Attentional and perceptual processes associated with the performance of autistic traits assessed using the drift-diffusion model.

Journal: Autism Research

ID:2418663

Supervisor Name: Carmel Mevorach

Word Count: 5641

Submitted in partial fulfilment of the requirements for the degree of Master of Science

School of Psychology

University of Birmingham

Table of Contents

ABSTRACT

Individuals who are neurodiverse exhibit variations in brain functioning as a result of inherent dissimilarities. Autism spectrum disorders (ASD), which fall under the category of neurodiverse traits, are characterised by cognitive control processes that deviate from those seen in neurotypical (NT) persons. Consequently, these variances in cognitive control processes contribute to disparities in attention, perception, and action. This observation suggests that there may be a correlation between ASD symptoms and variations in cognitive processes. Nevertheless, the precise delineation of the cognitive mechanisms underlying these variations remains elusive. Therefore, the objective of this study is to employ an attentional drift-diffusion model to accurately capture the entirety of the attentional and perceptual decision-making process using data from a visual search task. By utilising the fitted model, this study aims to explore the pertinent factors that impact the cognitive control processes of attention in populations characterised by ASD. In prior research, participants obtained model data via the execution of a T-task, whereby they searched for low-contrast targets that had similarities or saliency with non-target precepts. Consequently, previous research has previously gathered behavioural data pertaining to the attentional perceptual processes of the participants in the current investigation during the T-task task. Additionally, these former studies have also assessed autistic features using the Autism Quotient (AQ). In the current research, the model was parameterized within the given context by considering the components of attention and perception in the T-task. The previously gathered data was used to fit the model, allowing for the correlation of the parameters and the subsequent identification of the factors that influence this cognitive control process. The study's findings indicate a substantial association between the rate of attentional selection and AQ scores. The findings of the research suggest that there is a substantial association between the rate of attentional selection and AQ scores. This implies that the observed difference is likely attributed to the participants' active target selection process, namely the top-down proactive control mechanism.

Keywords: Autism spectrum disorders; T-task; Autism Quotient Score; cognitive control; proactive control.

1 Introduction

The current research aims to examine the potential differences between individuals with high autistic features and the neurotypical population regarding the existence of exploited distractors, via the use of parametric modelling of the attentional orienting process. The present research starts by providing a clear definition of the two focal points of investigation, namely individuals exhibiting elevated levels of autistic features and the mechanisms associated with attentional orienting. Neurodevelopmental diseases, being chronic and intricate conditions, are mostly attributed to variations in brain functioning resulting from congenital inheritance (Thapar, Cooper, & Rutter, 2017). Individuals with elevated levels of autistic traits, commonly referred to as ASD, are characterised by neurodevelopmental impairments that result in distinct constraints throughout their maturation and advancement. These limitations primarily manifest as deficiencies in social communication abilities, alongside the presence of repetitive behaviours and restricted interests (American Psychiatric Association, 2016). Consequently, scholarly investigations pertaining to ASD have mostly concentrated on its impairments. The capacity to engage with the surrounding environment via social skills may be shown by the aptitude to concentrate on a certain objective while disregarding any potential distractions (Abu-Akel, Apperly, Spaniol, Geng, & Mevorach, 2018). This implies that the capacity to concentrate on a specific stimulus while disregarding irrelevant stimuli might be advantageous in identifying the manifestation of characteristics associated with autism. For instance, previous research has shown that individuals with ASD exhibit heightened perception of the target stimulus during visual search tasks, as seen by pupillometry measurements (see Figure 1). This heightened perception in ASD individuals leads to faster search rates and an enhanced salience of the search target (Blaser, Eglington, Carter, & Kaldy, 2014).

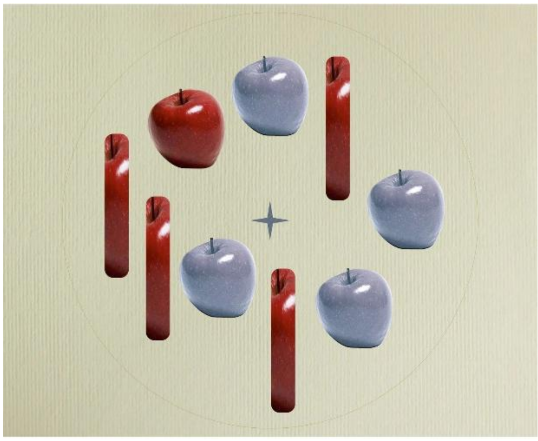

Figure 1 The process of differentiating the desired object from other objects that have similar attributes, such as colour (red rectangles) or form (blue apples), is achieved by using a mix of distinct hues and shapes (specifically, "red" and "apple-shaped").

Moreover, Blaser et al. (2014) demonstrated that individuals with typical neurodevelopment (TD) are able to effectively utilise information from cast shadows to enhance their recognition of target objects. In contrast, individuals with ASD tend to be distracted by extraneous factors such as shadows, leading to a diversion of attention away from the intended focus on ASD. This diversion is attributed to the attraction of individuals with ASD to visually salient features at a lower level of processing. According to Abu-Akel et al. (2018), there is a correlation between increased levels of ASD characteristics and the presence of prominent distractors that impede the cognitive control mechanisms responsible for directing attention towards specific targets. The cognitive process of selectively attending to information that is important to achieving a certain goal is often known as cognitive control (Amer, Campbell, & Hasher, 2016). This process involves the use of objectives or plans to guide and affect one's behaviour (nature). Furthermore, the cognitive control mechanism responsible for evaluating attention encompasses two distinct mechanisms pertaining to the management of distractions and the facilitation of focused attention. These mechanisms play a role in the utilisation and suppression of extraneous or potentially disruptive information, with the former being denoted as initiative-taking control and the latter as passive control (Braver, 2012). The framework referred to as the dual mechanism of control (DMC) encompasses the action of cognitive control via two separate modes: 'proactive control' and reactive control'. Braver's study demonstrated that active control is contingent upon the ability to anticipate and mitigate disturbances in advance, while passive control is predicated on the capacity to identify and address disturbances after to their occurrence. In other words, the effect of feedback signals on non-target competitors may be achieved by the autonomous volitional regulation of objectives and expectations from a top-down perspective. Alternatively, this influence can also be manifested through the physical salience of the disturbance, which refers to bottom-up stimulus-driven attentional signals (Blaser et al., 2014). Hence, the extent to which competing non-target information for distractors is considered important is a crucial obstacle in the process of attentional selection. In contrast, individuals who are neurotypical demonstrate a more effective utilisation of top-down goal-directed mechanisms, which serve to influence the selection process by diverting attention away from non-target salient stimuli that may cause distraction. The objective of the current research was to investigate the particular cognitive processes that exhibit a stronger correlation with elevated levels of autistic features. Research has shown that the dorsal attentional network (DAN) within the proactive control system functions as a top-down regulatory mechanism driven by internal goals or expectations. This mechanism is responsible for the establishment and preservation of goals. Moreover, it is worth noting that the neural mechanisms associated with reactive control systems involve the activation of the ventral attentional network (VAN), which is responsible for directing attention towards the relevant object of interest and enhancing goal-directed attention (Braver, 2012). Farrant and Uddin (2016) have observed significant developmental disparities in the functional connections within the two attention networks among individuals with autism spectrum disorders. Although some researchers have proposed that children with ASD exhibit typical top-down attentional control (Greenaway & Plaisted, 2005), other studies have indicated that the inclusion of non-social processes of attentional control may result in the suppression of certain regions of the dorsal anterior cingulate cortex in individuals with ASD (Vissers et al., 2012). This raises the possibility that atypical allocation of attention and cognitive biases may manifest in neurodiverse individuals during the active regulation of decision making. This research involved a cohort of approximately 69 individuals whose performance exhibited a spectrum of autistic characteristics. Consequently, the present study aims to use a mathematical model to effectively analyse the data and identify influential elements that contribute to the manifestation of autistic traits across the diverse range of autism spectrum disorders. Previous research has successfully captured autistic traits using AQ scores, and therefore established a correlation between AQ scores and the manifestation of autistic symptoms. This study aimed to investigate the relationship between changes in AQ scores and corresponding changes in model parameters. Specifically, the focus was on identifying factors associated with the consistent manifestation of autistic traits, regardless of the individual's level of autistic expression. Thus, to advance the investigation of the relationship between different cognitive control processes and autistic traits, this study uses the T-task of attention trials with salient and comparable distractors to collect empirical data for comparative analysis. The need for a model for understanding and interpretation arises from the inherent inability of facts to independently support inferences (Farrell & Lewandowsky, 2018). In this case, the investigation was conducted through mathematical modelling, a methodology that uses mathematical equations and algebraic expressions to represent real-world scenarios. Models are used in academic research as a means of representing and analysing complex phenomena. These models are often simplified and conceptualised versions of the actual problem, serving as abstractions. Through the process of modelling, researchers are able to gain insight into the characteristics and behaviour of the real-world abstract problem, facilitating the description and prediction of its associated phenomena. Therefore, through the formulation of governing equations, the incorporation of a sub-model, and the establishment of assumptions and constraints to define initial conditions and boundaries, the construction of a model is undertaken to maximise its validity. This is achieved by consistently comparing the model with real-world phenomena to ensure that it represents the described system as accurately as possible (Mathematical model, 2023). The research used the Attentional Drift Diffusion Model (ADDM), a variant of the drift diffusion model, to analyse the participants' decision-making process. The model was constructed by delineating sub-models for the processes of attentional perception and establishing initial prior values and eight constraining parameters. In addition, the research used a model to analyse participants' response time and accuracy in identifying targets among distractors in a T-task. In the current study, the data collected by Abu-Akel and colleagues (2018) was used to investigate the cognitive assumption that individuals with high AQ scores have difficulty using salient distractors effectively. The study applied the proposed model to the collected data. Furthermore, this study used a distributional measure to assess the appropriateness of the model fit. In addition, the model parameters were used to examine the extent of the association between autistic symptoms and the process. Specifically, the correlation between AQ scores and model parameters was calculated. Whilst previous work suggests that some processes may be affected, this study aims to predict a potential association.

2 Method

2.1 T-task

The current study utilises data obtained from the T-task visual search experiment conducted by Abu-Akel (2018). Given the necessity of incorporating data from prior behavioural studies into the present research, it is imperative to provide a comprehensive description and illustration of the paradigm employed in this collection of behavioural studies. The T-task, which is used to gather behavioural data, involves participants selecting a target while being influenced by a distractor. This task provides insight into the participant's capacity to differentiate non-targets and successfully identify the target. According to Mazaheri, DiQuattro, Bengson, and Geng (2011), the outcome of the rivalry for attention between top-down proactive control processes and bottom-up passive control processes may be anticipated using the T-task. This phenomenon can be attributed to the fact that participants possess prior knowledge regarding the trial, enabling them to anticipate whether the disregarded element will manifest on a global or local scale. Consequently, they retain pertinent information pertaining to the target and proactively inhibit any potential interactions, indicating the presence of a proactive attentional control mechanism originating from lower cognitive processes. Simultaneously, conversely, the participants' instant reaction to the distractor after the presentation of the stimulus may be seen as indicative of the reactive control process. The task consisted of two distinct trial types. In each trial, a low-contrast target was shown with a single distractor, as seen in Figure 1. One trial type had a non-target that was more visually prominent (contrast = 0.91), while the second trial type featured a non-target that was perceptually comparable (contrast = 0.45). The prominent non-target aspect served as a counter-cue, guiding participants towards the goal, and thereby enhancing their performance. The aforementioned attentional selection process, driven by salience from the top-down, has been extensively documented in the literature as a mechanism that initiates response selection. Furthermore, within the scope of the current investigation, the researchers conducted a comparative analysis of perceptually salient and perceptually identical tasks. This analysis aimed to discern variations in response selection processes across participants, as well as identify particular metrics that might serve as indicators of disparities in proactive control between individuals. The T-task is a method that assesses the effectiveness of the visual search process by measuring reaction time and accuracy of responses. It examines the correlation between these outcomes and AQ scores, which are then further correlated with ASD features in relation to attentional perceptual control. Consequently, the present stage was calibrated using the aforementioned data, and the model for each participant was constructed based on the distributions of reaction time (RT) and accuracy obtained throughout the experimental trials. In this study, individuals who obtained high scores on the AQ were categorised as having a generalised autistic phenotype. The research aimed to examine the impact of salient or similar distractor stimuli on the consistency of AQ scores. This was achieved by constructing models of attention and perception of visual search processes in the T-task, and by fitting these models using experimentally derived averages of reaction times and accuracies.

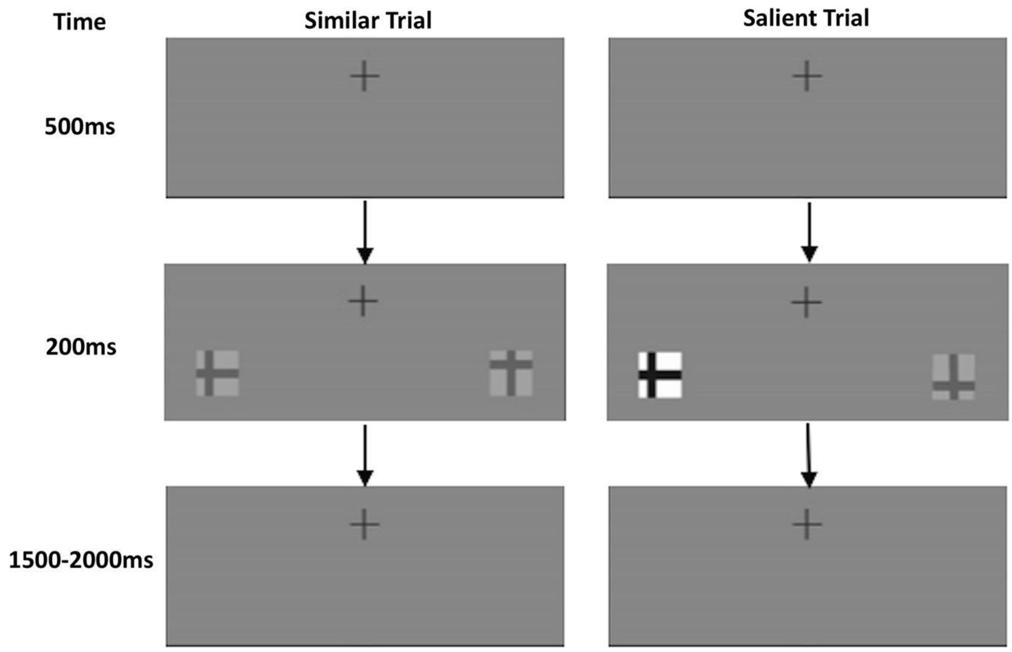

Figure 2 Experimental procedure for a visual search task under similar and salient conditions. Trials began with the appearance of the gaze cross for 500 ms. This was followed by a 200 ms search display. On 50% of the trials, the target appeared simultaneously with a similar contrast stimulus. In the other 50% of trials, the target appeared simultaneously with a salient (i.e., higher contrast) target. Trial intervals ranged from 1500 to 2000 ms.

2.2 Model

The Drift Diffusion Model (DDM) is a theoretical framework utilised to study the cognitive and neural mechanisms underlying decision making in visual search tasks. It quantifies the accumulation of uncertain evidence from the stimulus by measuring reaction time and accuracy. The DDM assumes that evidence is sampled from the stimulus and integrated until it surpasses a decision threshold, thus simulating the process of perceptual decision making. This continuous accumulation of evidence is conceptualised as a diffusion process, as described by Smith and Vickers (1988). The presented model elucidates the temporal processing of collected information by examining the association between average reaction time (RT) and the accuracy of replies. It posits that variations in RT are influenced by prior stimuli and responses within each experimental context. The methodology used in this research closely aligns with the T-task procedure, enabling a comprehensive quantitative representation of the whole visual search process and its outcomes. On the other hand, the Attentional Drift Diffusion Model (ADDM) used in the research is an adapted iteration of the Dual-Process DDM that incorporates attentional control mechanisms. The ADDM, being a two-process model, offers a distinct perspective. The underlying assumption of the model is that the participant's selection and recognition processes are simultaneously activated when encountering a stimulus. The selection process model pertains to the mechanism through which the participant's focus is directed towards either the distractor or the target. On the other hand, the recognition process model pertains to the mechanism through which the participant recognises the stimulus, specifically in this study, the process of identifying the orientation of the T. The underlying framework of the model is a two-process model. This model encompasses a total of eight parameters, as shown in the accompanying table. It is important to note that these parameters vary between participants, although each parameter adheres to a normal distribution. The use of the distributional measure in this research was employed to evaluate the adequacy of the fit.

Table 1 ADDM Parameter Sheet

PARAMETER NAME	PARAMETER DEFINITION
TARGET(T)	Rate of target identification
SALIENT RATE(SAS)	Rate of selection in salient trials
SIMILAR RATE(SIS)	Rate of selection in similar trials
SALIENT DISTRACTOR(DS)	Rate of salient distractor identification
SIMILAR DISTRACTOR(DNS)	Rate of similar distractor identification
THRESHOLD(THRESH)	When the boundary is reached, a decision will be made
NDT	Additional time for non-attentional processes
IOR	Inhibition of return (Additional weight to rate of selection after distractor is identified)

The parameters currently encompass two selection rate values, namely SAS and SIS, which are utilized in saliency and similarity experiments, respectively. Additionally, there is a basic rate denoted as T, which represents the recognition rate for the target. Furthermore, two rate values, DS and DNS, are employed for recognising distractors in saliency and similarity experiments. Lastly, the non-decision time, abbreviated as NDT, is also included in the parameters. Furthermore, there exist two decision thresholds, denoted as THRESH, for the two processes. This implies that the recognition process attains the decision threshold VALUE based on the status of the selection process. The recognition rate encompasses both recognition targets and recognition distractors, while the selection process is characterised by a singular selection rate. The phenomenon known as inhibition of return (IOR) is characterised by delayed reaction times to stimuli that appear at previously attended locations. It is believed that this process facilitates the detection of novel events in the surrounding environment by discouraging attention from repeatedly shifting back to previously explored locations. In other words, the IOR effect serves as a cue for efficient visual search, as suggested by Frischen, Smilek, Eastwood, and Tipper (2007). Simultaneously, it has been shown that individuals diagnosed with Asperger's Syndrome, a specific subtype of autism spectrum disease, exhibit eye gazing towards cues with IOR, a phenomenon linked to impairments in attentional processes while reacting to social stimuli (Marotta et al., 2013). Hence, this study incorporates the ADDM with the IOR as a parameter. IOR represents an extra

bias value that might influence the participants, resulting in a more biased selection process of the model towards the target stimulus. The mathematical representation of the model used in this investigation is presented as follows:
Selection Processes:

$$x^s(t+1) = x^s(t) + rate^s - IOR + 0.01 * \varepsilon^s(t)$$

Identification Processes:

$$rate^i(t) = T * 0.5 * (x^s(t) + 1) - D * \left(1 - 0.5 * (x^s(t) + 1)\right)$$

$$x^i(t+1) = x^i(t) + rate^i(t) + 0.01 * \varepsilon^s(t)$$

The aforementioned equation can be observed to represent the correlation between the processes of selection and recognition. Specifically, it indicates that the recognition process exhibits a greater bias towards distractors when the selection rate is higher and the weighting of the selection rate for the recognition target, T, is increased. The cognitive control mechanism in the model is predicated on the assumption of two distinct processes, namely selection and recognition. The T-task employed in this study involves the examination of the selection process, which determines whether participants' attention is directed towards the distractor or the target. A negative selection outcome indicates that participants' attention is focused on the distractor, whereas a positive selection outcome suggests that participants' attention is directed towards the target. This implies that a positive rate of selection is primarily influenced by the goal, whereas a negative rate indicates a greater inclination towards the distractor item. The underlying principle of the model is that the process of selecting a target is contingent upon the accumulation of positive evidence, whereas the selection of a distractor is contingent upon the accumulation of negative data. Furthermore, the identification process refers to the procedure by which participants discern the orientation of the T-marker. This process involves reaching a decision threshold, which is achieved through the identification process itself, ultimately defining the model's output.

2.3 Prior predictive checking

To enhance the credibility of the a priori and minimise reliance on empirical data, this study ploys a priori prediction checking to validate the parameters. This process involves generating random values that adhere to a normal distribution for each parameter, thereby ensuring that the a priori indicators reflect plausible beliefs. In order to align the a priori distribution with the observed real data, this study employs the normal distribution as the probability distribution for the complete set of a priori parameters. This adjustment aims to maximise the congruence between the previous experimental outcomes and the a priori expectations. The a priori parameters of the same type, such as the conspicuous dispersal recognition rate and comparable dispersal recognition rate, were assigned identical distributions for multiple tests of the model. The standard deviation of the a priori distribution was established to be equivalent to the mean of the a priori distribution, hence facilitating the model's ability to converge to the proper posterior distribution optimally.

2.4 Analysis

Following the application of the attentional drift diffusion model to the experimental data, it is necessary for this study to conduct a comparative analysis between the model's predicted data and the actual experimental data. This comparison will be performed using various statistical measures, including the cumulative distribution function (CDF), delta function (DF), error rate (ER), and conditional accuracy function (CAF). The objective of this analysis is to ascertain the level of accuracy exhibited by the model, with closer alignment between the predicted and experimental data indicating greater accuracy. Furthermore, this research used distributional metrics to evaluate the efficacy of the model that was fitted to the data. Additionally, correlation techniques were utilised to examine the degree to which the AQ scores are associated with the parameters of the fitted attention model.

3 Result

3.1 Posterior results

The posterior data is acquired by use of iterative applications of the Differential Evaluation Markov Chain Monte Carlo algorithm (DE-MCMC). The DE-MCMC algorithm is grounded in the principles of Bayesian statistics. It integrates a globally optimised Differential Evolutionary algorithm, which operates in a real parameter space, with a Markov Chain Monte Carlo (MCMC) algorithm. This combination enables the generation of samples from continuous random variables, specifically from the posterior distribution function(Sherri, Boulkaibet, Marwala, & Friswell, 2017). The reason for approximating the posterior density as a product of the prior distribution and the likelihood, using the formula $P(\theta|y) \propto P(y|\theta) \times P(\theta)$, in Bayesian parameter estimation is to efficiently estimate the posterior by updating the prior knowledge. This allows the samples to be proportional to the posterior density. The model demonstrates the degree to which the data aligns with the expected outcomes, as measured by reaction time and accuracy. This information is visually represented in the accompanying Figure1, with green indicating comparable trial statistics and red indicating noteworthy trial statistics. The posterior distribution will be constructed in a manner that minimises the discrepancy between the offset values, mean reaction time, and accuracy of the created posterior distribution and the corresponding values observed in the real data.
The posteriori parameters were derived by iteratively using the DE-MCMC algorithm using the predetermined normal distribution values of the a priori parameters, as depicted in Figure2. Subsequently, the process of a priori prediction validation was undertaken to verify that the a posteriori parameter values closely reflected the response time and accuracy values acquired from the actual experiments, as depicted in Figure3 and Table1. The offset values of both the model-generated and real data, together with the average response time and accuracy, are displayed.

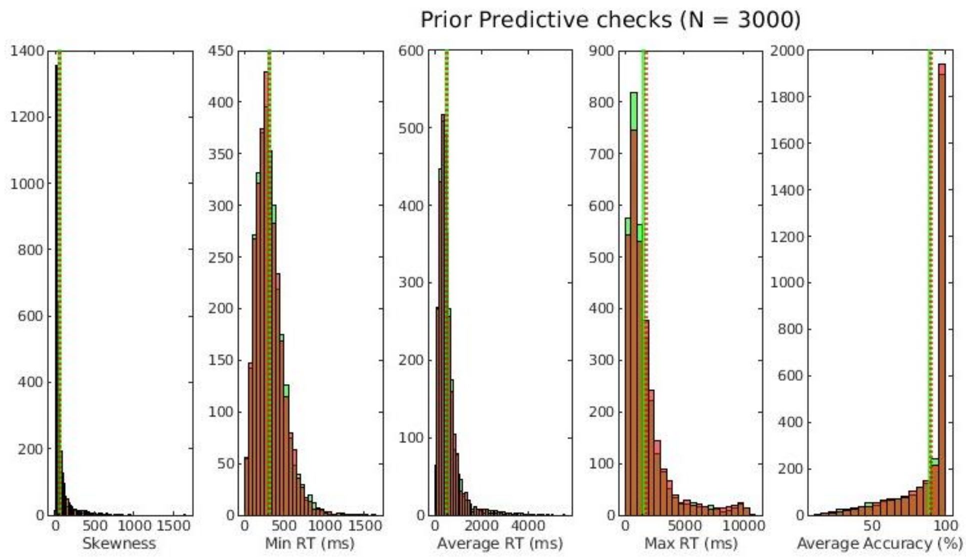

Figure 3 A visual representation of the statistics produced when research generate 3000 different models with a prior that has the same normal distribution.

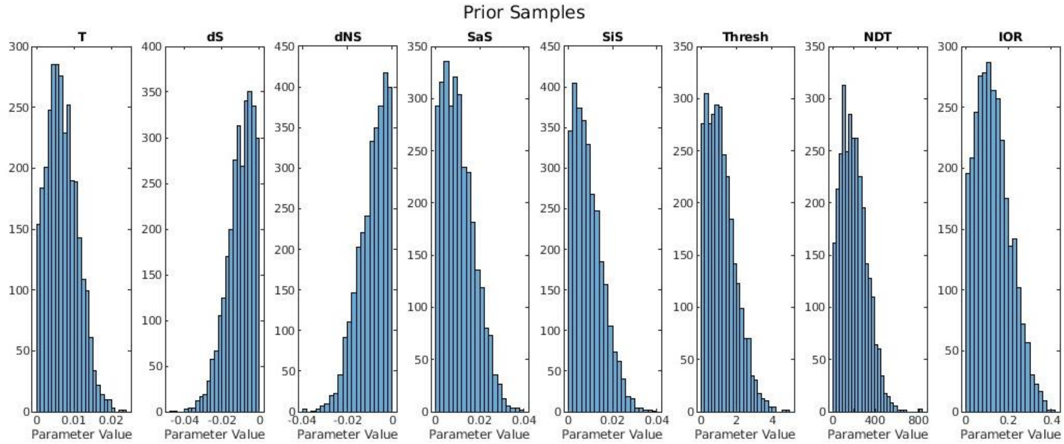

Figure 4 The distribution of the prior samples is characterised by eight criteria.

Table 2 Skewness, mean response time and accuracy of the posterior distribution of model predictions

	VALUE
SKEWSIM	51.6420
SKEWSAL	59.3646
MEDIANSIMRT	544.4842
MEDIANSALRT	551.2457
ACCSIM	88.9667
ACCSAL	89.6947

Table 3 Mean response time, standard deviation of response time and accuracy of real experimental data distribution.

	Mean RT (ms)	STD RT (ms)	Accuracy rate
Salient	647	499	0.937
Similar	676	357	0.926

3.2 Quality of fit

In this study, we conducted a comparison between the posterior parameters generated by the model and the actual data. This comparison was performed using various statistical measures, including the cumulative distribution function (CDF), delta plot (DP), error rate (ER), and conditional accuracy function (CAF). The results of this comparison, obtained by the difference comparison function, are presented in Figure 1. In this context, the prior distribution value is modified based on the discrepancy to bring the a priori generated posterior values closer to the actual data. Consequently, the adjustment of the prior distribution value is contingent upon the outcome of the difference comparison function. The CDF function in the difference comparison function allows for the calculation of the distribution probability value of the posterior parameter distribution, given the current a priori distribution. Additionally, in Figure a, the horizontal coordinate represents the average reaction time in seconds, while the vertical coordinate represents the integral value of the probability density function. In the shown figure, the blue hue represents the data that has been forecasted by the model, whilst the grey hue represents the actual data that has been collected from the experimental observations. The solid line and solid circles represent the dominant distractor trials, whereas the dashed line and hollow circles correlate to the trials including comparable distractors. Based on the delta function (DF) calculation depicted in Figure b, the analysis illustrates the disparity between two distinct trial scenarios, namely salient distractor trials and similar distractor trials. The grey colour in the plot signifies the percentage difference observed in the actual data, while the solid blue line represents the percentage difference between salient and similar trials as predicted by the fitted model. The error rate (ER) is a commonly utilised metric for models that involve classifications. It quantifies the extent of prediction error exhibited by the fitted model in relation to the actual scenario. The error rate is normally given as a percentage and may be calculated as ER = 1 - accuracy rate, where accuracy rate represents the proportion of correct predictions made by the model(Ting, 2010). In this context, Δ represents the discrepancy between the two sets of experimental trials. The term "grey" denotes the actual data value, while "blue" refers to the corresponding value generated by the model. The figure d displays the values of the conditional accuracy function (CAF). In this figure, the grey colour represents the actual data, the solid diamonds represent the distractor trials that have been highlighted, and the hollow diamonds represent the similarity trials. The blue colour represents the model data, with the solid line representing the distractor trials and the dashed lines representing the similarity trials.

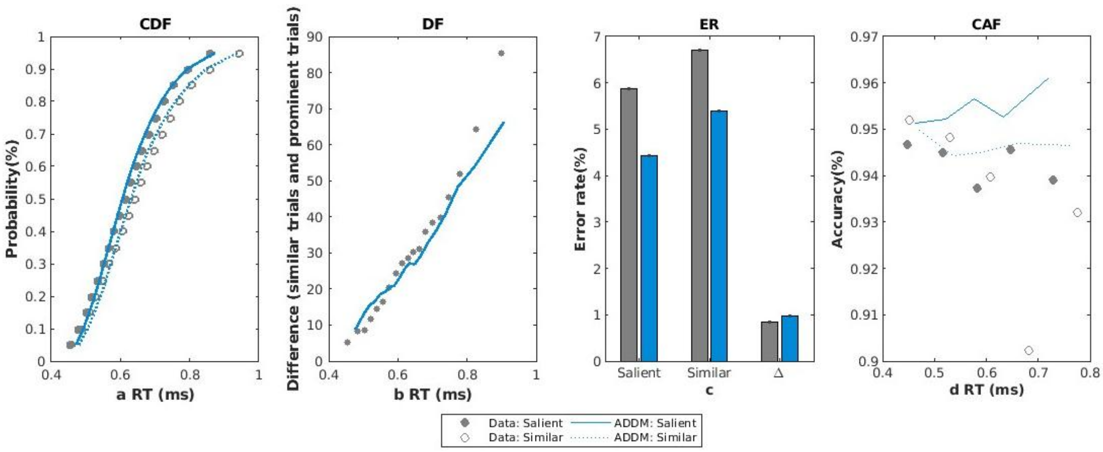

Figure 5 The result of comparable difference function

3.3 Correlation analysis

Subsequently, the investigation examined the association between the final posteriori parameters and the AQ scores. The R^2 value in the figure represents the degree of correlation between the parameter and the AQ scores. A R^2 indicates a negative correlation between the parameter and the AQ scores, while a positive R^2 indicates a positive correlation between the parameter and the AQ scores. The p-value represents the level of significance of the correlation. A p-value below 0.05 indicates a substantial connection between the parameter and the AQ score. This implies that the parameter is strongly associated with the AQ score when the p-value is considerably lower than 0.05.

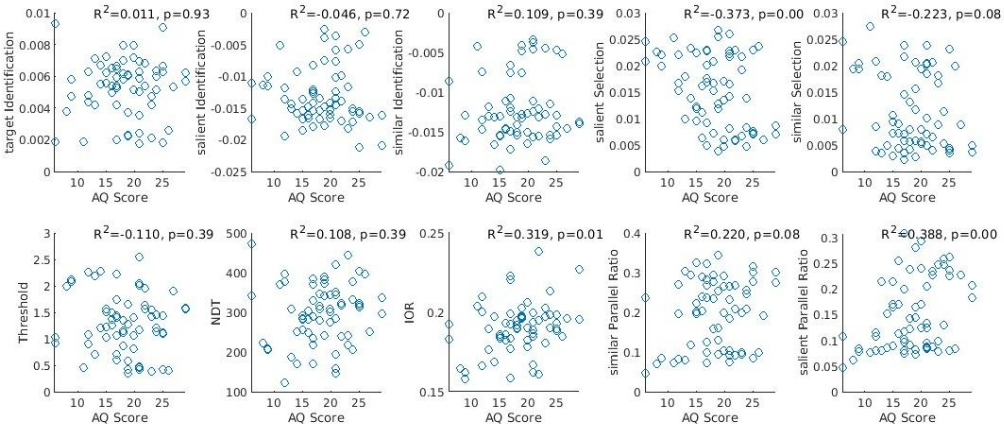

Figure 6 The scatter of the correlation between eight parameters and AQ Score

Furthermore, this study aims to analyse the dual phases of the comprehensive model to ascertain if the two phases of the attentional orienting process within the drift-diffusion model occur concurrently or sequentially. In the present study, the method of determining the parallel or sequential nature of the two phases of the model, referred to as "getParallelRatio," is described. This method involves assessing the status of all evidence associated with the identified processes and examining the selection of process evidence in trials that have been identified based on the accumulation time. This study aims to assess the relative durations of the evidence accumulation phase and the cognitive processing phase involved in attentional orientation. Specifically, we examine whether the time required for evidence accumulation during the selection process exceeds the reaction time for the overall cognitive process. This is achieved by calculating the ratio of the selection time to the total reaction time, and comparing it to a value of 1. Ultimately, the investigation revolves around ascertaining whether the selection and recognition processes of the attentional drift-diffusion model transpire in a parallel or sequential manner, as shown by the ratio of selection time to the total reaction time.

4 Discussion

The findings of the research exhibit a partial convergence with the experimental hypothesis, indicating a substantial link between certain parameters of the model and the AQ scores. Based on the presented scatter plot, the findings of this research indicate a statistically significant experimental association between elevated AQ scores and prominent distractors, suggesting a relationship between salient distractors and the distinctive features often seen in individuals with ASD. The focal point of discussion is in the findings of this research, which reveal a substantial negative correlation between the selection rate of salient distractors and the AQ score. The results indicate a significant association between AQ scores and the cognitive process of selectively attending to attention-grabbing distractors. The results of this study indicate that individuals with elevated Autism Quotient (AQ) scores, which are indicative of autistic features, have reduced rates of selection on trials including prominent distractors. The selection process is characterised by a hierarchical approach to actively controlling goal prediction. Consequently, individuals with higher AQ scores are inclined to exhibit less capacity for actively processing situational information, leading to a bias in cognitive processing and an increased likelihood of engaging in goal-directed activities. This finding aligns with the research conducted by Hogeveen, Krug, Elliott, Carter, and Solomon (2018), which indicates that engaging in active control is linked to a decrease in attention difficulties among individuals with ASD. Alternatively, taking into account Braver's (2012) DMC framework, this study has partitioned the cognitive control process of attention into active and passive control components. Consequently, the objective of this study was to examine the distinctions between active and passive control, particularly within the subset of individuals exhibiting high AQ scores. The current research primarily focuses on the manifestation of active control via target selection, whereas passive control is shown during the recognition of both the target and the distractor. These processes are believed to occur simultaneously in the ADDM. In the current study's framework, it was hypothesised that participants would engage in evidence accumulation for decision-making and recognition processes. Specifically, it was expected that participants would reach a decision or recognition threshold based on the accumulation of evidence. This threshold would determine whether participants correctly identified the target and whether their attention was influenced by other factors, such as distractors. The results indicate a substantial correlation between high AQ scores and decision rate on trials with prominent distractors. This suggests that characteristics often seen in individuals with ASD are closely linked to the cognitive processes involved in actively controlling attention. In essence, individuals with ASD have a greater susceptibility to the brain's inherent active cognitive processes, resulting in an increased tendency to exhibit attentional bias towards certain targets. Moreover, the model included an extra bias factor for IOR as an additional factor in the phase of the selection process, perhaps indicating the participant's acquired experience after their involvement in a trial as an inherent bias. However, it was determined throughout the testing process that this number was assigned as a random constant value during the model fitting. Hence, the findings of this investigation indicate that the model adequately accommodated the data, independent of the IOR parameter. Furthermore, the inclusion of the IOR parameter did not significantly impact the interpretation of the model within the context of the Attentional Drift Diffusion Model (ADDM) discussed in this work. Nevertheless, the research conducted by Frischen et al. (2007) shown that the impact of IOR on the reaction to gaze cues is contingent upon the removal of attention from the location of the cue. This finding contradicts the outcomes of the studies conducted in the current study regarding the significance of IOR for the model. Put simply, the current study's model was not influenced by the value of IOR in its selection of the target stimulus. This finding contradicts the results drawn from the majority of prior investigations. Consequently, this discrepancy presents an opportunity for additional investigation in future studies. However, despite the model's prediction of a parallel dual process for the active-passive cognitive control, the calculations conducted in this study indicate that the active selection process is more likely to occur before the passive control process. Furthermore, it is suggested that the drift of attention is achieved by accumulating evidence that influences attention until it reaches a certain threshold.

Further examination will be conducted on the degree of congruence between the model used in this research and the actual data, specifically focusing on the extent to which the model accurately represents the observed data. The outcomes derived from the use of the difference comparison approach are shown in Figure. The probability density function of the reaction time, as predicted by the model, is calculated and compared to the actual trial data. The results indicate that the model proposed in this paper is able to closely approximate the probability density value of the reaction time distribution observed in the real trial. This suggests that the attentional drift diffusion model developed in this study is highly likely to accurately represent the cognitive control process involved in attentional orientation in real-world scenarios. To facilitate a more accurate assessment of the distinctions between trials featuring similar distractors and trials featuring salient distractors, the current study employed a delta function to compute the disparity between the model-generated data and the experimental data pertaining to reaction times for both salient and similar distractors. This disparity was then graphically represented by plotting the linear difference between the predicted reaction times for the two trial types, as depicted in the figure. Notably, the figure illustrates that the reaction time surpasses 0.8ms. The dissimilarity in response times between the two trial types, as projected by the model, is comparatively less than that seen in the actual trials. This suggests that the model, when reaction time exceeds 0.8ms, may not correctly represent the phenomenon of attentional drift in real-world scenarios. Based on the model, it is evident that the cognitive control process of attentional orienting can be delineated into two consecutive stages: selection and recognition. Notably, the selection process precedes the recognition process, indicating that the model's recognition process does not sufficiently align with the actual recognition process. This study aims to determine the duration of the entire selection process once the final selection process has concluded. This can be achieved by calculating the rate of evidence accumulation during the selection process, which is less than 1, to identify the trial. Additionally, the time required for evidence accumulation during the successful judgement process can be obtained by screening the trials based on their rate of successful judgement process evidence accumulation.

This research aims to conduct a complete analysis of attentional processes that may be impacted or linked to autism. Additionally, the study seeks to enhance our comprehension of the underlying logic by using AQ scores as a representation of the expression of autistic features. This methodology enables an examination of the impacts produced by the whole attentional perceptual process concerning the manifestation of these characteristics. This work uses a mathematical modelling approach to construct the ADDM model, which accurately measures the cognitive mechanisms involved in the processes of attentional perception, including selection and discrimination. Additionally, for the purpose of ensuring consistency in the research, the current work employs the DE-MCMC technique to estimate the model and assesses the adequacy of the fit using distributional metrics. The findings of this research demonstrate a significant association between AQ scores and the rate at which the attentional selection process occurs. The results obtained from the AQ assessment are considered to be suggestive of ASD. In the current research, the selection of targets in the ADDM model is illustrative of the proactive cognitive control process. Nevertheless, the categorization of objectives and distractors mostly reflects the reactive control mechanism. Hence, this discovery offers additional support for the notion that characteristics associated with ASD have an unconventional relationship with proactive control systems.

Nevertheless, it is essential for the writers of this study to take into account other variables while analysing this correlation. Numerous studies have shown that nonstandard attentional control and fluctuations in cognitive processes play a significant role in the emergence and progression of anxiety disorders. The observed correlation between these two variables might perhaps be attributed, at least in part, to challenges related to attentional shifting and disengagement disorders (Sokolova et al., 2017).

Furthermore, research done by Maisel et al (2016) revealed that persons diagnosed with autism have a diminished capacity to recognise and comprehend their own feelings, leading to an elevated inclination to evade or respond unfavourably to emotional situations. Therefore, the correlation between the severity of autism symptoms and levels of anxiety may be ascribed to deficiencies in emotional expression and acceptance, indicating that persons diagnosed with ASD are prone to heightened anxiety levels. Therefore, the alternative hypothesis proposed in this research posits that the variations in attentional perceptual control mechanisms seen in persons diagnosed with ASD are anticipated to be linked to anxiety as well. Hence, this juncture marks the opportunity to enhance and modify the upcoming model by integrating diverse datasets including metrics pertaining to fundamental indications such as autism, anxiety, emotional acceptance, dysarthria, and intolerance of uncertainty (IU). The objective of this study is to examine the effects of deviations in attentional perceptual regulation linked to autistic characteristics. An area that warrants additional exploration in this study is the examination of later optimisations of the model.

5 Conclusion

The primary objective of this study is to examine the relationship between cognitive control processes and features associated with ASD. To achieve this, the study employs a diffusion model of attentional drift, incorporating correlation parameters derived from data collected during non-targeted perceptual similarity and salience trials of the T-task. The findings presented in this research suggest that the model put forward gives empirical support for the notion that cognitively regulated attentional selection processes may play a role in the manifestation of common symptoms associated with ASD, including impaired social interaction and repetitive behaviour. The negative connection seen between AQ scores and the rate of target selection on trials with salient distractors in this research may be attributed to the fitting of the ADDM model to the experimental data acquired from the T-task. In other words, those who obtained high scores on the AQ assessment had a decreased speed in selecting targets when faced with prominent distractors, compared to individuals who obtained low scores on the AQ assessment. Nevertheless, there is potential for further refinement of the model in the current investigation. For instance, exploring the impact of IOR as an additional bias factor on the selection process, as well as refining the functional approach to ascertain whether the selection process and the recognition process are dual processes with parallel responses or sequential processes conducted independently, can be further improved in future studies.

6 Reference

American Psychiatric Association, a. Q. P. A. (2016). Neurodevelopmental disorders : DSM-5 selections / American Psychiatric Association: Arlington, VA : American Psychiatric Association Publishing, 2016.

Di Martino, A., Ross, K., Uddin, L. Q., Sklar, A. B., Castellanos, F. X., & Milham, M. P. (2009). Functional Brain Correlates of Social and Nonsocial Processes in Autism Spectrum Disorders: An Activation Likelihood Estimation Meta-Analysis. Biological Psychiatry, 65(1), 63-74. doi:https://doi.org/10.1016/j.biopsych.2008.09.022

Sherri, M., Boulkaibet, I., Marwala, T., & Friswell, M. I. (2017). A Differential Evaluation Markov Chain Monte Carlo algorithm for Bayesian Model Updating. doi:10.48550/arxiv.1710.09486

Ting, K. M. (2010). Error Rate. In C. Sammut & G. I. Webb (Eds.), Encyclopedia of Machine Learning (pp. 331-331). Boston, MA: Springer US.

Nature, https://www.nature.com/subjects/cognitive-control

Abu-Akel, A., Apperly, I., Spaniol, M. M., Geng, J. J., & Mevorach, C. J. S. r. (2018). Diametric effects of autism tendencies and psychosis proneness on attention control irrespective of task demands. 8(1), 8478.

Amer, T., Campbell, K. L., & Hasher, L. (2016). Cognitive Control As a Double-Edged Sword. Trends Cogn Sci, 20(12), 905-915. doi:10.1016/j.tics.2016.10.002

American Psychiatric Association, a. Q. P. A. (2016). Neurodevelopmental disorders : DSM-5 selections / American Psychiatric Association: Arlington, VA : American Psychiatric Association Publishing, 2016.

Blaser, E., Eglington, L., Carter, A. S., & Kaldy, Z. (2014). Pupillometry Reveals a Mechanism for the Autism Spectrum Disorder (ASD) Advantage in Visual Tasks. Scientific Reports, 4(1), 4301. doi:10.1038/srep04301

Braver, T. S. J. T. i. c. s. (2012). The variable nature of cognitive control: a dual mechanisms framework. 16(2), 106-113.

Farrant, K., & Uddin, L. Q. (2016). Atypical developmental of dorsal and ventral attention networks in autism. 19(4), 550-563. doi:https://doi.org/10.1111/desc.12359

Farrell, S., & Lewandowsky, S. (2018). Computational Modeling of Cognition and Behavior: Cambridge University Press.

Frischen, A., Smilek, D., Eastwood, J. D., & Tipper, S. P. (2007). Inhibition of return in response to gaze cues: The roles of time course and fixation cue. Visual Cognition, 15(8), 881-895. doi:10.1080/13506280601112493

Greenaway, R., & Plaisted, K. (2005). Top-Down Attentional Modulation in Autistic Spectrum Disorders Is Stimulus-Specific. Psychological Science, 16(12), 987-994. doi:10.1111/j.1467-9280.2005.01648.x

Hogeveen, J., Krug, M. K., Elliott, M. V., Carter, C. S., & Solomon, M. (2018). Proactive control as a double-edged sword in autism spectrum disorder. J Abnorm Psychol, 127(4), 429-435. doi:10.1037/abn0000345

Maisel, M. E., Stephenson, K. G., South, M., Rodgers, J., Freeston, M. H., & Gaigg, S. B. J. J. o. a. p. (2016). Modeling the cognitive mechanisms linking autism symptoms and anxiety in adults. 125(5), 692.

Marotta, A., Pasini, A., Ruggiero, S., Maccari, L., Rosa, C., Lupiáñez, J., & Casagrande, M. (2013). Inhibition of Return in Response to Eye Gaze and Peripheral Cues in Young People with Asperger's Syndrome. Journal of Autism and Developmental Disorders, 43(4), 917-923. doi:10.1007/s10803-012-1636-3

Mazaheri, A., DiQuattro, N. E., Bengson, J., & Geng, J. J. (2011). Pre-stimulus activity predicts the winner of top-down vs. bottom-up attentional selection. PLoS One, 6(2), e16243. doi:10.1371/journal.pone.0016243

Sokolova, E., Oerlemans, A. M., Rommelse, N. N., Groot, P., Hartman, C. A., Glennon, J. C., . . . Buitelaar, J. K. (2017). A Causal and Mediation Analysis of the Comorbidity Between Attention Deficit Hyperactivity Disorder (ADHD) and Autism Spectrum Disorder (ASD). Journal of Autism and Developmental Disorders, 47(6), 1595-1604. doi:10.1007/s10803-017-3083-7

Thapar, A., Cooper, M., & Rutter, M. (2017). Neurodevelopmental disorders. The Lancet Psychiatry, 4(4), 339-346. doi:https://doi.org/10.1016/S2215-0366(16)30376-5

7 Appendix

Link to github with all relevant modelling data and functions as well as statistical analysis: https://github.com/DietmarHeinke/FittADDM2TTask1.git