstrapping (1000 resamples), with 95% confidence intervals (CIs), assessed the accuracy of the network's edge weights. Differences in edge weight were statistically compared using the bootstrapped edge weight difference test (*bootnet*, Epskamp *et al.*, 2018). To investigate the relative importance of each node in the network, multiple centrality measures were inspected. *One-step Expected Influence* indicates the strength of a node's connections through the sum of its edge weights when accounting for association direction. *Closeness* indicates the proximity of a node's connections through the shortest path length (number of edges) needed to connect with all nodes in the network. *Betweenness* indicates the influence of a node over other associations, characterising the frequency it falls within the shortest path of other nodes (Bringmann *et al.*, 2019; Robinaugh *et al.*, 2016). Centrality stability was assessed through case-drop bootstrapping (1000 resamples), with resultant correlation stability coefficients (CS) of $>.50$ (minimum CS $>.25$) indicating sufficient stability (Epskamp *et al.*, 2018).

Results

There were no missing data and the distribution of AQ10 scores is provided in the Supplementary Materials (Figure S1). Of the 45 possible edges, 28 (62.22%) showed non-zero associations with a mean edge weight of 0.24 (Figure 1). Estimated edge weights were largely positive ($N = 23$, 82.14%, *Range* [0.03, 1.66]), with 5 (17.86%) edges representing negative associations (*Range* [-0.33, -0.11]).

Non-parametric bootstrapping suggested that edge weights were determined with acceptable accuracy (Figure S2). The strongest relative associations were found within the attention switching (Item3–Item4 = 1.66) and communication (Item5–Item6 = 1.42) subscale items, with strong associations also found between i) communication and imagination (Item5–Item7 = 1.24; Item6–Item7 = 1.00) and ii) social skill and imagination (Item8–Item10 = 1.13; Item7–Item10 = 0.97) subscale items (see Table S1 for all edge weight values). Edge weight difference tests found that the abovementioned six associations were significantly larger than most others in the network (Figure 2). The two strongest within subscale associations (i.e., the association between the attention switching items and the association between the communication items) did not significantly differ in edge weight (95% CIs[-0.48, 0.05]), however they were larger than the greatest associations between subscales (see Table S2).

Case-drop bootstrapping indicated that, whilst measures of closeness ($CS = 0.28$) and betweenness ($CS = 0.36$) met the minimal levels of acceptance, they did not reach the preferred stability level of $CS >.50$ (Figure S3). When considered in addition to research questioning the appropriateness of these measures in psychological research (Bringmann *et al.*, 2019), we only report expected influence ($CS = 0.75$), with metrics for closeness and

betweenness centrality available in the supplementary materials (Figure S4; Table S3). Item5 ($z = 1.39$), Item7 ($z = 0.96$), and Item6 ($z = 0.82$) showed the greatest expected influence across the network, whilst Item1 ($z = -1.67$) and Item2 ($z = -1.13$) showed the least expected influence across the network (Figure 3, see Table S3 for centrality values).

Discussion

The current study aimed to investigate the AQ10 at the individual item level using network analysis, towards informing the utility of the measure. The resulting network showed largely positive and well-connected associations, with the strongest connections found between *intra*-subscale items. The strongest *inter*-subscale associations were found between communication, social skill, and imagination items, which also showed the strongest expected influence centrality (i.e., the strongest connections with other nodes in the network).

The network showed widespread connectivity after accounting for network sparsity (Epskamp *et al.*, 2018). Strong associations between *intra*-subscale items, specifically attention switching and communication, suggest that individuals may typically show multiple autistic traits within a trait domain. Strong connections between social skill and communication items also align with the social-communication differences inherent to autism (American Psychiatric Association; APA, 2013). Whilst Item7, within the imagination subscale, also connected strongly to social skill and communication items, a closer inspection of the item wording – “*When I’m reading a story, I find it difficult to work out the characters’ intentions*” – demonstrates it too reflects social-communication challenges. Moreover, this follows the latest autism diagnostic criteria, where imagination differences fall under the broader “social communication and interaction” criterion (APA, 2013). Overall, the current edge-weight associations indicate items reflecting social-communication differences are

strongly interconnected within the AQ10. This suggests that the various socially relevant traits associated with autism might feed into one another and, potentially, that clinical intervention with one might have knock-on consequences for others.

When investigating network centrality, Item5 – “*I find it easy to ‘read between the lines’ when someone is talking to me*”; Item6 – “*I know how to tell if someone listening to me is getting bored*”; and Item7 – “*When I’m reading a story, I find it difficult to work out the characters’ intentions*” showed greatest expected influence, indicating that these items are most connected to other nodes in the network. Such information could in turn inform clinical practice, for it may be likely that an individual scoring highly on these particular items will also have an overall higher total AQ10 score because of this greater connectivity to items across the network. Items 5, 6, and 7 also tap into challenges with theory of mind (ToM), the ability to understand others’ minds. Interestingly, these items with greatest centrality in the AQ10 broadly correspond with the Four-Item Mentalising Index (FIMI), a recently developed self-report measure of ToM ability (Clutterbuck *et al.*, 2021, 2022). Our findings suggest the possibility that ToM-associated differences are key markers for indicating overall levels of autistic traits, aligning with theories that ToM differences are crucial for understanding autism (Livingston & Happé, 2021; Livingston *et al.*, 2019, 2021).

We investigated the AQ10 as scored in the binary manner used in clinical settings, however the network relationships may differ with continuous scoring, including the recently proposed 6-point Likert scale (Bertrams, 2021). The 6-point scale was not available in the current open-access dataset, but further investigation of this AQ10 scale, using network analysis, would be an interesting avenue for future research. Given its brevity, the AQ10 also measures a limited range of autistic traits, therefore our study may have overlooked other

clinically important traits (e.g., sensory differences). Further evaluation of the AQ10, in comparison to emerging autism trait measures (e.g., The Comprehensive Autistic Trait Inventory; English et al., 2021) will of course be required to continually assess the AQ10's utility in both research and clinical practice.

Conclusions

The current research aimed to extend efforts to inform the utility in the AQ10 by focussing on the interrelationships between its items through network analysis. The network showed strong interrelationships between items pertaining to communication, imagination, and social differences, and the items with greatest influence on the network conceptually corresponded to ToM differences. Our findings align with common cognitive models of autism and suggest that the utility of the AQ10 could be enhanced by focussing on specific items – as part of a system of autistic traits – in addition to the overall AQ10 score.

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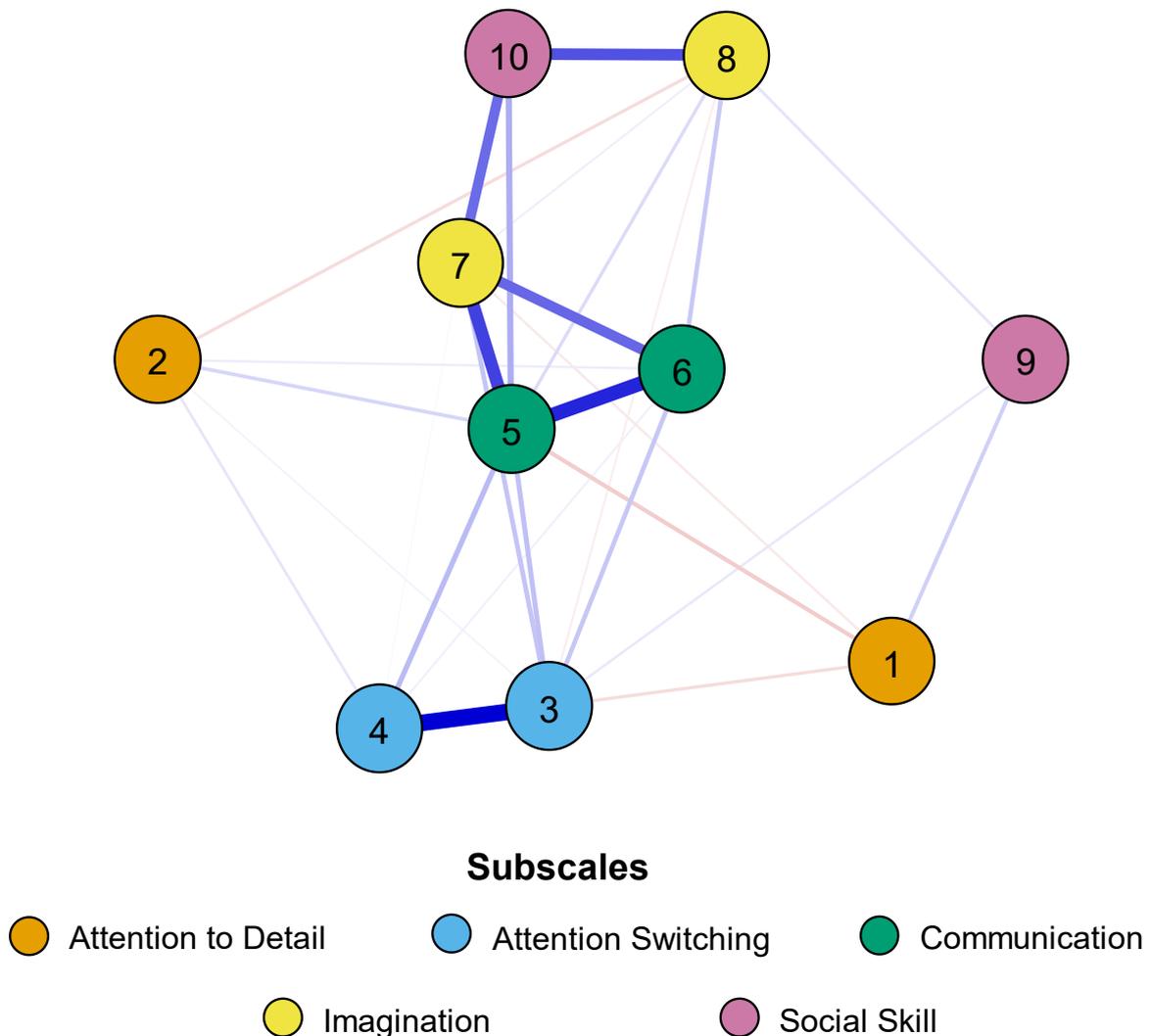
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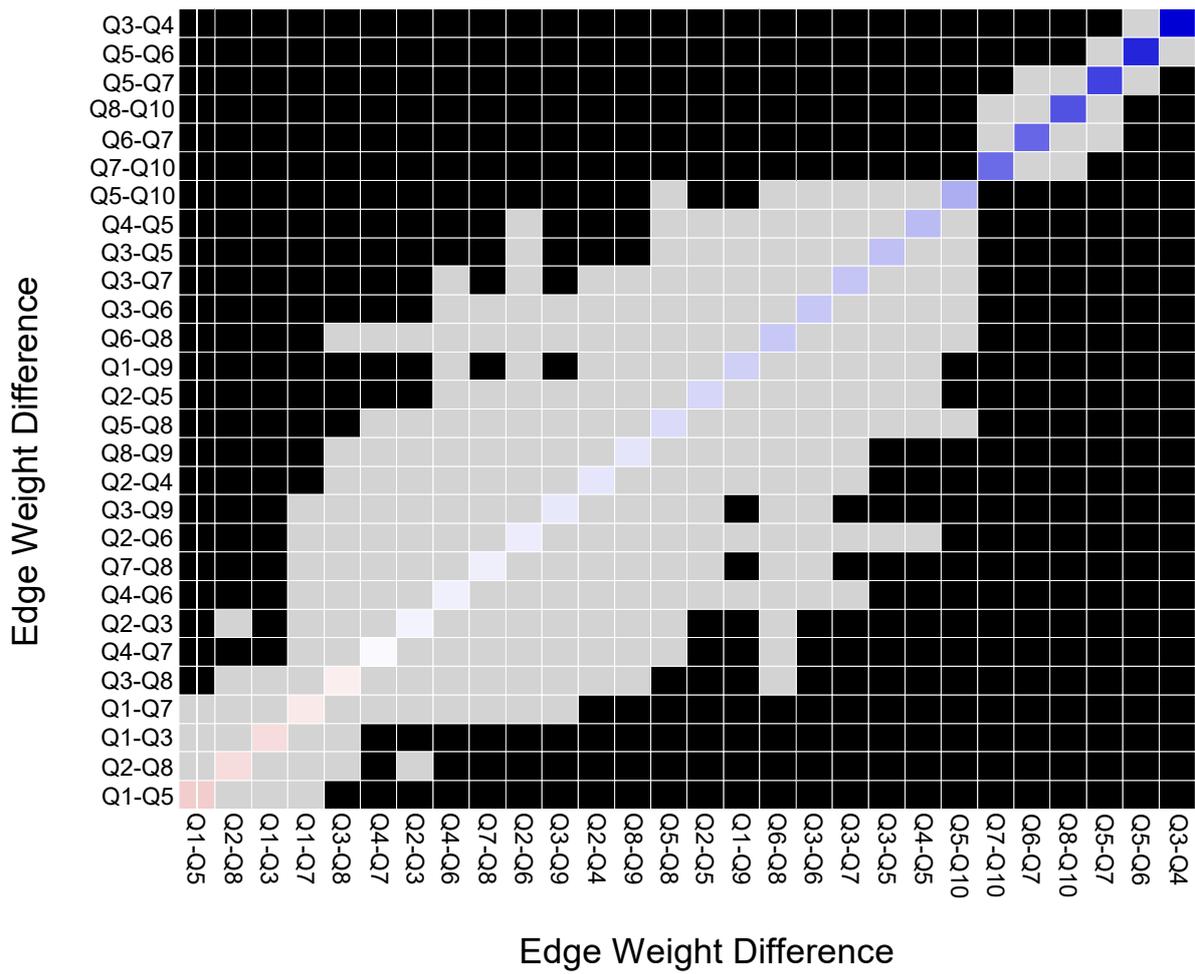
Figure 1



- ① I often notice small sounds when others do not
- ② I usually concentrate more on the whole picture, rather than the small details
- ③ I find it easy to do more than one thing at once
- ④ If there is an interruption, I can switch back to what I was doing very quickly
- ⑤ I find it easy to 'read between the lines' when someone is talking to me
- ⑥ I know how to tell if someone listening to me is getting bored
- ⑦ When I'm reading a story I find it difficult to work out the characters' intentions
- ⑧ I like to collect information about categories of things (e.g. types of car, types of bird, types of train, types of plant etc)
- ⑨ I find it easy to work out what someone is thinking or feeling just by looking at their face
- ⑩ I find it difficult to work out people's intentions

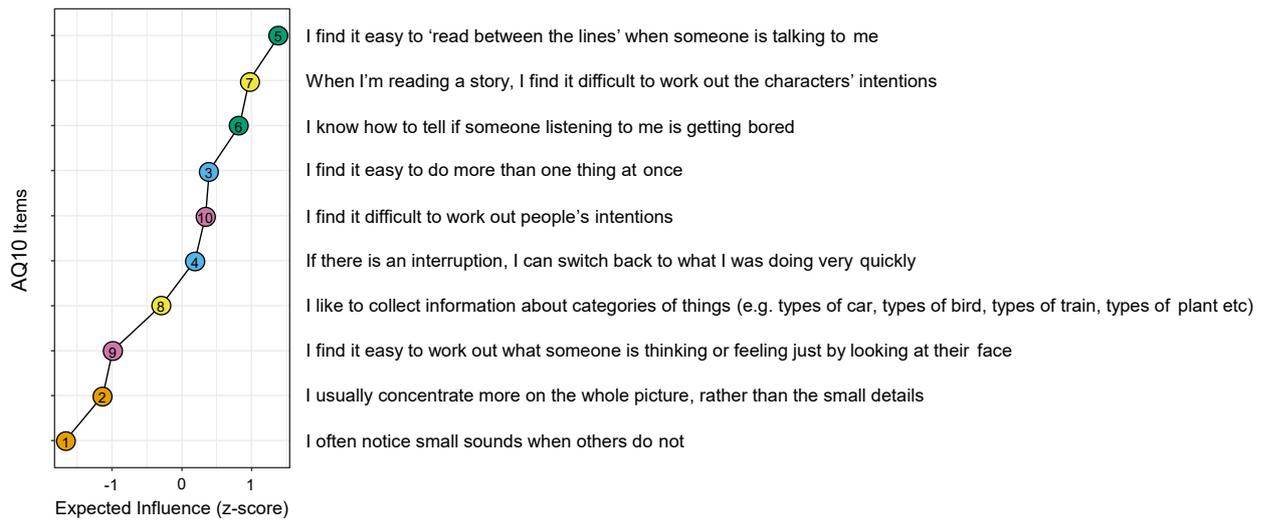
Note. Network analysis of AQ10 items. Each node (circle) represents its corresponding numeric AQ10 item, coloured to its subscale membership. Edges (lines) represent the non-zero conditional relationships between two nodes when accounting for all others in the network. Association direction (blue = positive, red = negative) and strength (line thickness) are shown (*qgraph*, Epskamp *et al.*, 2012).

Figure 2



Note. Edge weight difference test using 95% confidence interval bootstrapping with 1000 resamples. Black squares indicate a significant difference between the edge weights, and grey squares indicate no significant difference. Edges are arranged in order of association strength (pink = weak association, blue = strong association).

Figure 3



Note. Expected influence centrality (z-score) for each AQ10 item, coloured to their associated subscale.