A Multivariate Analysis Reveals Benefits of Specific ADHD Characteristics in Trial-and-Error Learning

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Abstract

Attention Deficit Hyperactivity Disorder (ADHD) impacts academic and occupational performance through symptoms of impulsiveness, hyperactivity, and inattention. While deficits in cognitive functions such as executive function (EF) are well-documented in ADHD, the link between ADHD characteristics and the ability to solve problems via trial and error is more cloudy. We tested 70 adult participants, with ADHD and without, in trial-and-error reasoning problems called ‘Virtual Tools’. Performance metrics included success rates, number of attempts, completion time, and strategy measures. Multivariate analysis revealed distinct patterns of ADHD characteristics that are beneficial for trial and error. Individuals with higher inattention performed better, those with balanced ADHD profiles performed similarly to non-ADHD controls. Profiles with high inattention switched trial-and-error strategies more often, supporting their performance. Findings imply that elevated levels of inattention may enable individuals to avoid becoming trapped in cognitive attractors, where they persist in using a single strategy with only marginal adjustments.

Introduction

Attention Deficit Hyperactivity Disorder (ADHD) is a well-recognized neuro-developmental condition, primarily characterized by symptoms of impulsiveness, hyperactivity, and inattention, which often persist from childhood into adulthood (Polanczyk et al., 2007; Asherson & Agnew-Blais, 2019). ADHD is prevalent, affecting approximately 5% to 10% of school-aged children globally, with over 4.4% of these cases extending into adulthood (Cai et al., 2023; Waltereit et al., 2023). ADHD symptoms influence many domains of life, leading to significant academic and occupational challenges (Loe & Feldman, 2007; Fuermaier et al., 2021).

Some of the most serious challenges in ADHD have been attributed to executive function (EF) deficits. Executive functions are high-level neurocognitive processes essential for goal-oriented behavior, decision-making, and adapting to changing environments (Willcutt et al., 2005; Colomer et al., 2017). Traditionally, ADHD-related differences in EF have been explained by the "frontal hypothesis," which posits that ADHD is associated with structural and biochemical changes in the prefrontal cortex and delays in the development of fronto-striatal systems, leading to hypofrontality and decreased executive functioning (Pennington & Ozonoff, 1996; Boucugnani & Jones, 1989).

Another fundamental cognitive process that corresponds to EF is rapid trial-and-error learning (Hughes & Graham, 2005). This learning mechanism, which plays a critical role in human development and adaptation, involves attempting various solutions to a problem until a successful outcome is achieved, allowing individuals to acquire knowledge and skills through direct experience (Cyr & Anderson, 2012). This is done through optimization of 'trial-and-error' learning, which is rapid because it consists of only a few successive attempts (Allen et al., 2020). Rapid trial-and-error learning is important because it underlies individuals' ability to discern beneficial actions from detrimental ones in a world full of uncertainties (Van Duijvenvoorde et al, 2008), making them functional when they are required to navigate the complexities of daily life.

In the context of ADHD, trial-and-error learning takes on particular significance because inattention, hyperactivity, and impulsivity significantly impact the ability to learn from previous experiences (American Psychiatric Association, 2013). Yet, how ADHD affects trial-and-error learning is not straightforward. On the one hand, the impulsivity associated with ADHD might lead to more frequent attempts and a greater willingness to try different solutions, potentially enhancing the trial-and-error process. Conversely, difficulties with sustained attention and working memory may hinder the ability to effectively retain information gained from each trial, potentially impeding learning outcomes (Barkley, 1997). Furthermore, executive function deficits may impact the efficiency of trial-and-error learning because inhibitory control and cognitive flexibility are essential functions for monitoring performance and adjusting strategies based on feedback (Willcutt et al., 2005).

Despite this theoretical connection between ADHD and trial-and-error learning, empirical research directly examining this relationship is limited. While studies have investigated various aspects of learning and cognitive functioning in ADHD, the specific impact of the condition on trial-and-error learning processes remains largely unexplored. This is surprising as the potential impact of ADHD on trial-and-error learning has important implications for educational and therapeutic interventions. Understanding how individuals with ADHD process trial-and-error experiences could inform the development of targeted strategies to support their learning and skill acquisition. For instance, structured learning environments that provide clear feedback and opportunities for guided practice might help compensate for difficulties in self-monitoring and strategy adjustment (Luman et al., 2005).

In the current study, we examined the relationship between ADHD characteristics and trial-and-error problems by encouraging participants to play the "Virtual Tools" game (Allen et al. 2020; Grandchamp des Raux et al., 2024) which involves trial-and-error learning. Individuals with diagnosed ADHD and without completed well-established questionnaires to assess their ADHD characteristics and were presented with dynamic two-dimensional virtual environments (Figure 1A) containing various virtual objects and shaded areas. Although the design of the environment differs from game to game, the objective for each game remained the same: participants were encouraged to select and place a shape ('tool') to bring an object into a goal area. The environment—initially static—becomes dynamic once the tool is placed as the world physics is activated (e.g., gravity; Figure 1A). To succeed, participants must apply reasoning to anticipate changes in the environment based on physical laws, such as how objects will interact once they have positioned and released their selected tool. Participants were given six attempts to complete each game, and they were tested on 25 different games.

We first aimed to test differences in trial-and-error problem solving between the group of participants with diagnosed ADHD and those without. We predicted that adults without ADHD would achieve the goal more frequently, faster, with fewer attempts per game, and with more efficient strategies after failed attempts.

Our second aim was to test how variations in ADHD characteristics relate to the ability to solve reasoning problems through trial and error. To test this, we used univariate and multivariate analytical approaches (Figure 1B). In the univariate analysis, we examined the correlations between participants' scores on cognitive control and EF questionnaires and their performance and strategies in the virtual tools game. This approach allowed us to identify specific ADHD-related characteristics that might influence trial-and-error skills. For the multivariate analysis, we clustered all participants based on their questionnaire responses. We then compared the performance and strategies in the virtual tools game across these clusters. This approach examines how different profiles of ADHD characteristics might relate to trial-and-error performance. We expected that attention levels, and not EF, would have the most significant impact.

Methods

Participants

We tested 70 participants (M = 32.12 years, SD = 10.63; 29 Females, 25 Males, 4 non-binary). Participants were recruited through an online portal (Prolific.io). 12 participants did not complete the questionnaires and therefore were excluded from further analysis. The other 58 participants were allocated to the ADHD Diagnosis Group (n = 31; M = 31.19 years, SD = 9.74; 13 Females, 15 Males, 3 non-binary) or the non-ADHD Diagnosis Group (n = 27; M = 33.19 years, SD = 11.73; 16 Females, 10 Males, 1 Non-Binary) based on their self-disclosed ADHD diagnosis via the Prolific portal.

All participants were fluent in English, and with healthy vision. They were selected from Australia, United States, United Kingdom, and Ireland as countries of residence. This choice was made to ensure access to a wide pool of participants on the Prolific portal and the cohesiveness of language and cultural background. All participants were remunerated £9 per hour (per Prolific wage guidance). The study received ethical approval from the Birkbeck College, University of London School of Science committee under reference: #2223025.

Procedure & Materials

Participants completed an online experiment that spanned over 2 days. On the first day, participants completed the Conners' Adult ADHD Rating Scales–Self Report: Long Version (CAARS–S: L; Conners et al., 2011) to determine their ADHD characteristics. The CAARS-S is a widely used assessment tool that includes 66 questions designed to assess ADHD, sectioned post-hoc into four groups corresponding to the cognitive control differences in accordance with the guidance often provided for clinical use (Conners et al., 2011). The CAARS-S questionnaire was followed by the Barkley Deficits in Executive Functioning Scale (BDEFS; Barkley, 1997)—a self-report questionnaire which consists of 89 questions, divided into five sections: management, problem-solving, self-inhibition, motivation, and emotional regulation (Barkley, 1997). Both questionnaires are based on a Likert scale, where participants are asked to select an option that best reflects their behavior. To that end, participants were asked to indicate how often they experience or engage in certain behaviors (Conners' scale 0-3, where 0- Not at all, 1- Just a little, once in a while, 2- Pretty much often, 3- Very much, very frequently; BDEFS scale 1-4, where 1- Never or rarely, 2- Sometimes, 3- Often, 4- Very often).

On the second day, participants who completed the questionnaires in full were invited to play the Virtual Tools (Allen et al., 2020; Allen et al., 2022)—a digital gaming platform featuring a collection of two-dimensional virtual environments, containing various virtual objects and shaded areas (Figure 1). Although the design of the environment differs from game to game, the objective for each game remained the same: to move a red object into the green area using blue shapes (tools) on the right of the screen. The environment—initially static—becomes dynamic once the tool is placed as the world physics gets activated (e.g., gravity). Importantly, participants played the game only by placing a single object in one click. There were no additional motor movements involved; therefore, participants had to reason about the complex relations of the effect on the environment and their actions. Participants were allowed up to 6 attempts per game, without time constraints, to achieve this goal. Each game automatically reverted to its starting configuration following an unsuccessful try. Successful completion advanced the participant to the subsequent game. We recorded the selected tool, its placement, timing, and the outcome of each attempt. Participants started with four practice games, followed by 25 experimental games. They had a short break after 12 games.

We evaluate participants' *trial-and-error performance* by calculating their (1) success rate across games; (2) average number of attempts; and (3) average attempt duration. We also determined their *trial-and-error strategy*—how they attempted to solve each game. To that end, we measured (1) the percent of tool switching and (2) the average tool-positioning distance. In this analysis, we focused only on games in which the child failed to solve the game on the first try.

To calculate the percentage of tool switching, we compared the selected tool in each attempt with the one used in the preceding attempt for each game, beginning with the second attempt. We then determined the percentage of attempts in which a different tool was selected for each game. These percentages were averaged across all games within each physical action concept to obtain a general measure of tool switching.

For the average tool-use positioning distance, we computed the Euclidean distance in pixels between the positions of the tool in successive attempts for each game. This calculation was performed starting from the second attempt, and the average distance for each game was obtained by averaging these Euclidean distances across all attempts. Finally, we averaged these distances across all games within each physical action concept to derive an overall measure of tool-use positioning distance.

Clustering Analysis

We took a multivariate analysis approach and clustered participants to different groups based on the pattern of their responses to the questionnaires. We used a clustering procedure based on a k-means algorithm (Likas et al., 2003) in which the number of clusters is derived from the data and is not pre-defined. Thus, we made no assumptions about the number of clusters or number of participants per cluster. Any number of clusters greater than one would suggest multiple patterns of ADHD characteristics, as the patterns of participants within a cluster have more similarities than participants in other clusters. Using the nine sections of questions in both questionnaires as input for the clustering analysis, we calculated the Euclidean "distance" between each pair of participants. Short distances are equated with high similarity and vice versa.

Next, we used a k-means algorithm (an unsupervised machine learning method used to partition a dataset into k distinct clusters; (Likas et al., 2003). We iteratively assigned data points to the nearest centroid in the Euclidean space and recalculated the centroids based on the new assignments until convergence, aiming to minimize the sum of squared distances between data points and their assigned centroids. We performed this with the number of clusters as a parameter ranging from 2 to 30 clusters and calculated the ratio between the average similarity within clusters and the average similarity across subjects. The number of clusters that yielded the maximal ratio was the optimal one for clustering and was selected.

Dirichlet Process Gaussian Mixture Model

We replicated the approach applied by Allen et al. (2024) leveraging a Dirichlet Process Gaussian Mixture Model (DPGMM) to model the latent structure underlying participants' behavior during task performance. The DPGMM, an extension of the Gaussian Mixture Model, is particularly suited for clustering data with an unknown number of clusters, as it automatically adjusts the complexity of the model by inferring the number of clusters from the data (Ferguson, 1973; Neal, 2000). For each stimulation type and trial, we used the DPGMM to identify distinct clusters, which we interpret as different trial-and-error strategies employed by each participant in each Virtual Tools game. This approach allows for a probabilistic assignment of *each attempt* to a strategy, providing insights into the heterogeneity of strategies used across different contexts (Blei & Jordan, 2006; Rasmussen, 2000).

To capture dynamic changes in behavior, we focused on strategy switches operationalized as transitions between clusters. A switch occurred when the cluster with the highest posterior probability in one trial differed from that in the subsequent trial (Smith et al., 2019). By identifying these switches, we aimed to understand how participants adapt their strategies in response to the outcome of the previous attempt. Finally, we used a logistic regression model to predict the likelihood of a strategy switch for each participant.

Results

We first looked at differences in trial-and-error learning between participants who had self-disclosed ADHD diagnoses compared to those who did not. Figure 2 shows that the two groups did not differ in success rate (M = 0.50, SD = 0.16 and M = 0.51, SD = 0.13 for participants with ADHD and without, respectively; $t(53) = -0.298$, p = .767), or in number of attempts to succeed (M = 1.99, SD = 0.39, and M = 1.96, SD = 0.33; $t(53) = 0.185$, p = .854). Participants with no ADHD diagnosis were slower on average to complete an attempt but not significantly (M = 11,328.16, SD = 5701.30 and M = 9009.62 seconds, SD = 3916.92 respectively; $t(53) = -1.82$, p = .075). Finally, we did not find differences in the strategy measures—tool switching or placement distance—between the two groups ($t(53) = .0552$, p =.293 and $t(53) = -.650$, p = .261, respectively.

Next, we used a univariate approach to test the link between variations in ADHD characteristics and trial-and-error learning by correlating the different ADHD characteristics, as measured by the questionnaire scores, with the trial-and-error measures. Table 1 shows no association in either of the groups, or when the groups are combined, between the questionnaire scores and performance or strategy in the virtual tools game.

Figure 3 shows the outcomes from our multivariate approach. Based on the clustering of participants' answers to the questionnaires, we identified four groups of participants (Figure 3A), which we mapped to different profiles of variations in ADHD characteristics. Each group was characterized based on the median scores of their responses to the questionnaires and based on the count of responses to the two questionnaires (Figure 3B). To be able to interpret differences between profiles in trial-and-error skills, we ranked the profiles according to the level of ADHD traits from the 'least-ADHD-characteristics' (profile 1) to the 'most-ADHD-characteristics' (profile 4). Nevertheless, the profiles are a combination of different characteristics. A one-way ANOVA confirmed a significant difference across profiles in the self-motivation section in the BDEFS (F(3,53) = 6.30, p < .05), and inattention section in CAARS-S (F(3, 53) = 8.36, p < .05). A Tukey post-hoc test showed that profiles differed in the inattention domain, Profile (2) with mainly non-ADHD participants differed significantly in the score for this domain from Profile 1 and 4 (p < .05), and Profile 1 differed from Profile 4 (p < .05). In the self-motivation domain, post-hoc Tukey test revealed that Profile 2 differed in the score significantly from Profile 1 and 4 (p < .05). Taken together, the differences between profiles seemed to have been driven by specific domains, inattention from CAARS-S-L and self-motivation domain from BDEFS. Not necessarily by all domains.

The profiles differed in their performance and strategy measures in the Virtual Tools game. A one-way ANOVA confirmed a significant difference between profiles in the average rate of success (F(3,53) = 7.05, p < .05; Figure 4A) and average number of attempts (F(3,53) = 7.3, p < .05; Figure 4B). A post-hoc Tukey test revealed a significant difference in attempts between Profile 2 and Profile 4, p < .05. Similarly, in the average of success, Profile 2 differed from Profile 4, p < .05. There was no difference in the time taken to solve the game tasks (F(1,55) = 1.40, p = .24; Figure 4C). We also found significant differences in strategy across profiles. A one-way ANOVA confirmed significant differences between profiles in the average number of tool changes and the average tool positioning distance (F(3,53) = 3.71 and F(3,53)=2.98 respectively, p < .05; ; Figure 4D-E). Post-hoc Tukey showed significant differences between Profile 2 and Profile 4 p < .05.

To further understand why profiles with higher levels of ADHD characteristics are better in trial-and-error problem solving, we performed additional analysis in which we tested how much participants from each profile switched between trial-and-error strategies. To that end, we ran a Dirichlet Process Gaussian Mixture Model to identify how many groups of strategies were used by each profile and the probability of each attempt to be in one of the identified trial-and-error strategies (Figure 4F; see Methods). A strategy switch was then identified as a change from one trial-and-error strategy to another between successive attempts. A simple logistic model confirmed that participants in Profile 2 (odds ratio of 1.17, 95% *CI*[1.09, 1.26], p < .05 and in Profile 4 (odds ratio of 0.70, 95% *CI*[0.66,0.73], p < .05) were more likely to switch strategies across all games.

Discussion

In the current study, we explored the relationship between ADHD and trial-and-error skills through an online gaming platform—Virtual Tools. We aimed to identify differences in trial-and-error strategies between adults with diagnosed ADHD and those without. We also tested how variations in ADHD characteristics relate to trial-and-error performance. In contrast to our prediction, we did not find significant differences between individuals with ADHD and those without in terms of success rate, number of attempts, completion time, or strategy measures. However, using a multivariate analysis, we found four distinct clusters of ADHD characteristics corresponding to differences in trial-and-error, with profiles that have specific ADHD characteristics as inattention showing better performance. Importantly, these profiles highlight the diversity within the ADHD population.

The absence of significant differences in trial-and-error performance between the ADHD and non-ADHD groups supports previous research indicating that while ADHD is often associated with deficits in cognitive control and EF, these deficits do not uniformly translate to all cognitive domains (Willcutt et al., 2005; Fuermaier et al., 2021). It is possible that trial-and-error skills, as measured by the Virtual Tools game, are not directly influenced by the presence of ADHD. The lack of difference between the groups might also reflect the compensatory strategies individuals with ADHD develop to navigate this cognitive challenge (Valori et al., 2022; Dahan & Reiner, 2017).

Nevertheless, our multivariate analysis provided a more detailed association between ADHD and trial-and-error by identifying distinct profiles within the ADHD and non-ADHD population. This approach highlights the heterogeneity of ADHD and the importance of considering individual variations in ADHD characteristics when studying cognitive functions (Wiebe et al., 2023). Specifically, the clustering procedure identified significant differences in the EF domains of self-motivation and inattention, which were associated with different performances in the Virtual Tools games. These findings support the notion that ADHD is not a monolithic condition but rather a spectrum of traits that can manifest in varied cognitive profiles (Colomer et al., 2017; Musculus et al., 2021).

The profile characterized by high inattention and other EF deficits (Profile 4) was better in trial and error than the one with fewer attentional deficits (Profile 1). However, a logistic model revealed that Profile 4 switched trial-and-error strategies most frequently—suggesting less efficacy in planning. This aligns with existing literature on the importance of attention in learning from errors (Blair et al., 2009; Middleton et al., 2022; Valori et al., 2022). In addition, these findings support previous findings showing that hyperactivity is not linked to decreased problem-solving abilities, whereas inattention is (Li et al., 2023), and that impulsivity characteristics can even be advantageous in problem-solving (Tymms & Merrell, 2011). We argue that elevated levels of inattention may enable individuals to avoid becoming trapped in cognitive attractors, where they persist in using a single strategy with only marginal adjustments. While attention is often advantageous in solving many problems, it may be less effective in situations that demand substantial shifts in strategy. Moreover, physical impulsivity in such dynamic environments can be advantageous.

Finally, participants in Profile 1, which exhibited moderate ADHD characteristics and relatively balanced EF profiles, performed similarly to the non-ADHD group, indicating that a balanced EF profile may mitigate the adverse effects of ADHD on trial-and-error performance. It highlights the potential benefits of targeted therapeutic strategies that enhance EF components, such as self-motivation and problem-solving, to support individuals with ADHD (Musculus et al., 2021; Allen et al., 2020).

Further research is needed to test the role of other cognitive skills in individuals with ADHD that may support learning from errors. Longitudinal studies could provide deeper insights into how ADHD characteristics evolve over time and their long-term impact on trial-and-error abilities. Investigating the role of comorbid conditions, such as anxiety and learning disabilities, which frequently co-occur with ADHD, could also clarify the complexities of how this population learn from errors (Loschiavo-Alvares et al., 2023).

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Figures

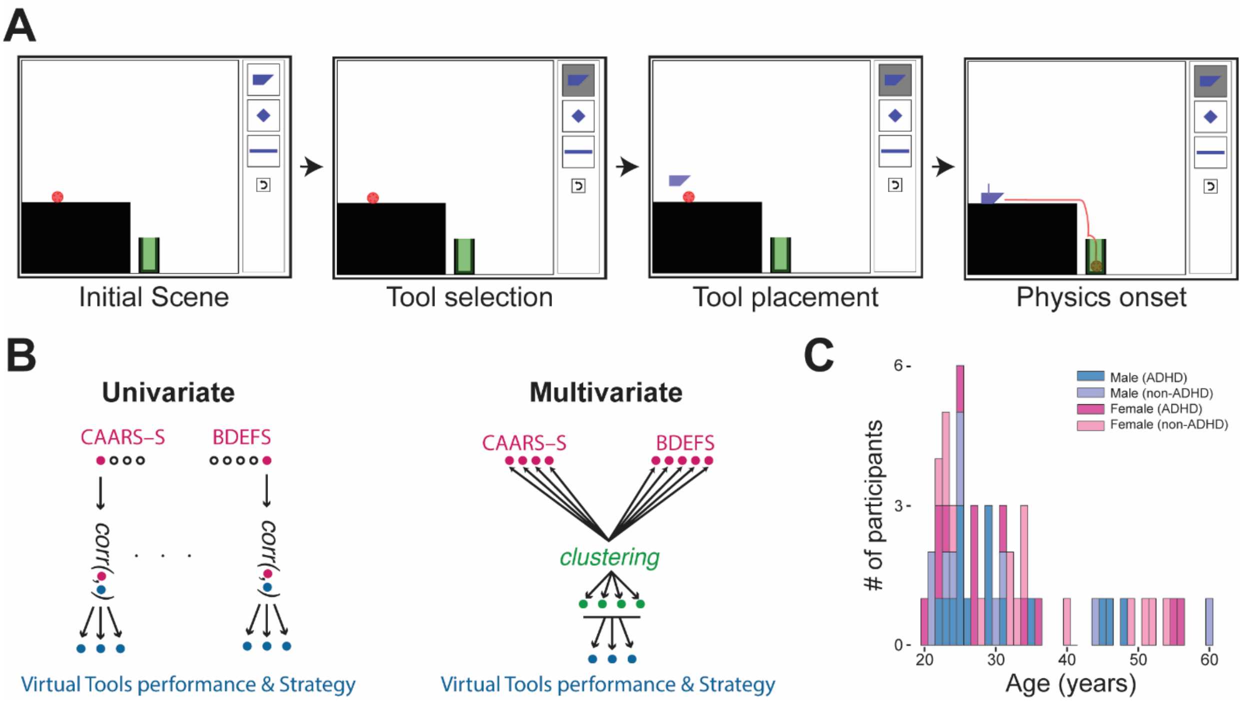

Figure 1. (A) Illustrative trial of one of the Virtual Tools games participants played. The aim of the game is to bring an object (a ball in this example) into a designated area (light grey) using one of the three shapes on the right (tools). Once the initial scene appears (left box), the child must select a tool on the right-hand side of the screen and place it in the scene (middle boxes). Once the tool was placed, the laws of physics started, generating object movement (right box). **(B)** Different approaches for examining how variations in ADHD characteristics relate to trial-and-error learning. Left panel: univariate approach focuses on one section of the questionnaires and correlate it with the measures of performance and strategy in the Virtual Tools game (e.g., level of attention corresponds to trial-and-error learning). Right panel: Multivariate approach where we provided all the sections across questionnaires as input to a clustering procedure that yielded groups of ADHD characteristics. We then examined differences in performance and strategy across groups. **(C)** Age and gender for the ADHD and non-ADHD groups.

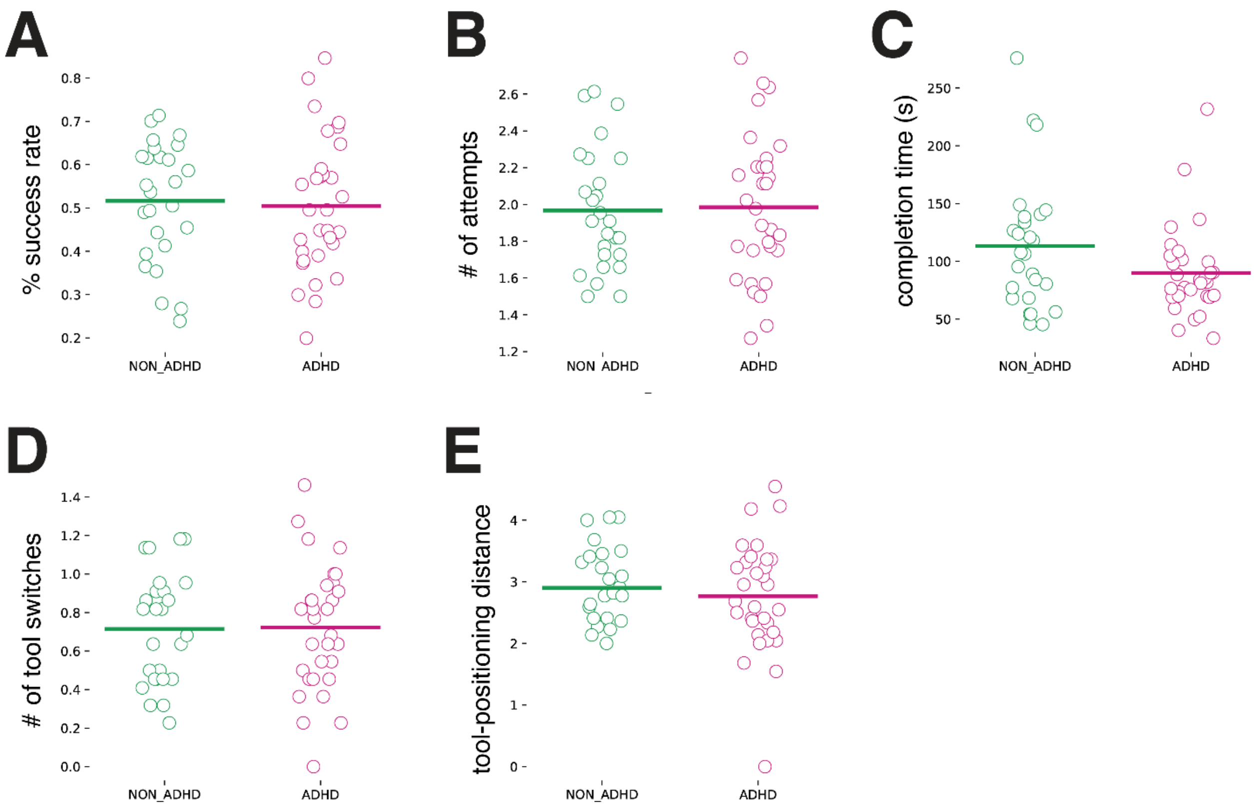

Figure 2. Differences between participants who were diagnosed with ADHD (pink) and the non-ADHD control group (green) in **(A)** success rate, **(B)** number of attempts, **(C)** attempt duration, **(D)** number of tool switches from one attempt to another, and **(E)** the average distance of tool-positioning from one attempt to another. None of the comparisons were significant.

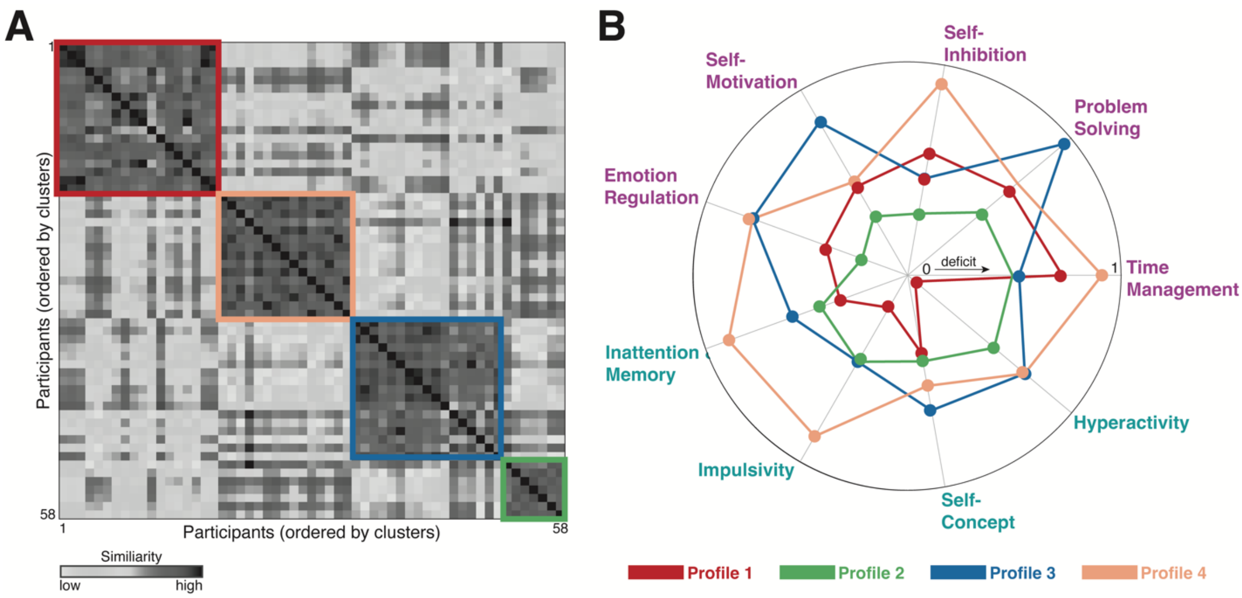

Figure 3. Clustering results. **(A)** Clustering based on the similarity among participants' responses to the CAARS-S and BDEFS. The panel shows the similarity matrix ordered according to clusters. The square borders match the profiles in panel B. **(B)** Participants' scores in each section, normalize between 0 to 1, where 0 is no deficit and 1 is high deficit. Characteristics scored in the CAARS-S questionnaire are colored in turquoise (bottom) and characteristics scored in the BDEFS are colored in purple (top).

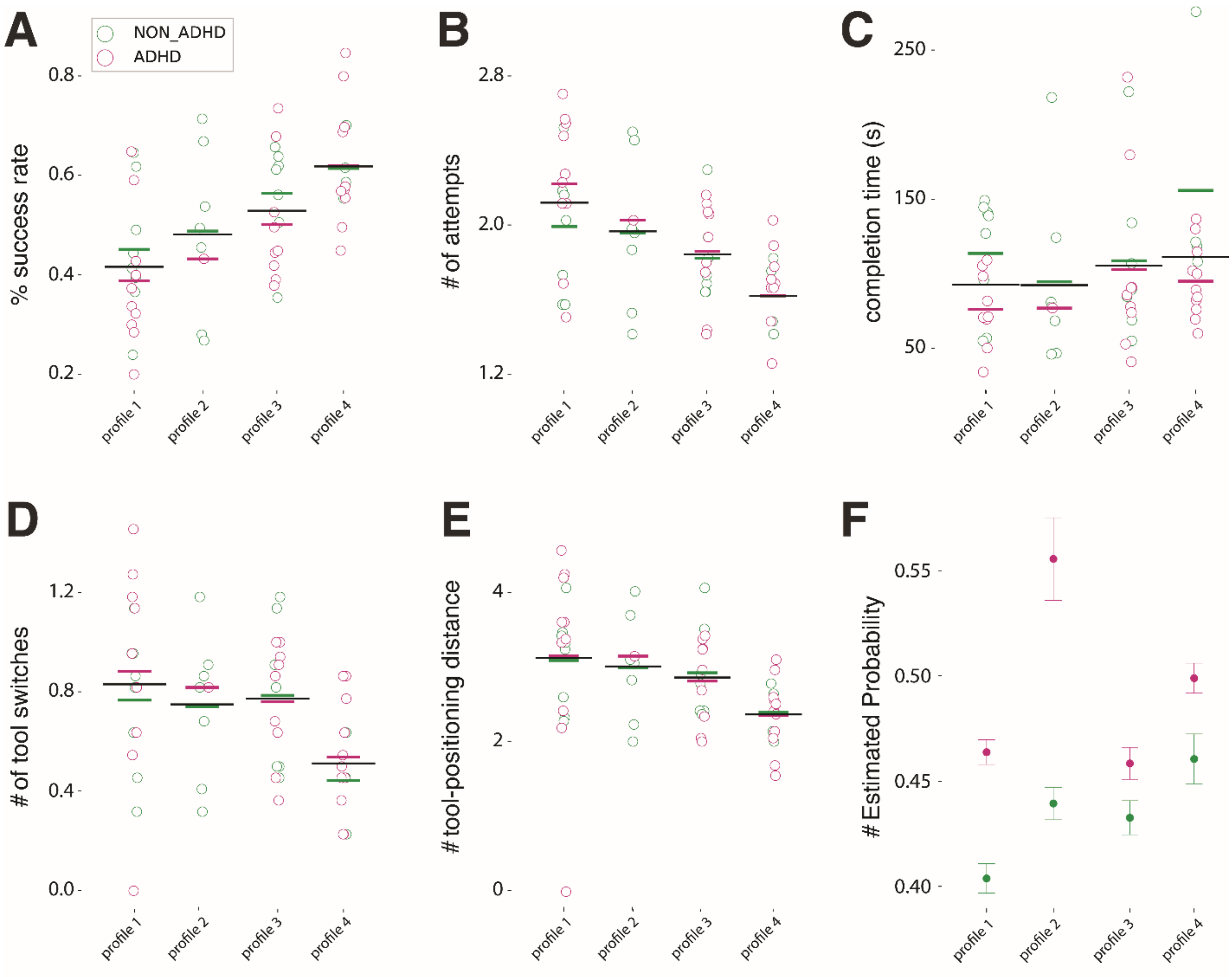

Figure 4. Profile comparison in Virtual Tools performance. Differences between participants in each one of the profiles in **(A)** success rate, **(B)** number of attempts, **(C)** attempt duration, **(D)** number of tool switches from one attempt to another, and **(E)** the average distance of tool-positioning from one attempt to another. The pink data points represent individuals in the ADHD group, while the green data points correspond to individuals in the non-ADHD group. **(F)**

GROUP		1	2	3	4	5	6	7	8	9	10	11	12	13	14
ADHD															
1.	**EF Time Management**														
2.	**EF Problem Solving**	.65**													
3.	**EF Self Inhibition**	.63**	,												
4.	**EF Self Motivation**	.72**	.43*	.45*											
5.	**EF Emotional Regulation**	.61**	.53**	.73**	.51**										
6.	**C Innatention & Memory**	.89**	.63**	.64**	.65**	.64**									
7.	**C Impulsivity**	.66**	.37*	.85**	.40*	.76**	.71**								
8.	**C Self Concept Problem**	.60**	.63**	,	.49**	.44*	.56**	.43*							
9.	**C Hyperactivity**	.41*	,	.64**	,	.51**	.51**	.74**	,						
10.	**Attempt**	,	,	,	,	,	,	,	,	,					
11.	**Success**	,	,	,	,	,	,	,	,	,	-.97**				
12.	**Time**	,	,	,	,	,	,	,	,	-.53**	-.46**	.53**			
13.	**Tool Changes**	,	,	,	,	,	,	,	,	,	.70**	-.74**	-.49**		
14.	**Unique Tool Placement**	,	,	,	,	,	,	,	,	,	.63**	-.64**	-.46**	.92**	

GROUP		1	2	3	4	5	6	7	8	9	10	11	12	13	14
Non-ADHD															
1.	**EF Time Management**														
2.	**EF Problem Solving**	.85**													
3.	**EF Self Inhibition**	.83**	.83**												
4.	**EF Self Motivation**	.82**	.74**	.71**											
5.	**EF Emotional Regulation**	.62**	.79**	.83**	.52**										
6.	**C Innatention & Memory**	.87**	.88**	.82**	.73**	.76**									
7.	**C Impulsivity**	.64**	.70**	.79**	.63**	.78**	.80**								
8.	**C Self Concept Problem**	.74**	.78**	.75**	.68**	.73**	.86**	.74**							
9.	**C Hyperactivity**	.56**	.65**	.59**	.67**	.67**	.68**	.77**	.69**						
10.	**Attempt**	,	,	,	,	,	,	,	,	,					
11.	**Success**	,	,	,	,	,	,	,	,	,	-.98**				
12.	**Time**	,	,	,	,	,	,	,	,	,	,	,			
13.	**Tool Changes**	,	,	,	,	,	,	,	,	,	.83**	-.79**	,		
14.	**Unique Tool Placement**	,	,	,	,	,	,	,	,	,	.89**	-.84**	,	.90**	

Table 1. All correlations between the different features of the questionnaires and the different measures.

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